Assessing Impacts of Abnormal Events on Travel Patterns Leveraging Passively Collected Trajectory Data

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Abstract

Travel patterns can be impacted by abnormal events. Assessing the impacts has important implications for relief operations and improving preparedness or planning for future events. Conventionally, the assessment is done followed by data collection from post-event surveys, which are economically costly, suffering low-response rate, time-consuming and usually delayed for months (or even years) after an event, leading to inefficient and unreliable assessment and creating obstacles for relief organizations to reach people in need. Penetration of smartphones and services enabled by them continuously generate large amount of trajectory data (e.g., Call Records Data, App-based data), containing trajectories of massive users. These trajectory data are passively and timely collected and without additional cost and contain information of travel patterns of the massive number of individuals in a region for a prolonged time period (e.g., months to years). We propose a framework to assessing the impacts on travel patterns using these data. Utilizing the passively collected trajectory data, the proposed framework seeks to capturing and understanding the full spectrum of travel pattern changes, which helps to assess who, when and how people in a certain area were impacted. The proposed framework is applied to a mobile phone trajectory dataset containing about half-year trajectories of a million anonymous users to assess the impacts of Hurricane Harvey (the second-costliest hurricane in US history). The results are validated and show that the proposed framework can provide a comprehensive assessment of impacts of Harvey on travel patterns, which could guide the response to and the recovery from the impacts.

Key words:
Abnormal Events, Travel Patterns, Mobile Phone Trajectory Data, Hurricane Harvey

1. Introduction

Transportation systems can be disrupted by abnormal events of small to extreme, including unplanned accidents such as bridge collapse (Zhu et al., 2010), planned road closures (Zhang et al., 2012), and natural or human-caused disasters (Donovan and Work, 2017; Lindell et al., 2019). Consequently, travel patterns of system users (e.g. the number of trips, where the trips are from and to, mode and route used) would be impacted. Assessing these impacts guides responses and recovery and would also benefit planning and operations for future events.

Conventional data sources that have been used to assess the impacts on travel patterns under various events typically include traffic count data to capture changes in traffic flow patterns (Zhang et al., 2012), ridership data from transit and other modal uses (Donovan and Work, 2017), and surveys of individual

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users on their travel patterns (Zhu et al., 2010). These data sources have a number of limitations. The first limitation is their often low spatial and temporal coverage: traffic counters are typically available on highways but not on local streets; counts for transit uses and other modes (e.g., bike and walking) are often incomplete; and individual surveys are typically of small sample sizes ranging from 0.5% to 1% due to their high costs (Michalowski, n.d.). These surveys also only capture a snapshot of the pattern changes (e.g., right after the event), ignoring the dynamics that play out over time. These limitations, both spatially and temporally, make it hard to capture regional-level and long-term impacts. The second limitation is related to the underlying population of the data: each data source may capture travel patterns of one specific group of people independently (e.g., transit users) rather than that of generic population. Though the integration of different data sources or findings from different data sources is a potential solution, its implementation would be challenging, as it is unclear how one data relates to another (Zhang et al., 2018).

In recent years, passively collected trajectory data, including mobile phone data, social media data and vehicular GPS data, are emerging and show opportunities for capturing and understanding travel patterns (Chen et al., 2016, 2014; Hasan et al., 2012; Wang et al., 2019; Wang and Chen, 2018; Yabe and Ukkusuri, 2019). These emerging data sources typically contain trajectories (a sequence of time-stamped geolocations) of a massive number of users. They are less limited in spatial and temporal coverage, as a dataset could pervasively cover an entire region of interest for several years. Important trip-related information could be extracted and inferred from these data, including the origin and destination of each individual trip, identification of commuting trips, and associated mode and route choices. This study proposes and demonstrates a framework for leveraging such data to assess impacts of an abnormal event through capturing the full spectrum of travel pattern changes.

More specifically, the framework leverages the passively collected trajectory data to present a comprehensive picture of changes in travel patterns from both collective and individual perspectives. The collective perspective seeks to identify who are impacted, when they are impacted and how travel patterns of travelers are impacted; the individual perspective conducts detailed, individual-level trajectory-based analysis, allowing us to gain additional insights on how changes of travel patterns at collective level may emerge from changes in individual trajectories. We apply this framework to a mobile phone trajectory data to understand the impacts of Hurricane Harvey in 2017. The dataset consists of half-year trajectories generated by 20% population in South Texas (Ban et al., 2018). The results show that changes of travel patterns under the impacts of Harvey could be captured, including spatio-temporal changes of exit-entry balance, the number of trips, total length travel, and center and size of individual trajectories. These changes could be understood as results from preparation, evacuation and return activities: individuals started traveling away from their homes as early as three days before the Harvey landfall (August 23) and gradually returned within the three days after the landfall. We show that individual-level measures could explain patterns that emerge from collective measures: the temporal evolution of trajectory center and size, for example, explain the reason why the total length traveled do not increase coherently with the total number of trips on the morning of August 24. At last, we discuss future directions, including addressing potential limitations of the proposed framework relating to both data issues as well as the potential for integrating the current framework with conventional data sources.
2. Related work

Conventionally, data for capturing impacts of abnormal events on travel patterns involves active data collections. Traffic count data from installed detectors are commonly used. Using this data, researchers investigate the impacts of various types of abnormal events on traffic flow patterns. Zhang et al. (Zhang et al., 2012) examined the impacts of the planned closure of a major freeway on the network of downtown Sacramento, California; He and Liu (He and Liu, 2012) modeled the traffic evolution after the collapse of I-35W Mississippi River Bridge in Minneapolis, Minnesota; Archibald and McNeil (Archibald and McNeil, 2012) explored traffic flows before, during and after Hurricane Irene. As noted earlier, being often only available on highways and on selected local streets, count data are either not available or sparsely distributed. More importantly, count data only tells the number of vehicles passing certain points on the road network; they are measures of road performance but cannot directly tell where the vehicles come from or go to. Similarly, ridership data on transit or bike and pedestrian count are measures for performance and also cannot tell changes in travel patterns involving where the trips are from and to, mode and route changes (Bia

Another useful data are these collected from surveys of individual users. It is a common practice to conduct post-disaster surveys to collect data, which could be used for understanding the evacuation process (Lindell et al., 2019; Yin et al., 2014). As an example, Zhu et al. (Zhu et al., 2010) conducted a survey after the collapse of I-35W Bridge and investigated travelers’ reactions to changing their morning commute trips. Survey data, despite of its rich information, are expensive to collect and typically have very limited spatial and temporal coverage: Zhu et al. (Zhu et al., 2010) collected information of morning commute trips before and after the bridge collapse from 141 individuals whose homes or workplaces located within two communities that are close to (within 5 miles) the bridge.

Passively generated data are emerging as a useful data source for analyzing travel patterns. These data are byproducts of certain purposes that are not intended for any travel pattern analysis and examples include cellular data generated for billing and operation (Ban et al., 2018), taxis GPS data for taxi operation (Bian et al., 2019; Bian and Wilmot, 2019; Donovan and Work, 2017) and social media data (Guan et al., 2016; Guan and Chen, 2014; Yabe and Ukkusuri, 2019). Each data would contain trajectories (sequence of time-stamped geolocations) of massive users, typically lasting for months or even years and covering one entire region. These emerging data have been extensively utilized for understanding people’s travel patterns in the last decade. Recently, some studies are conducted to explore the potentials of utilizing emerging data for analyzing travel patterns during a disaster. Using cellular data, researchers analyzed population displacements after earthquakes (Lu et al., 2012; Song et al., 2017). Data from social media were used to examine people’s activity spaces (Wang and Taylor, 2014) and return behaviors (Yabe and Ukkusuri, 2019) under impacts of hurricanes. These studies provide important insights in one or multiple aspects of travel patterns, and yet, we still lack a framework that can provide a comprehensive picture of the changes in travel patterns. It is the objective of this paper to propose such a framework and demonstrate its usefulness in capture travel pattern changes following a major event (Hurricane Harvey).
3. Data

The mobile phone trajectory dataset has a temporal span of August and September of 2017 for analyzing the impacts of Hurricane Harvey, which made landfall along the Texas Center Coast on late August 25, 2017. Harvey is the second-costliest hurricane in US history, exceeded only by Hurricane Katrina (National Weather Service, 2018). The data collected covers 122 counties in South Texas and Southwest Louisiana, which either issued emergency declaration or were severely impacted with flooding or strong wind (FEMA, 2017).

The data includes anonymous users (represented by encrypted and hashed identification number (ID)) who opted in to share location data in the study area (about 10% of population). Each observation passively records time-stamped geolocation when users use mobile phone apps (around 200 apps including shopping and navigation, among others). The trajectory of a user is represented by a sequence of time-stamped geolocations. The trajectory has to be processed to extract stays (i.e. where people stay for a certain amount of time to do activities), which are the foundation of analyzing travel patterns. The processing depends on the temporal and spatial properties of the data:

- **Temporal**: Observations are not evenly distributed in time. Half of the intervals are within 20 s, and 20% of them could be longer than 50 s, ranging from several minutes to hours and even days. The long time intervals illustrate the issue of temporal sparsity to the data (Chen et al., 2016; Wang et al., 2019; Wang and Chen, 2018).

- **Spatial**: Locations recorded contain uncertainties and may not reflect a device’s true location. 80% of observations have an accuracy smaller than 100 meters whereas others range between 100 meters to several thousands of meters.

Considering the temporal sparsity issue, we keep only users who have observations in every day of the two-month study period, yielding 725,173,388 observations of 102,727 users. We apply a recently developed DCI framework (Wang et al., 2019) to extract stays from the trajectory data, where the large variance of location accuracy is considered. The framework identifies a stay as a cluster of time-ordered observations that are close in space and have a sufficiently-long duration (the time difference between the first and the last observation belonging to the cluster). A typical stay obtained satisfies two constraints: the distance between any two observations in the cluster is shorter than 200 meters and the duration is longer than five minutes. With the DCI framework, a common stay that is visited at different times (e.g., two days) is also identified, which allows us to analyze travel patterns such as frequently returning home. The home location of a user is identified as the location where the user frequently visited during nighttime of the normal days, which are three weeks before the release of hurricane watch by National Hurricane Center on August 23 of 2017. Here, three weeks are selected as studies suggest that observations of three weeks are long enough for capturing travel patterns in normal days (e.g., travel regularity) (Chen et al., 2017; Schlich and Axhausen, 2003; Song et al., 2010). Previous investigations show that the home density is coherent with census population density at census tract level (with a correlation coefficient of 0.91 in (Wang et al., 2019)).

More properties of the applied mobile phone trajectory data and the DCI framework can be found in previous works by the authors (Ban et al., 2018; Wang et al., 2019).
4. Methodology

4.1. Overview

Table 1 presents the framework at both collective and individual levels along with their associated measures and questions of interest. We discuss the associated hypotheses in the texts following Table 1.

Table 1. The proposed framework and the associated measures

| Perspective | Measure                        | Question of interest                                      |
|-------------|--------------------------------|----------------------------------------------------------|
| Collective  | Relative flow balance          | Who were impacted?                                       |
| Collective  | Relative flow balance          | When was impacted?                                       |
| Collective  | Number of trips;               | How were properties of travel patterns impacted?         |
| Collective  | Length traveled;               |                                                          |
| Collective  | Road usage pattern;           |                                                          |
| Collective  | Spatial distribution of trip ends; |                                                        |
| Individual | Trip rate                     | Was trip rate of an individual impacted?                 |
| Individual | Trajectory center and size     | Was activity space of an individual impacted?            |
| Individual | Exploration ratio             | Was an individual’s travel regularity (exploration & return) impacted? |

4.2. Collective measures

4.2.1. Who

To identify impacted areas/population in the study region during a time interval $t$, we calculate the exit-entry balance for each area $c$ within the region$^2$ as:

$$b^c_t = \text{exit}^c_t - \text{entry}^c_t. \quad (1)$$

Here $\text{exit}^c_t$ and $\text{entry}^c_t$ are total number of trips exited and entered area $c$ during time period $t$. An exit trip for area $c$ has its origin inside and its destination outside of the area; an entry trip has its origin outside and its destination inside of the area. In our study, instead of observing either $\text{exit}^c_t$ or $\text{entry}^c_t$ alone, we compute the exit-entry balance such that we ignore passing-by areas that lie between evacuation zones and destination zones and are observed both large $\text{exit}^c_t$ and $\text{entry}^c_t$. One may observe both $\text{exit}^c_t$ and $\text{entry}^c_t$ independently, if, for example, passing-by areas are of interest. To quantify the influence of an abnormal event on travel patterns, the exit-entry balance $b^c_t$ is compared with that of normal days $b^c_H$ to obtain a relative exit-entry balance, where the subscript $H$ refers to a time period within normal days (historical data). We define normal days as a period of three weeks prior to impacts of any abnormal events (e.g. prior to the release of hurricane watch notice on August 21). Area $c$ is impacted by an abnormal event if $b^c_t$ is found significantly deviating from $b^c_H$. Formally, relative exit-entry balance $\beta^c_t$ is calculated as:

$$\beta^c_t = \frac{b^c_t - b^c_H}{|b^c_H|}. \quad (2)$$

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$^2$ The definition of an area could be following any administrative boundaries or customized zoning systems (Donovan and Work, 2017).
Here, $|\cdot|$ is the absolute operation to normalize the effect of area/population size, which helps to differentiate an impacted small area with a large area that is not impacted but under normal fluctuations. The observations from the mobile phone trajectory data indicate that $|b_{c}^{H}|$ is always non-zero as it is not likely to observe exit $v_{c}^{e}$ and entry $v_{c}^{e}$ being identical. A positive value of $\beta_{c}^{e}$ indicates area $c$ is dominated by exit trips compared with normal days and a negative value indicates area $c$ being dominated by entry trips. By setting a threshold $\beta^{*}$, an area $c$ is affected if $|\beta_{c}^{e}| > \beta^{*}$. The hypothesis of using relative exit-entry balance $\beta_{c}^{e}$ as an indicator for identifying impacted areas is that, the exit-entry balance in an impacted area would significantly deviate from that of normal days due to some activities such as evacuations.

Reference set: In Equation 2, we set the flow balance during normal days $b_{c}^{H}$ as the reference for detecting and quantifying deviations. $b_{c}^{H}$ has a periodic weekly pattern: its temporal patterns are different from day to day but are similar from week to week. For example, the pattern on a Monday would be different with the pattern on a Sunday but similar to another Monday. Therefore, a desirable treatment is to calculate $b_{c}^{H}$ as a reference set, representing flow balances of all time intervals of a week. And the flow balance during a time interval is the average flow balances of three corresponding time intervals in the three weeks. For example, if the reference set contains seven values with the first one corresponding to the first day of the week, the first value is the average of three first days of the three weeks. Given a reference set, $b_{c}^{H}$ will be compared with the corresponding time interval within the set.

4.2.2. When

Following the previous calculations, the time period of an area $c$ being impacted is when $|\beta_{c}^{e}|$ is larger than $\beta^{*}$. The hypothesis is that the flow balance would significantly deviate from that of normal days when an area is under impacts.

4.2.3. How

For an impacted area $c$, to investigate how travel patterns of its inferred residents (users whose home located within $c$) would be impacted, we propose to measure properties of travel patterns and their evolution over time, including the number of trips, the length traveled, road usage pattern and distribution of trip ends. Similarly, all these measures are compared with these of normal days. Different from individual-level metrics that are introduced later for measuring individual patterns, these metrics try to capture the changes in demand on the system. Each metric is introduced below. For convenience, notation $c$ is omitted in symbols introduced below.

a) The total number of trips $N_{t}$ by all residents of area $c$ during time period $t$ is a direct and simple measure. The hypothesis is that the number of trips would be different with normal days due to activities in response to risks such as preparation activities, evacuation and staying at safe places.

b) Similar to the previous measure, the total length traveled by all residents of area $c$ $l_{t}$ during time period $t$ in area $c$ is a straightforward measure of travel patterns. It is calculated as the total length of all trips observed in time period $t$ and area $c$: $l_{t} = \sum_{i=1}^{N_{t}} length_{i}$ with $i$ being one observed trip. The hypothesis is that under impacts people would travel for longer or shorter distance to meet their unusual needs such as evacuations or stays at safe places, compared with normal days.
c) Road usage patterns intends to assess how roads are utilized under impacts, which could guide operations to reduce cost and to accelerate recovery. The hypothesis underlying road usage analysis is that, due to infrastructure interruptions, operations or travelers’ route-changing behaviors, how roads are utilized under impacts would be different from that of normal days. Using survey data, previous studies found that evacuees prefer interstate highways to locals. Though traffic count data would directly provide information on how a road is utilized, the information is not sufficient for a region-level analysis, as limited roads (usually highways only) have detectors installed. Emerging data, with their region-wide coverage, offer us opportunities. Different from traffic count data, trajectories recorded in emerging data do not directly give us road usage patterns, but need some techniques for the translation. Ideally, one could conduct a map-matching process for each trip to find out which route (road segments) the trip follows and the road usage pattern would be the frequency of each road being used. However, due to the temporal sparsity and spatial uncertainty in the mobile phone trajectory data (Ban et al., 2018), existing map-matching methods would not be effective. On the other hand, conducting a map matching process to the massive data set would be computationally costly as it typically seeks an optimal solution to each match. Instead of applying map-matching, we propose an efficient method to evaluate road usage using the mobile phone trajectory data:

- Split the space into small grids (e.g., each grid being 100meters by 100meters);
- Map observations between any two trip ends upon the grids and count the number of observations falling in each grid $k_t^{xy}$; note that only observations resulting from travel activities of residents in area $c$ are mapped.
- To obtain a spatial distribution of observations, normalize the count $k_{xy}$ by dividing it by the summation of counts in all grids $p_t^{xy} = k_t^{xy} / \sum_{xy} k_t^{xy}$.
- Comparing the spatial distribution with the one of normal days could be done in two ways: (1) visualize the difference between the two distributions (i.e. $p_t^{xy} - p_H^{xy}$) on a road network and provide a qualitative description of visualized differences; (2) compute Kullback–Leibler (KL) distance for a quantitative measure:

$$D_t^{KL} = -\sum_{xy} p_H^{xy} \log\left(\frac{p_t^{xy}}{p_H^{xy}}\right)$$

Here, a large $D_t^{KL}$ means a large difference.

d) Another measure of properties of travel patterns is to observe the spatial distribution of activities (trip ends), i.e. where residents conduct their activities during a time interval. The observations could be important to understand residents’ decision making of destination choice as well as to humanitarian relief in terms of identifying area in need. The hypothesis here is that abnormal events would influence where people conduct their activities in space such that they either reduce or increase their activities around the impacted area during a time interval. The spatial distribution of activities during a time period could be measured in various ways. Here, we propose a simple measure—the fraction of activities $f_t$ that are located further than a certain threshold away from home among all the activities observed during time interval $t$. The threshold
depends on the size of area \( c \) and we recommend to use its radii (i.e., the largest distance between the centroid and any location within the area).

4.3. Individual-level measures

Individual-level measures are trajectory-based, which is on each individual’s trajectory. Besides providing a close examination of the dynamics of travel patterns, these measures would be helpful for understanding findings from collective measures. We propose three metrics to capture the temporal evolution of an individual’s trajectory, including trip rate, its center and size, and exploration ratio.

4.3.1. Trip rate

Trip rate \( n_t^a \) counts the number of trips conducted by individual \( a \) during time \( t \) (\( t \) is typically one day). As a simple measure of a traveler’s trajectory, it has long been used in studies on individuals’ travel patterns (Schlich and Axhausen, 2003). By adopting this metric, we hypothesize that travelers under impacts would conduct either more or less trips during a time interval, compared with normal days. As we show in Results section, the temporal evolution of mean trip rate per individual per day may be similar to the evolution of the previously introduced metric \( N_t \) (the number of trips by all residents). The difference between the two is that the former could provide more details if its distribution over all individuals is examined.

4.3.2. Trajectory center and size

An individual trajectory during time period \( t \) can be characterized by its center \( \overline{s_t^a} \) and size \( r_t^a \):

\[
r_t^a = \sqrt{\frac{1}{N_t^a} \sum_{i=1}^{N_t^a} (s_t^a - s_t^a)^2},
\]

(4)

where \( s_t^a \) represents the geolocation of a stay within the trajectory and \( \overline{s_t^a} \) is calculated as the center of all stays: \( \overline{s_t^a} = \frac{1}{N_t^a} \sum_{i=1}^{N_t^a} s_t^a \) with \( N_t^a \) being the number of stays visited by user \( a \) during time interval \( t \). The size \( r_t^a \), as shown in the equation above, is calculated as the average Euclidean distance of the center to all stays. To capture the temporal evolution of an individual’s trajectory, instead of using its center \( \overline{s_t^a} \) directly, we calculate the distance from its center to the individual’s home \( h_t^a \).

Figure 1 illustrates how \( r_t^a \) and \( h_t^a \) together characterize individual trajectories during time period \( t \). Three types of trajectories are shown in the figure:

- Type 1 shows a trajectory with trip ends that are centered at one place which is close to home. In this case, it has both small \( r_t^a \) and \( h_t^a \).
- Type 2 shows a trajectory with trip ends scattering in the space, which can be characterized by a large \( r_t^a \).
- Type 3 shows a trajectory with trip ends that are centered at one place which is far away from home. In this case, it has a small \( r_t^a \) but a large \( h_t^a \).

The hypothesis is that the center and size of an individual’s trajectory under impacts would be different from that of normal days and a unique evolution pattern over time could be observed. For example, an individual’s activities such as preparation, evacuation and stay from risks could be indicated
by the deviations of trajectory center and size from normal days: preparation activities around her house result into both small $r_t^a$ and $h_t^a$ observed (Type 1); an evacuation trip leads to large $r_t^a$ (Type 2) and $h_t^a$; and staying at a safe place that is far away from home results into small $r_t^a$ and large $h_t^a$ (Type 3).

![Figure 1 Example trajectories to explain $r_t^a$ and $h_t^a$.]

**4.3.3. Exploration ratio**

Exploration ratio $e_t^a$ is calculated as the fraction of new places (these not visited during normal days) visited during time period $t$. It is a close examination of stays contained in an individual’s trajectory. The hypothesis is that, during normal days, an individual’s travel pattern exhibits a high level of regularity as noted by previous studies (González et al., 2008; Song et al., 2010), meaning that the individual frequently returns to places that have been frequently visited, and this regularity is disrupted under impacts, which is reflected by the higher tendency of exploring new places (i.e. larger $e_t^a$) than normal days.

**5. Results: application to the dataset on hurricane harvey**

**5.1. Impacts on collective travel pattern**

**5.1.1. Impacted area (who)**

For each county, we calculate relative exit-entry balance $\beta$ during the 48 hours before the landfall. Note that a notice of hurricane watch would be released 48 hours before a predicted landfall by US National Hurricane center (National Weather Service, 2018). **Figure 2** shows the spatial distribution. Setting the threshold $\beta^* = 1$, counties with $\beta$ larger than 1 are colored in red, suggesting they were dominated by exit trips, compared with the 48 hours one week earlier. On the contrary, counties with $\beta$ smaller than -1 are colored in green, suggesting that these counties were dominated by entry trips. The
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Figure shows that coastal counties close to the landfall location were featured with massive exit trips during the 48 hours before Harvey’s landfall, which is consistent with a map of counties that received mandatory evacuation orders.

**Figure 2** Relative exit-entry balance $\beta$ during 48 hours before the landfall (color online).

5.1.2. **Impacted time period (when)**

To illustrate how the framework works to identify the impacted time period for an area, we focus on a small area that is close to Harvey’s landfall location—SNA area (selected in Figure 2). SNA area consists of three coastal counties (San Patricio, Nueces and Aransas), has a large population (454,008 according to the census 2017) and includes the 6th largest city (Corpus Chris) of Texas. Figure 3 shows the temporal evolution of the relative exit-entry balance in this area. Significant number of exit trips during the two days before the landfall (i.e. August 24 and 25) can be observed, suggesting evacuations on these two days. On the other hand, significant entry trips can be observed during the three days following the landfall, suggesting the reentry process.
5.1.3. Impacted dynamics of travel patterns (how)

Following the framework, properties of trips conducted by 3,280 residents in the SNA region are measured. Figure 4 shows the evolution of the total number of trips and length traveled by these residents over time. Results of three weeks around the landfall are overlapped, including the week before the landfall (the week of August 14), the week of the landfall (the week of August 21) and the week after the landfall (the week of August 28). The week of August 14 represents the reference here.

Large temporal variations can be observed in the number of trips around the landfall of Harvey: it increased on August 23 (the third day before the landfall), surged during the daytime of August 24 and reduced during the afternoon of August 25 and the entire day of August 26 due to the landfall. The increases may represent preparation and evacuation activities of SNA residents, while the decreases may represent their stays in safe places.

More variances are observed in the evolution of length traveled (LT), suggesting LT is a more sensitive measure than the number of trips. Specifically, LT increased significantly during the two days before and the three days after August 26. This could be caused by two mixed reasons: (1) total number of trips increased; (2) the proportion of long-distance travels increased during these days. Since we do not observe significant increases in the number of trips on August 25, 27, 28 and 29, the increase of LT on these four days would be attributed to the increased proportion of long-distance trips. The temporal pattern of LT on August 24 is interesting: (1) the increased LT in the evening could be attributed to the long-distance travels; (2) in the afternoon LT surged as the number of trips did, which may result from the mixed effect of the two reasons but not clear for the moment; (3) while the number of trips increased significantly in the morning, LT did not. This interesting pattern will be revisited and explained in the individual-level analysis.
Figure 4 The temporal evolution of (a) the total number of trips and (b) total length traveled by SNA residents. (In 3-hours intervals and colored online).

Results above suggest that, compared with normal days, during the 48 hours before the landfall, more trips can be observed from SNA residents, and these trips are dominated by trips exiting SNA area and featured as long-distance travels. The following part focuses on spatial distributions of these trips. Figure 5 shows the map of road usage pattern during the 48 hours before the landfall. We can observe that there are relatively more observations on interstate highways (in red) than other roads during the 48 hours before the landfall. This finding is consistent with existing studies, which discovered that people tend to use interstate highways during their evacuations from hurricanes (Lindell et al., 2019). Interestingly, one exception is observed on the highway connecting SNA area and Houston area (in green), as the Houston area was impacted by Harvey as well. The usage pattern of highways also suggests that SNA residents tended to used highways that connect SNA with cities such as Austin, San Antonio and Laredo, which are about 200 Km away from the SNA area. Beside the evacuation process, by plotting the road usage patterns after the landfall, we could identify roads/segments being underutilized, which may be helpful in guiding resource allocation for recovery.
Figure 5 Road usage pattern showing the difference of road usages between the 48 hours before the landfall and the 48 hours of a week earlier (red and green grids represent relatively heavier and lighter usage, respectively).

By mapping spatial distributions of trip ends and comparing them with home locations, we could compute the temporal evolution of trip ends distribution as shown in Figure 6. It is observed that from August 24 to 29, there are more activities at places that are beyond 50 Km away from home\(^3\), compared with other days. The peak on August 25 indicates that SNA residents were conducting activities far away from their home, suggesting the majority of residents had evacuated before August 25. This finding is consistent with previous ones, where massive exit trips and long-distance travels are observed before August 25 (Figure 3 and 4).

\(^3\) 50 Km is about the radius of the SNA region, as shown by the circle in Figure 5a.
5.2. Measuring Individual-level travel patterns

5.2.1. Trip rate

For each trajectory of an individual, we count how many trips the individual made on each day (i.e. daily trip rate). A weekly pattern is observed during the normal days but is interrupted around the Harvey landfall. It is found that, compared with normal days (on average 4.8 and 5.2 on weekdays and weekends, respectively), higher trip rates (5.0 on average) are observed as early as August 23. This is consistent with existing studies which found that people may start to evacuate from hurricanes as early as three days before the landfall (Lindell et al., 2019). The peak and the valley are observed on August 24 and 27 with mean value at 5.5 and 3.5, respectively. The weekly pattern recovered one week after the landfall.

Figure 6 Fractions of trip ends that are 50Km away from home (the 50Km circle is shown in the left panel). Weekends are marked in red to show a weekly pattern in normal days.
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5.2.2. Trajectory center and size

Figure 7 gives the temporal evolution of trajectory center to home $h_t$ and trajectory size $r_t$ of residents in the SNA area. The evolution curves are means values of all residents and are compared with the reference sets that are calculated as the mean of the first three weeks. We can observe that, starting in the afternoon (15:00 PM) of August 24, $h_t$ increases sharply approaching to the landfall and decreases gradually afterward, suggesting the process of evacuating and returning home. Interestingly, $r_t$ shows complicated patterns. These patterns contain rich information that could be drawn to explain findings that are not clear in collective measures. For example, we can explain why in Figure 4 the number of trips increased in the morning on August 24 but the length traveled did not. To explain this, we observe that, $r_t$ starts deviating from normal days in the morning (9:00 AM) of August 24, which is earlier than the 15:00 PM of $h_t$. This suggests that from 9:00 AM to 15:00 PM on August 24, individuals were more likely conducting preparation activities around their home than evacuating from their home and traveling away.

This observation could be validated using Point-Of-Interest data. Using Google Map API, the place types visited on the morning of August 24 are compared with these visited on the morning a week ago (i.e. August 17). Specifically, for each location visited on the Moring of August 24, its place type (e.g., a store, a gas station) is checked and then we compute the density distribution of place types of all locations visited by all users. The distribution is then compared with the one computed on the morning of August 17 and the difference is shown in Figure 8. It can be observed that users visited more places including different types of stores (the top ten store names are The Home Depot located at different cities/towns), pharmacy, finance, movie_rental (the top one place name is Redbox which is a company specializing in DVD, and video game rentals) and gas_station, etc.
Figure 8. Place types that were visited more compared with normal days. More frequently visited place types are indicated by larger font size.

5.2.3. Exploration ratio

Figure 9 shows the evolution of exploration ratio that is calculated as the fraction of places that were not visited in normal days (the first three weeks of August). Before the impact of Harvey, a regular daily pattern can be observed showing peaks in daytime and valleys at night. The regular pattern is interrupted starting 15:00 PM of August 24, indicating that individuals started visiting new places, which likely resulted from evacuation trips. It is also observed that even one week after the landfall, the exploration ratios do not return to the pre-impact level, suggesting the on-going recovery process.

Figure 9. The evolution of exploration ratio of individual trajectories. Binned in 3-hours intervals and showing averages of all individuals.
6. Discussion

The analysis has shown that following the proposed framework, the impacts of abnormal events like Hurricane Harvey on travel patterns can be assessed by leveraging emerging data such as the mobile phone trajectory data. The framework captures the full spectrum of travel pattern changes via combination of collective- and individual-level investigations, leading to a comprehensive assessment of the impacts. The assessment is shown helpful in guiding a fast response to the impacts. Since mobile phone trajectory data as well as other trajectory data such as taxi trajectory data and social media data are passively collected and have large temporal and spatial coverage, the analysis proposed is considered of low economic cost, and not limited to devices for data collection.

The study is an ongoing effort and can be improved in the future. One direction is to investigate how the analysis could be influenced by several data issues that commonly exists in emerging data. One data issue is that it is not clear whether users are representative samples of the population. Although a previous work (Wang et al., 2019) shows that the spatial distribution of the number of users aligns well with that of census population, the users may be different with the population in terms of their socio-demographic/economic and other profiles. We will investigate this issue with some cross-validations that compare some patterns observed from emerging data (e.g., road usage) with these from conventional data (e.g., traffic flow from detectors). The second issue is that the observed trajectory of one individual may not capture her true trajectory, as the former relies on the app/device usage that may be not travel-related. The current framework is designed to mitigate the potential effects of this issue. For example, we select users who have observations every day to control the variation in app/device usage along the study period; we adopt normalized measures (e.g., normalized spatial distribution of observations for evaluating road usage, fraction of trip ends beyond 50Km away from home among all observed trip ends) and keep in line with difference-in-difference analysis (e.g., comparisons with normal days to obtain relative changes, computing exit-entry balance for comparisons instead of using exit/entry trips directly). However, these treatments are under the assumption that the device usage pattern does not change over time such that the bias between the observed trajectory and true trajectory is stable. The future work will relax this assumption and see how the analysis is influenced. Following the influence of the data issues on the analysis being understood, a further study is to address these issues.

Another direction is to integrate conventional data into the framework. As mentioned earlier, conventional data have their advantages despite their limitations, allowing us to understand impacts on travel patterns from angles that are different from these emerging data do. For example, data from transit or other mode provide information on changes in travel modes and survey data, if available, remain a great source for understanding travel patterns and behaviors. Since each data source (conventional data or emerging data) contain information of different groups of population, of various spatial and temporal coverage and of different levels of details with other data sources, an expected integration that one data source would fill the others’ gaps, allowing us to answer questions of interest. For example, although travel time is an important measure for individual travels and a transportation system, it could not be reliably extracted from mobile phone trajectory data due to the temporal sparsity issue but can be obtained from Bluetooth system installed on roads.
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