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Disaster Resilience through Diverse Evacuation and Emergency Transportation Systems (Phase II) Final Report

by

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EXECUTIVE SUMMARY

Cities are facing unprecedented challenges from natural disasters due to climate changes in recent years. A lot of work has been done recently to obtain a better understanding of human behaviors and resilience to natural disasters utilizing large-scale human mobility datasets. Despite the efforts, there still lacks a comprehensive exploration of disaster preparedness, disaster impact, as well as disaster response and recovery with quantification indicators. To fill the knowledge gap, the objective of this study is to develop a comprehensive understanding of disaster resilience through preparation, disaster impact, and disaster residual effect using human mobility data under a natural disaster. To this end, a quantification methodology was proposed to measure unique characteristics of human mobility patterns in specific North American Industry Classification System (NAICS) sectors under disaster. Three metrics, including the preparation indicator, the impact indicator, and the residual effect indicator, were proposed for different disaster stages. The proposed method was implemented in a case study of four cities, including Panama City, Panama City Beach, Lynn Haven, and Tallahassee in Florida under the impacts of Hurricane Michael. Through the case study, human mobility patterns across different cities under different levels of disaster severity were examined. The patterns and relationships between the NAICS sector function, the preparation indicator, the impact indicator, and the residual effect indicator in different cities were compared. This study provides new methods and knowledge regarding disaster resilience and can help decision-makers to make informed decisions to better prepare for and respond to future disasters.

Chapter 1. Introduction

1.1 Problem Statement

Cities are facing unprecedented challenges from extreme weather events, sea-level rise, and heat waves due to climate changes in recent years (Hong et al. 2021). Many researchers have studied human mobility under the influence of natural disasters. Human mobility is human movement, as individuals or groups, in space and time. A comprehensive understanding of human mobility patterns under disasters is crucial for strategies aimed at improving community resilience.

To have a comprehensive understanding of human mobility patterns in a city in the context of a natural disaster, three questions were raised: First, do different levels of disaster severity have an impact on human mobility patterns in a region? Second, for disaster resilience quantification using human mobility data, what unique aspects need to be recognized? Third, how do different NAICS sector functions play a role in the overall human mobility pattern under disaster, from the preparation stage to the recovery stage?

1.2 Objectives

The objective of this study is to have a comprehensive understanding of human mobility patterns under a natural disaster. Specifically, three research objectives were proposed:

Objective 1: Compare human mobility patterns across different cities with different levels of disaster severity.

Objective 2: Propose a quantification methodology to measure unique characteristics of human mobility patterns in specific NAICS sectors.

Objective 3: Build connections of NAICS sector function, preparation, disaster impact, and recovery in the context of human mobility.

1.3 Expected Contributions

The potential benefits of the projects are twofold. First, it proposed different metrics to quantify human mobility patterns of different NAICS sectors under disaster, including the preparation indicator, the impact indicator, and the residual effect indicator. These indicators can capture unique characteristics of different stages of human mobility patterns under disaster. Second, it investigated relationships between the NAICS sector function, the preparation indicator, the impact indicator, and the residual effect indicator. The relationships identified can help decision-makers to make informed decisions regarding resilience development in a city.

1.4 Report Overview

Chapter 2 presents the methodology for human mobility pattern calculation, and quantifications of different indicators of human mobility under disaster. Chapter 3 presents a case study and its results of human mobility characteristics in different NAICS sectors using the proposed methodology. Chapter 4 further discusses results from the case study. Chapter 5 is the conclusion and future work part.

Chapter 2. Human Mobility Pattern and Quantification of Indicators

2.1 Literature Review

Previous research explored different types of data sources to get insights into human mobility behavior under disasters in a quantitative way. Human mobility data sources can be classified into two streams: the self-reported datasets and the location-based human sensor datasets (Yabe et al. 2022). One stream of studies investigated individual reactions to natural disasters using self-reported data (e.g., surveys, interviews, and questionnaires). For example, Duan et al. (2019) quantitatively evaluated the relationship between modal choice in emergency evacuation and different influencing variables, including socio-demographic indicators, journey characteristic indicators (e.g., evacuation distance), psychological indicators (e.g., perceptions, commuting priority), and spatial indicators (e.g., residential density, employment density). Wong et al. (2020) explored and modeled individual evacuation decision-making behavior (e.g., whether to evacuate or not, departure time, destination, shelter type, mode, route) using discrete choice theory. The limitation of this study is that samples gained from the survey are non-representative of the whole population, and the low sample size lacks accuracy in predicting human mobility patterns under disaster (Collins et al. 2021). Another stream of studies investigated aggregated human mobility behaviors under disasters using location-based human sensor datasets, such as mobile phone call detail record (CDR) data (Jiang et al. 2017; Thuillier et al. 2017), social media check-in data (Han et al. 2019; Roy and Hasan 2021), and GPS-based smartphone location data (Dargin et al. 2021; Han et al. 2021; Hong et al. 2021; Juhász and Hochmair 2020; Podesta et al. 2021; Yang et al. 2016). The CDR datasets contain information such as the unique ID of the user, timestamp, and location information of the observed cell phone tower (Calabrese et al. 2011; Cinnamon et al. 2016). The CDR datasets only record location information of cell phone towers when making calls or texting messages. It is not the actual location of the user, and it ranges from around 100 meters to several kilometers (Hasan et al. 2013; Song et al. 2010). For GPS-based smartphone location data, GPS data is collected and aggregated from third-party data partners such as mobile location-based application developers (Oliver et al. 2020; Wilson et al. 2016; Yabe et al. 2020). The GPS-based smartphone location datasets contain information such as a user identifier, timestamp of observation, as well as longitude and latitude information (Wang et al. 2020). GPS data can also be collected and aggregated from platforms of companies (Kryvasheyeu et al. 2016; Muniz-Rodriguez et al. 2020). For example, Hong et al. (2021) defined and quantified community resilience capacity using large-scale mobility data, and identified racial and socioeconomic disparities in resilience capacity and evacuation patterns. Roy and Hasan (2021) explored twitter data by users from Florida to predict evacuation decisions in real-time under Hurricane Irma. Han et al. (2019) analyze spatiotemporal aspects of evacuation travel patterns during hurricanes using Twitter data. The location-based large-scale human mobility dataset can objectively track real-time human movement (Barbosa et al. 2018). The limitation is that it fails to capture individual information, and it also lacks exploration of comprehensive factors influencing mobility patterns (Akter and Wamba 2019; Yu et al. 2018).

2.2 Methodology

The methodology diagram was proposed in Figure 2.1. First, the natural disaster and affected cities are selected. Then, based on human mobility datasets, point of interest (POI) visits under a natural disaster are aggregated by different NAICS sectors, and POI visits baseline is also determined. According to POI visits under a natural disaster and POI visits baseline, the percentage change is calculated. Different disaster stages (i.e., pre-disaster, during-disaster, post-disaster stages) are determined. In addition, three indicators, including the preparation indicator, the impact indicator, and the residual effect indicator, are proposed and quantified. Based on human mobility patterns across different cities, the impact of different disaster severity levels on human mobility can be concluded. Based on three indicators, unique characteristics of human mobility patterns in specific NAICS sectors can be measured. Finally, an overall connection of NAICS sector function, preparation, disaster impact, and recovery in a human mobility context under disaster can be built.

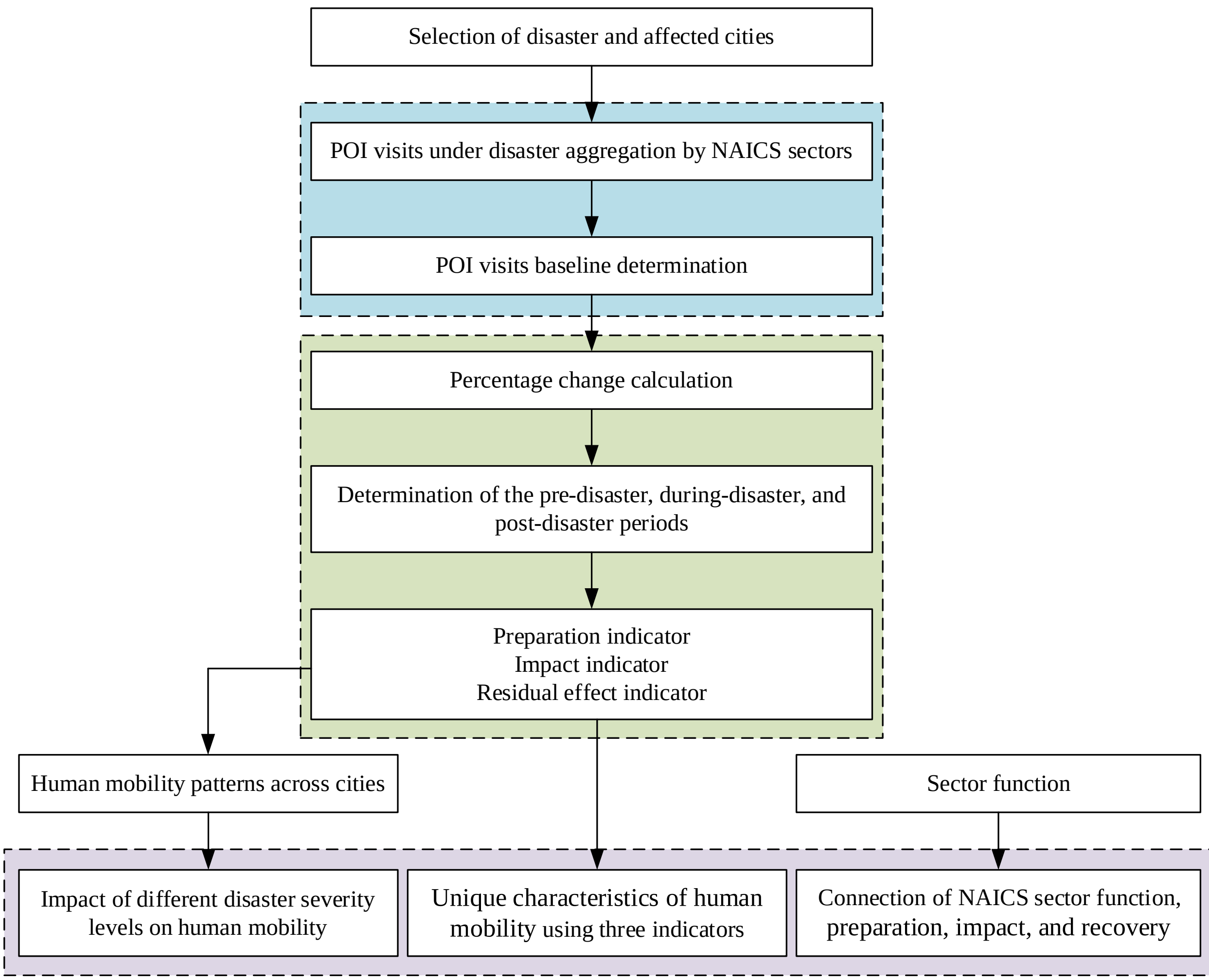


Figure 2.1: Methodology diagram

2.2.1 Human Mobility Pattern

There are multiple types of human mobility datasets from data marketplace companies. For instance, several companies (e.g., VenPath Inc., Cuebiq Inc.) provide large-scale individual spatiotemporal movements via smartphone GPS trajectories (Cuebiq Inc 2021; VenPath Inc 2021). Companies such as SafeGraph Inc. provide datasets mapping aggregated individual movements from neighborhoods to points of interest (POIs) (SafeGraph Inc 2021). Some social media companies, such as Twitter, indirectly identify users' trajectories and behaviors through time- and geo-tagged Twitter posts (Twitter Inc 2021). In this study, the "patterns" dataset from SafeGraph Inc. was used to study human mobility in disaster content. Safegraph Inc. is a company that provides points of interest (POIs), building footprints, and foot traffic data. Point of interest (POI) is defined as "a place you spend time or money". SafeGraph Inc. provides three major types of datasets, including core places, geometry, and patterns. The "Patterns" dataset includes visitor and demographic aggregations for POIs in the US. This contains aggregated raw counts of visits to POIs from a panel of mobile devices, answering how often people visit, how long they stay, where they come from, where else they go, and more (SafeGraph Inc 2021).

The first step is to determine the disaster and affected cities so that POI visits of certain date ranges and city locations from the "patterns" dataset can be extracted. Based on the North American Industry Classification System (NAICS) (US Census Bureau 2022), individual POI visits were aggregated into 13 different sectors that correlate with disaster preparation, response, or recovery.

To identify and summarize POI visit patterns of different sectors under disaster, two types of POI visits need to be determined: baseline POI visits and disaster POI visits. The concept of "baseline POI visits" refers to POI visits for the previous month of the disaster, and the concept of "disaster POI visits" refers to POI visits for the current and the following month of the disaster. The "baseline POI visits" were determined using previous month data for two reasons: first, human mobility data in a previous month without disaster can reflect the business-as-usual situation; second, the human mobility dataset of the previous month is usually available. For both baseline and disaster POI visits, a 7-day-rolling average was applied to eliminate abnormal daily visits and generate smooth visit change. The 7-day-rolling average is calculated using equation (1).

$$\text{7 day rolling average} = \frac{\text{sum of last 7 daily POI visits}}{7} \tag{1}$$

To calculate the percentage change value using baseline and disaster POI visits, data extension and alignment are needed. Days of baseline POI visits should match days of disaster POI visits. Therefore, baseline data points should be extended to exactly the number of data points of the disaster POI visits through repetition of baseline POI visits and the same weekday alignment. For example, assume that dates from 9/1/2018 (Sunday) to 9/30/2018 (Sunday) are selected as the POI visits baseline, and dates from 10/1/2018 (Monday) to 11/15/2018 (Thursday) are selected as the POI visits under disaster. At the step of data extension, baseline data points are extended by repeating the POI visits starting from 9/3/2018 (Monday) to 9/20/2018 (Thursday). At the step of data alignment, the baseline POI visit on 9/3/2018 (Monday) is selected as the starting point, since it is aligned with disaster the POI visit on 10/1/2018 (Monday). To summarize, data points of baseline POI visits start from 9/3/2018 (Monday) to 9/30/2018 (Sunday), concatenating data points from 9/3/2018 (Monday) to 9/20/2018 (Thursday); data points of disaster POI visits start from 10/1/2018 (Monday) to 11/15/2018 (Thursday). As a result, data consistency for baseline and disaster POI visits can be achieved.

Based on data points of baseline and disaster POI visits, the percentage change can be calculated using equation (2).

$$\text{percentage change} = \frac{(\text{Disaster POI visits} - \text{Baseline POI visits})}{\text{Baseline POI visits}} \tag{2}$$

A typical POI visit pattern under disaster concerning a specific sector is shown in Figure 2.2, using an example of POI visits under Hurricane Michael concerning the construction sector in Panama City, Florida.

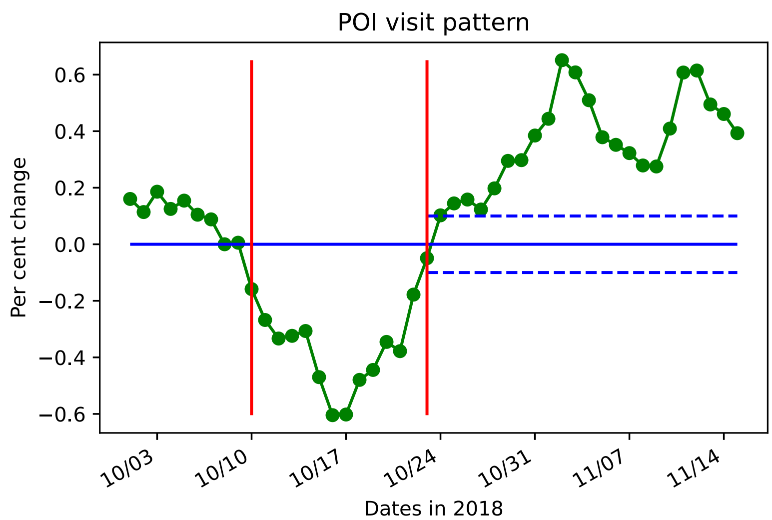


Figure 2.2: A typical POI visit pattern

In Figure 2.2, the green curve represents the percentage change trend in a disaster context. The horizontal solid line is the percentage change where the value is 0, which means the baseline POI visits are equal to disaster POI visits. The horizontal dashed lines are thresholds of the percentage change, and ±10% are selected as the upper and lower limits of normal percentage change fluctuation. The left vertical line is the date that separates the pre-disaster and during-disaster stages. The right vertical line is the date that separates the during-disaster and the post-disaster stages.

Human mobility shows different characters at different disaster stages. Specifically, residents usually get prepared for the coming disaster at the pre-disaster stage; they tend to avoid visiting unnecessary POIs at the during-disaster stage; residents usually return to normal visitation to POIs at the post-disaster stage. Therefore, there is a need to separate different disaster stages. The pre-disaster stage starts from one week before the disaster to a day before the disaster. The during-disaster stage starts from the day disaster comes to the date that the percentage change value returns to -0.1 for the first time if it exists. Otherwise, the ending date will be when the percentage change value is the highest at the recovery stage. The post-disaster stage starts from the next day of the end of the during-disaster stage to the ending date.

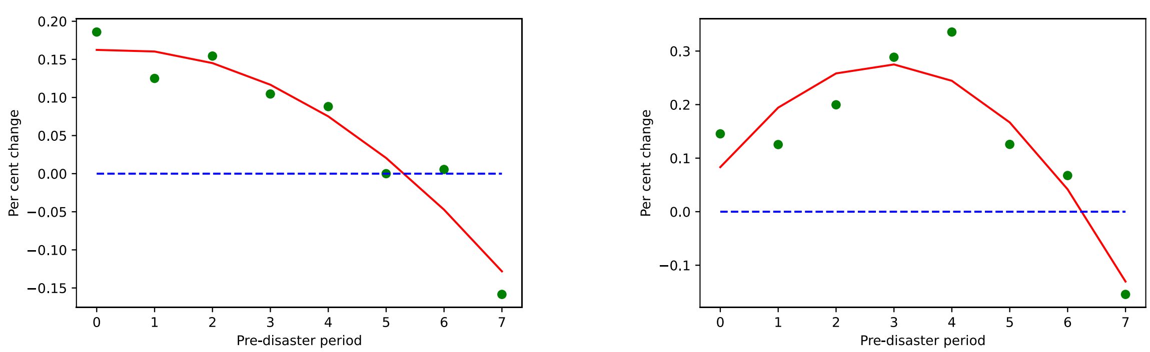
2.2.2 Quantification of Indicators

(1) Preparation indicator:

For the pre-disaster stage, the “preparation indicator” was proposed. There are two types of patterns for the pre-disaster stage: “no preparation” and “with preparation”.

For data points of percentage change during the last 7 days of hurricane landing, fit them with a quadratic function. Find the value of the first derivative of each data point. If the number of positive values is no greater than 2, or the maximum percentage change value is not positive, it is identified as “no preparation”. For data points of percentage change during the last 7 days of hurricane landing, fit them with a quadratic function. Find the value of the first derivative of each data point. If the number of positive values is greater than 2, and the maximum percentage change value is positive, it is identified as “with preparation”.

For the “no preparation” pattern, the value of the preparation indicator is 0; for the “with preparation” pattern, the value of the preparation indicator is the area of the triangle enclosed by the curve and the horizontal solid line. Examples of “no preparation” and “with preparation” patterns are shown in Figure 2.3.



(a) “No preparation” pattern (b) “With preparation” pattern

Figure 2.3: Examples of “no preparation” and “with preparation” patterns

(2) Impact indicator:

For the during-disaster stage, the “impact indicator” was proposed. There is usually a significant drop in visits on the date of the disaster, and it gradually returns to the business-as-usual situation. This stage is defined as the during-disaster stage, as it can represent the degree of visit drop under disaster and the time interval that visits return to business-as-usual.

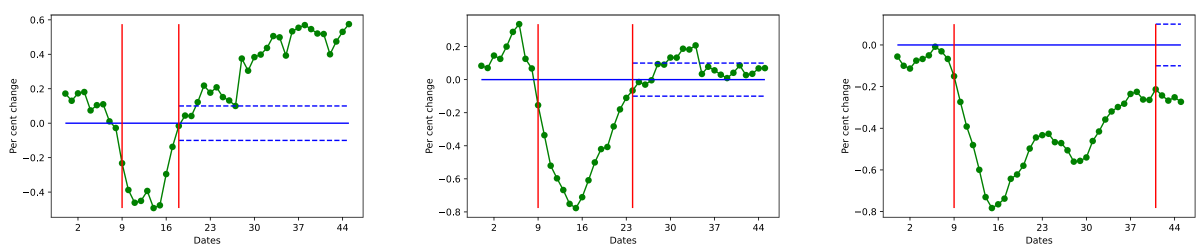
The value of the disaster impact indicator is the area of the concerning to the horizontal solid line, from the disaster date to the date that the percentage change value returns to -0.1 for the first time if it exists. Otherwise, select the ending date when the percentage change value is the highest at the recovery stage.

(3) Residual effect indicator:

For the post-disaster stage, the “residual effect indicator” was proposed. There are three types of patterns for the post-disaster stage: “recovery beyond normal”, “recovery to normal”, and “recovery below normal”.

Find the date that the percentage change value is no smaller than -0.1 for the first time if it exists; otherwise, find the date that the percentage change value is the highest at the recovery stage. Compute the average percentage change value from the date found to the ending date of the recovery stage. If the average percentage change value is greater than 0.1, it is defined as “recovery beyond normal”. If the average percentage change value falls into [-0.1, 0.1], it is defined as “recovery to normal”. If the percentage change value is smaller than -0.1, it is defined as “recovery below normal”.

Examples of “recovery beyond normal”, “recovery to normal”, and “recovery below normal” patterns are shown in Figure 2.4.



(a) “Recovery beyond normal”

(b) “Recovery to normal”

(c) “Recovery below normal”

Figure 2.4: Examples of “recovery beyond normal”, “recovery to normal”, and “recovery below normal” patterns

To conclude, the schematic diagram of all human mobility cases mentioned above is shown in Figure 2.5. There are three different stages concerning human mobility under disaster. At the pre-disaster stage, the preparation indicator is proposed and quantified in two cases: “no preparation” and “with preparation”. In the during-disaster stage, the impact indicator is proposed and quantified with a negative value, since there is always a drop in POI visits during a disaster. At the post-disaster stage, the residual effect is proposed and quantified in three cases: “recovery beyond normal”, “recovery to normal”, and “recovery below normal”. If the average POI visits at the post-disaster stage are beyond the upper dashed lines (+10% percentage change), it is considered as “recovery beyond normal”. If the average POI visits at the post-disaster stage are below the lower dashed lines (-10% percentage change), it is considered as “recovery below normal”. Otherwise, it is considered as “recovery to normal”.

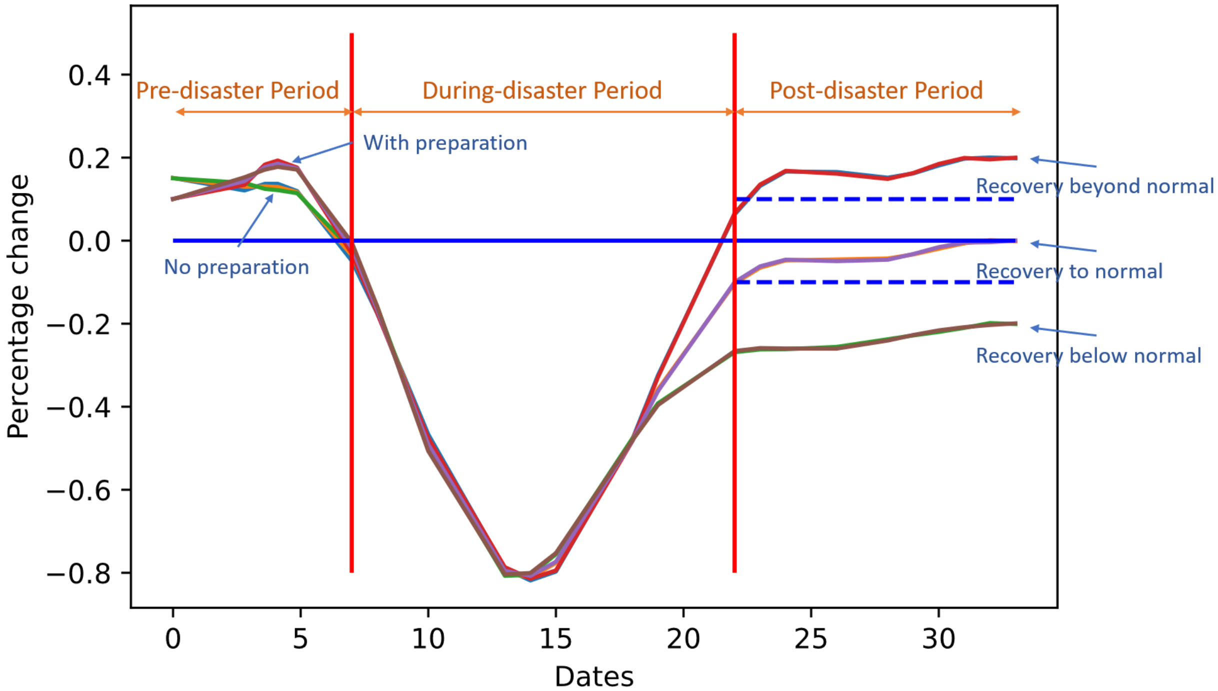


Figure 2.5: Schematic diagram of human mobility

Chapter 3. Case Study

3.1 Case Study Background

The case study examined Hurricane Michael landing in Florida on 10/10/2018. Four cities, including Panama City, Panama City Beach, Lynn Haven, and Tallahassee, were selected. The severity of hurricanes is similar across Panama City, Panama City Beach, and Lynn Haven. The property damage is at a similar scale across the three cities, while the property damage in Tallahassee is less than the other three cities. The "Patterns" dataset from SafeGraph Inc. was used. The "Patterns" dataset includes visitor and demographic aggregations for POIs. Some important columns used in this study are summarized in Table 3.1.

Table 3.1: Columns description in the "Patterns" dataset (SafeGraph Inc 2021)

Column name	Description	Example
"placekey"	Unique and persistent ID tied to this POI	222-222@222-222-222
"location_name"	The name of the POI	Salinas Valley Ford Lincoln
"top_category"	The label associated with the first 4 digits of the POI's NAICS category	Automobile Dealers
"sub_category"	The label is associated with all 6 digits of the POI's NAICS category. For POIs with a 4-digit NAICS category, this column is null.	New Car Dealers
"naics_code"	4-digit or 6-digit NAICS code describing the business	441110
"city"	The city of the POI	Irvine
"postal_code"	The postal code of the POI	92602
"date_range_start"	Start time for measurement stage in ISO 8601 format of YYYY-MM-DDTHH:mm:SS±hh:mm	2020-03-01T00:00:00-06:00
"date_range_end"	The end time for the measurement period in ISO 8601 format of YYYY-MM-DDTHH:mm:SS±hh:mm. The end time will be the last day of the month at midnight local time.	2020-03-31T00:00:00-06:00
"raw_visit_counts"	Number of visits to this POI during the date range	1542
"raw_visitor_counts"	Number of unique visitors to this POI during the date range	1221
"visits_by_day"	The number of visits to the POI each day over the covered period	[33, 22, 33, 22, 33, 22, 22, 21, 23, 33, 22, 11, 44, 22, 22, 44, 11, 33, 44, 44, 44, 33, 34, 44, 22, 33, 44, 44, 34, 43, 43]

POI visits dataset for the whole of September 2018 was selected as the original baseline POI visits. After applying ng 7-day-rolling average, baseline POI visits start from 9/3/2018 (Monday) to 9/30/2018 (Sunday), concatenating data points from 9/3/2018 (Monday) to 9/20/2018 (Thursday). The data extension and the same weekday alignment were also applied. POI visits datasets in October and November 2018 were selected as the original disaster POI visits. After applying a 7-day-rolling average, disaster POI visits start from 10/1/2018 (Monday) to 11/15/2018 (Thursday). Based on data points of baseline and disaster POI visits, the percentage change values were first calculated.

The pre-disaster stage starts from 10/03/2018 to 10/09/2018. The during-disaster stage starts from 10/10/2018 to the date that the percentage change value returns to -0.1 for the first time if it exists. Otherwise, select the ending date when the percentage change value is the highest at the recovery stage. The post-disaster stage starts from the ending date of the during-disaster stage to 11/15/2018.

Three indicators, including the preparation indicator, impact indicator, and residual effect indicator, were computed and summarized in Table 3.2 - Table 3.5, based on POI visits in four cities.

Table 3.2: Quantification of indicators and patterns for the case study of Panama City under Hurricane Michael

Panama City	Preparation indicator	Impact indicator	Residual effect indicator	Pattern
23: Construction	0	-4.892	0.352	(1a)
31-33: Manufacturing	0	-14.778	-0.249	(1c)
42: Wholesale Trade	0	-3.329	0.346	(1a)
44-45: Retail Trade	0.218	-7.683	-0.012	(2b)
52: Finance and Insurance	1.288	-7.025	0.066	(2b)
53: Real Estate and Rental and Leasing	0.011	-6.603	-0.008	(1b)
61: Educational Services	0	-14.592	-0.185	(1c)
62: Health Care and Social Assistance	0	-4.844	-0.093	(1b)
72: Accommodation and Food Services	0.213	-13.655	-0.049	(2b)

(Note: For the “Pattern” column, 1 represents “no preparation”, 2 represents “with preparation”; “a” represents “recovery beyond normal”, “b” represents “recovery to normal”, “c” represents “recovery below normal”)

Table 3.3: Quantification of indicators and patterns for the case study of Panama City Beach under Hurricane Michael

Panama City Beach	Preparation indicator	Impact indicator	Residual effect indicator	Pattern
23: Construction	0	-4.925	0.764	(1a)
31-33: Manufacturing	0.417	-5.973	0.309	(2a)
42: Wholesale Trade	0	-6.046	0.411	(1a)
44-45: Retail Trade	1.141	-4.912	0.053	(2b)
52: Finance and Insurance	0.790	-4.087	0.505	(2a)
53: Real Estate and Rental and Leasing	0.832	-4.893	0.220	(2a)
61: Educational Services	0	-8.356	-0.421	(1c)
62: Health Care and Social Assistance	0.114	-6.162	0.224	(2a)
72: Accommodation and Food Services	1.815	-9.557	-0.018	(2b)

(Note: For the "Pattern" column, 1 represents "no preparation", 2 represents "with preparation"; "a" represents "recovery beyond normal", "b" represents "recovery to normal", "c" represents "recovery below normal")

Table 3.4: Quantification of indicators and patterns for the case study of Lynn Haven under Hurricane Michael

Lynn Haven	Preparation indicator	Impact indicator	Residual effect indicator	Pattern
23: Construction	/	/	/	/
31-33: Manufacturing	0.053	-7.536	0.037	(2b)
42: Wholesale Trade	0	-9.200	0.139	(1a)
44-45: Retail Trade	0.324	-5.580	0.162	(2a)
52: Finance and Insurance	0	-4.843	0.355	(1a)
53: Real Estate and Rental and Leasing	0.912	-16.091	-0.447	(2c)
61: Educational Services	0	-21.796	-0.157	(1c)
62: Health Care and Social Assistance	0	-7.369	0.013	(1b)
72: Accommodation and Food Services	0.247	-12.242	0.002	(2b)

(Note: For the "Pattern" column, 1 represents "no preparation", 2 represents "with preparation"; "a" represents "recovery beyond normal", "b" represents "recovery to normal", "c" represents "recovery below normal")

Table 3.5: Quantification of indicators and patterns for the case study of Tallahassee under Hurricane Michael

Tallahassee	Preparation indicator	Impact indicator	Residual effect indicator	Pattern
23: Construction	0	-0.764	0.097	(1b)
31-33: Manufacturing	0.482	-1.943	0.121	(2a)
42: Wholesale Trade	0	-1.701	0.160	(1a)
44-45: Retail Trade	0.233	-1.203	0.128	(2a)
52: Finance and Insurance	0.889	-2.285	0.116	(2a)
53: Real Estate and Rental and Leasing	0.140	-1.304	0.104	(2a)
61: Educational Services	0	-4.914	-0.031	(1b)
62: Health Care and Social Assistance	0	-2.683	0.048	(1b)
72: Accommodation and Food Services	0	-2.362	0.022	(1b)

(Note: For the "Pattern" column, 1 represents "no preparation", 2 represents "with preparation"; "a" represents "recovery beyond normal", "b" represents "recovery to normal", "c" represents "recovery below normal")

3.2 Comparison of visit patterns across cities at different disaster-severity scales

In the case study, Panama City, Panama City Beach, and Lynn Haven are all located in Bay County, Florida. The property damage in Bay County is around $1.2 billion (NOAA.gov 2022). Tallahassee is in Leon County, Florida. The property damage in Leon County is around $100 million (NOAA.gov 2022). As a result, Panama City, Panama City Beach, and Lynn Haven can be considered as cities that were strongly affected by Hurricane Michael; Tallahassee can be considered a city that was moderately affected by Hurricane Michael. Table 3.6 shows the comparison of impact indicator values across different cities. It can be seen from Table 3.6 that different levels of disaster severity do have an impact on human mobility patterns. Values of impact indicators of all NAICS sectors in Tallahassee are significantly smaller than those in the other three cities. It means Hurricane Michael had a smaller impact on human mobility in Tallahassee.

Table 3.6: Comparison of impact indicator values across different cities

	Impact indicator of Panama City	**Impact indicator of Panama City Beach**	**Impact indicator of Lynn Haven**	**Impact indicator of Tallahassee**
23: Construction	-4.892	-4.925	/	-0.764
31-33: Manufacturing	-14.778	-5.973	-7.536	-1.943
42: Wholesale Trade	-3.329	-6.046	-9.200	-1.701
44-45: Retail Trade	-7.683	-4.912	-5.580	-1.203
52: Finance and Insurance	-7.025	-4.087	-4.843	-2.285
53: Real Estate and Rental and Leasing	-6.603	-4.893	-16.091	-1.304
61: Educational Services	-14.592	-8.356	-21.796	-4.914
62: Health Care and Social Assistance	-4.844	-6.162	-7.369	-2.683
72: Accommodation and Food Services	-13.655	-9.557	-12.242	-2.362

Table 3.7 shows the comparison of human mobility patterns across different cities. It can be seen from Table 3.7 that most of the NAICS sectors in Tallahassee show (1a) “with preparation, recovery beyond normal” pattern and (2b) “no preparation, recovery to normal” pattern. In hurricane strongly affected cities, there are no particular patterns of NAICS sectors. There are relations between NAICS sector functions, preparation, impact, and residual effect, which are detailed and illustrated in section 3.3.

Table 3.7: Comparison of human mobility patterns across different cities

	Panama City Pattern	**Panama City Beach Pattern**	**Lynn Haven Pattern**	**Tallahassee Pattern**
23: Construction	(1a)	(1a)	/	(1b)
31-33: Manufacturing	(1c)	(2a)	(2b)	(2a)
42: Wholesale Trade	(1a)	(1a)	(1a)	(1a)
44-45: Retail Trade	(2b)	(2b)	(2a)	(2a)
52: Finance and Insurance	(2b)	(2a)	(1a)	(2a)
53: Real Estate and Rental and Leasing	(1b)	(2a)	(2c)	(2a)
61: Educational Services	(1c)	(1c)	(1c)	(1b)
62: Health Care and Social Assistance	(1b)	(2a)	(1b)	(1b)
72: Accommodation and Food Services	(2b)	(2b)	(2b)	(1b)

(Note: 1 represents "no preparation", 2 represents "with preparation"; "a" represents "recovery beyond normal", "b" represents "recovery to normal", "c" represents "recovery below normal")

3.3 Comparison of visit patterns across cities at a similar disaster-severity scale

(1) NAICS 44-45 "Retail Trade" sector:

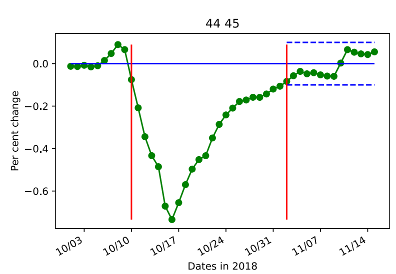
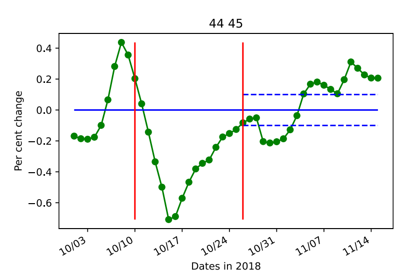
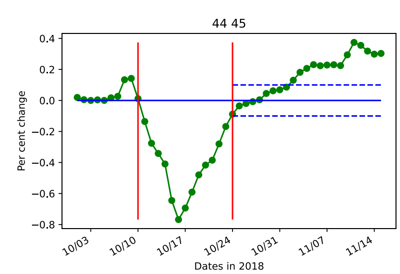
Panama City	Panama City Beach	Lynn Haven
		
Preparation: 0.218 Impact: -7.683 Residual effect: -0.012	Preparation: 1.141 Impact: -4.912 Residual effect: 0.053	Preparation: 0.324 Impact: -5.580 Residual effect: 0.162

Figure 3.1: NAICS 44-45 "Retail Trade" pattern

NAICS 44-45 sector consists of several subsectors such as food and beverage stores, health and personal care stores, gasoline stations, and clothing stores. The NAICS 44-45 sector is strongly related to disaster preparedness since residents tend to purchase and store food and daily goods to resist the coming disaster. It is found from Figure 3.1 that this sector in Panama City Beach has the highest values of both preparation indicator and impact indicator. Visits of the sector in Lynn Haven recovered beyond normal, while visits of the sector in the other two cities recovered to normal. The preparation indicator in the NAICS 44-45 sector reflects the disaster awareness of preparing goods, and the impact indicator reflects the resilience of the sector in a city. The more disaster awareness residents have, the more resilient the sector is against disasters. The residual effect reflects the shopping behavior after a disaster. Table 3.8 shows vehicles available in three cities (US Census Bureau 2019a). It can be seen from Table 3.8 that residents in Lynn Haven had more access to groceries since the percentage of no vehicles available is the smallest in this city. In addition, infrastructures in Lynn Haven suffered less damage compared with the other two cities under disaster, which will be explained in NAICS 42 "Wholesale Trade" sector. Therefore, residents in Lynn Haven have higher purchasing potential after a disaster.

Table 3.8: Vehicles available in three cities

	Panama City	Panama City Beach	Lynn Haven
No vehicle available	6.4%	2.6%	2.3%
1 vehicle available	26.0%	26.4%	18.7%
2 vehicles available	44.1%	46.1%	49.3%
3 or more vehicles are available	23.5%	24.9%	29.7%

(2) NAICS 23 "Construction" sector:

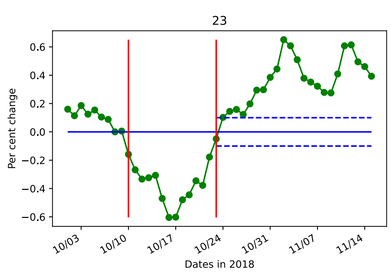
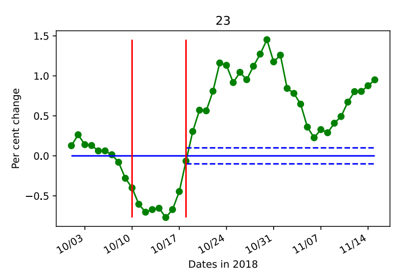
Panama City	Panama City Beach	Lynn Haven
		/
Preparation: 0 Impact: -4.892 Residual effect: 0.352	Preparation: 0 Impact: -4.925 Residual effect: 0.764	/

Figure 3.2: NAICS 23 "Construction" pattern

NAICS 23 sector consists of several subsectors, including: "construction of buildings" (e.g., residential building construction, non-residential building construction), "heavy and civil engineering constructions" (e.g., utility system construction, highway, street, and bridge construction), and "special trade contractors" (e.g., building contractors). The NAICS 23 sector is strongly related to disaster recovery since there are some construction activities after a disaster due to infrastructure damage. It is found in Figure 3.2 that for both Panama City and Panama City Beach, the value of the preparation indicator is 0, and the values of the impact indicator are similar. Visits of this sector both recovered beyond normal. The value of the preparation indicator illustrates that there is a lack of disaster preparedness in the construction sector. Buildings are susceptible to damage from high wind speeds; utilities such as water and power lines are susceptible to getting interrupted by rainstorms; highways, streets, and bridges are sometimes destroyed by flooding. As a result, there is an increasing demand for repairs and reconstruction under hurricanes (Arneson 2019; Barattieri et al. 2021). The impact indicator reflects the severity of infrastructure damage in a city. The higher value of the impact indicator, the more severe the damage to a city's infrastructure, since there is an urgent need to get infrastructures repaired instantly under disaster. Under a similar hurricane impact, the residual effect in Panama City Beach is higher than Panama City. A possible reason is that Panama City Beach is more wealthy (high-income level residents contribute more taxes), which could provide more funding for infrastructure repair and reconstruction. The residual effect can be treated as the preparation for the next disaster since the renewed infrastructures are more resilient to cope with future disasters.

(3) NAICS 42 "Wholesale Trade" sector:

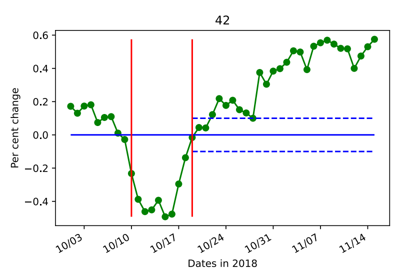
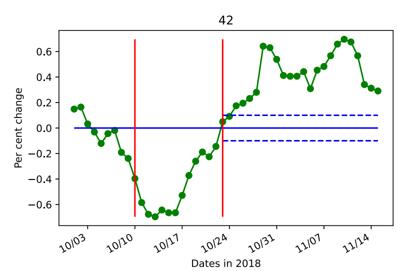
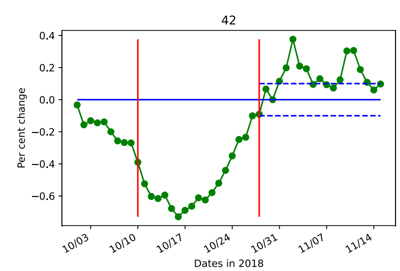
Panama City	Panama City Beach	Lynn Haven
		
Preparation: 0 Impact: -3.329 Residual effect: 0.346	Preparation: 0 Impact: -6.046 Residual effect: 0.411	Preparation: 0 Impact: -9.2 Residual effect: 0.139

Figure 3.3: NAICS 42 "Wholesale Trade" pattern

NAICS 42 sector includes "durable goods" (e.g., construction materials, furniture, construction machinery, and equipment), and "nondurable goods" (e.g., grocery products, drugs). For the three cities in this case study, most wholesale trade-related POIs belong to the "durable goods" subsector, which indicates that "durable goods" POIs take a leading role in visitation fluctuation in the NAICS 42 sector. The NAICS 42 sector is also strongly related to disaster recovery since there is a need for construction materials, machinery, and equipment after a disaster. Similar to NAICS 23 "Construction" sector, it is found from Figure 3.3 that the preparation indicator of all three cities is 0, which means there is a lack of disaster preparedness in the wholesale trade sector. The impact indicator also reflects the severity of infrastructure damage in a city. It was found that Panama City suffered the most in terms of infrastructure damage, and Lynn Haven suffered the least in terms of infrastructure damage. Visits to this sector all recovered beyond normal in the three cities. A possible reason is that residents tend to purchase lumber and other construction materials, as well as construction machinery and equipment, to repair damage due to hurricanes (Arneson 2019). The residual effect can also be treated as the preparation for future disasters.

(4) NAICS 52 “Finance and Insurance” sector:

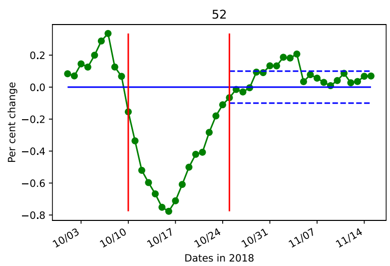
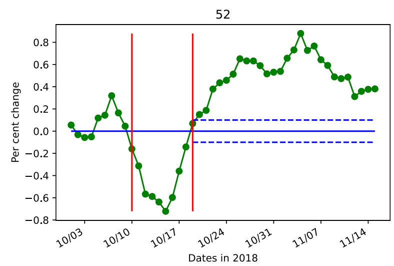
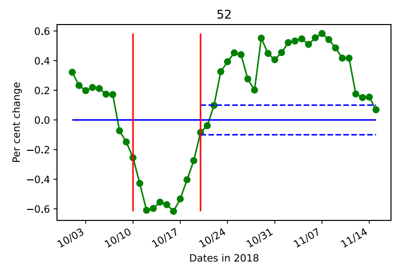
Panama City	Panama City Beach	Lynn Haven
		
Preparation: 1.288 Impact: -7.025 Residual effect: 0.066	Preparation: 0.790 Impact: -4.087 Residual effect: 0.505	Preparation: 0 Impact: -4.843 Residual effect: 0.355

Figure 3.4: NAICS 52 “Finance and Insurance” pattern

NAICS 52 sector includes credit-related institutions, financial investments, and insurance carriers. The NAICS 52 sector is related to human rights of ownership of property and life in a disaster context. It is found from Figure 3.4 that this sector in Panama City has the smallest values of both impact indicator and residual effect indicator, while the sector in Panama City Beach has the highest values of both impact indicator and residual effect indicator. The impact indicator and the residual effect indicator both reflect the awareness of property protection and insurance. Table 3.9 shows the health insurance coverage of different income levels across three cities (US Census Bureau 2019b). Two insights can be found in Table 3.9: first, residents with higher income levels usually have more awareness of property protection and insurance; second, Panama City has the lowest health insurance coverage. Figure 3.5 shows the income distribution across three cities (US Census Bureau 2019c). It can be seen from Figure 3.5 that Panama City also has the lowest income level. It might explain that residents in Panama City have the least awareness of property protection and insurance. Visits of the sector in both Panama City Beach and Lynn Haven recovered beyond normal, indicating that the disaster also enhances residents’ awareness of property protection and insurance. It is encouraged that decision-makers in Panama City promote the benefits of getting insured of health and property so that residents can be more resilient in coping with disasters.

Table 3.9: Health insurance coverage of different income levels

	Panama City	Panama City Beach	Lynn Haven
Under $25,000	79.6%	74.3%	87.5%
$25,000 - $49,999	84.0%	91.3%	88.9%
$50,000 - $74,999	80.4%	90.8%	89.0%
$75,000 - $99,999	89.3%	86.4%	95.2%
$100,000 and over	91.2%	92.4%	94.2%
Total percent insured household population	84.4%	89.4%	91.3%

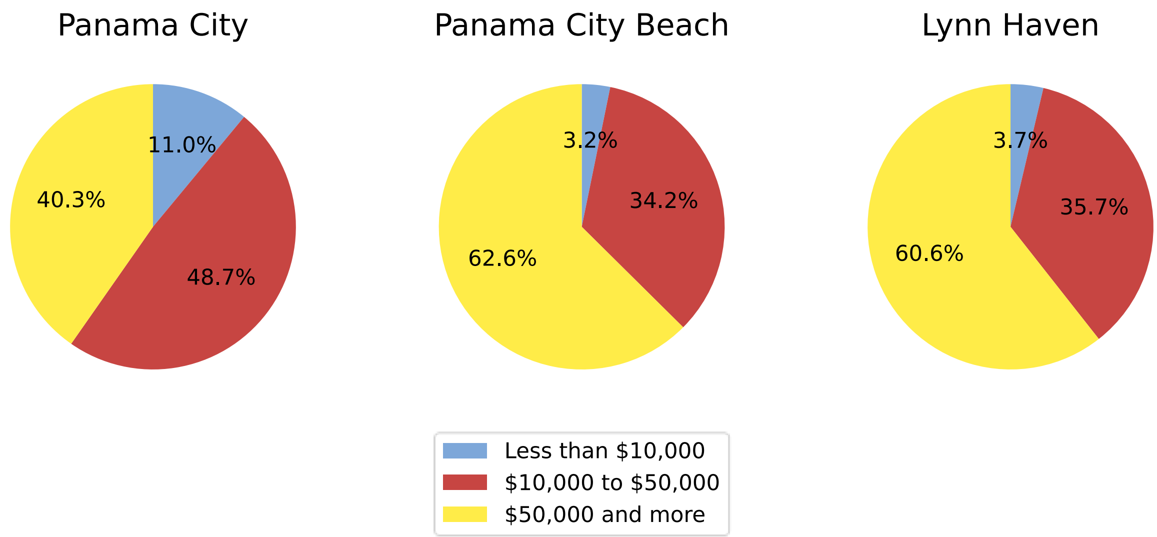


Figure 3.5: Income distribution across three cities

(5) NAICS 31-33 “Manufacturing” sector:

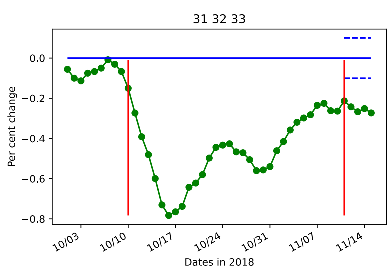
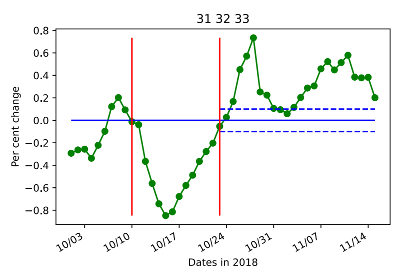
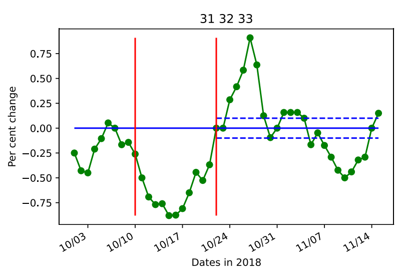
Panama City	Panama City Beach	Lynn Haven
		
Impact: -14.778 Residual effect: -0.249	Impact: -5.973 Residual effect: 0.309	Impact: -7.536 Residual effect: 0.037

Figure 3.6: NAICS 31-33 “Manufacturing” pattern

NAICS 31-33 sector consists of subsectors such as food and apparel manufacturing, printing and related support activities, electrical equipment, appliance, and component manufacturing. The NAICS 31-33 sector is related to human rights of free choice of employment. It is found from Figure 3.6 that Panama City has the smallest values of impact indicator and residual effect indicator, and Panama City Beach is the opposite situation. The impact indicator reflects the resilience of this sector. The higher the impact indicator, the more residents return to work as soon as possible, and the more resilient the sector is against disaster. The residual effect indicator reflects the employment status after a disaster. It is positively related to the impact indicator since a more resilient manufacturing sector in a city could provide more job opportunities to help more residents get rid of unemployment. Therefore, visits to the sector in Panama City Beach recovered beyond normal due to high resilience, while visits to the sector in Panama City recovered below normal due to low resilience. In addition, it can be seen from Table 3.10 that Panama City has the highest percentage of unemployment compared to the other two cities, which makes the employment status even worse. Decision-makers in Panama City should create more job opportunities for those unemployed residents to recover from the disaster.

(6) NAICS 53 “Real Estate and Rental and Leasing” sector:

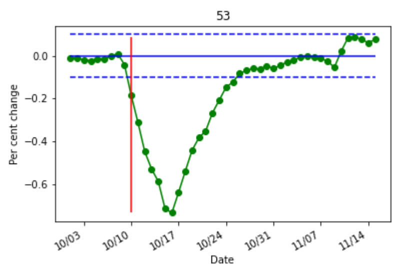
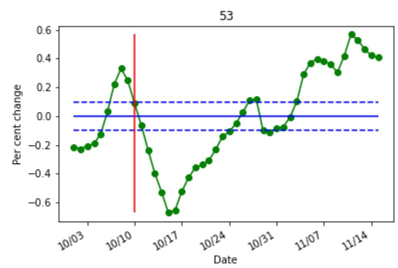
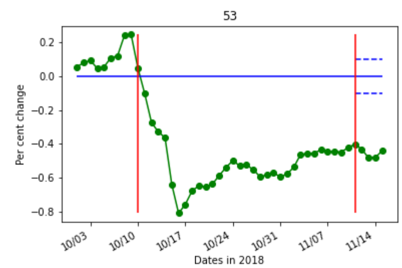
Panama City	Panama City Beach	Lynn Haven
		
City-level preparation: 0.195 Impact: -6.603 Residual effect: -0.008	City-level preparation: 1.460 Impact: -4.893 Residual effect: 0.220	City-level preparation: 0 Impact: -16.091 Residual effect: -0.447

Figure 3.7: NAICS 53 “Real Estate and Rental and Leasing” pattern

NAICS 53 sector includes real estate, automotive rental, and leasing, as well as other rental and leasing services. Most POIs are related to real estate rental and leasing in three cities, which indicates that real estate rental and leasing POIs take a leading role in visitation fluctuation in the NAICS 53 sector. The NAICS 53 sector is related to human rights of an adequate standard of living in a disaster context. A city-level preparation indicator is calculated based on the total visit fluctuation in a city, and it reflects residents’ disaster awareness in the city. It is found from Figure 3.7 that this sector in Panama City Beach has the highest values of city-level preparation indicator, impact indicator, and residual effect indicator, while Lynn Haven is the opposite. The impact indicator reflects the resilience of this sector in a city. The higher the impact indicator, the more resilient the sector in a city. The residual effect indicator reflects the disaster awareness of residents, which is consistent with the city-level preparation indicator. Residents in Panama City Beach have strong disaster awareness, so they tend to seek safer residential areas to live in under disaster, which can be reflected by the impact and the residual effect values. Lynn Haven is the opposite situation, and it is encouraged that decision-makers in Lynn Haven strengthen the disaster awareness of residents through multiple ways such as social media or different workshops.

(7) NAICS 61 “Educational Services” sector:

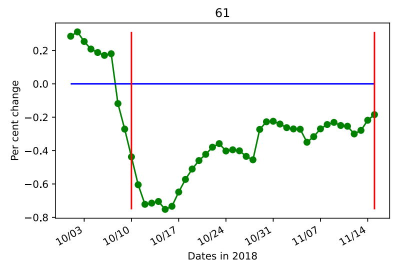
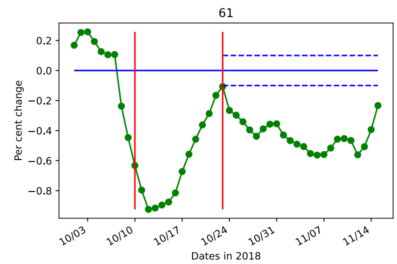
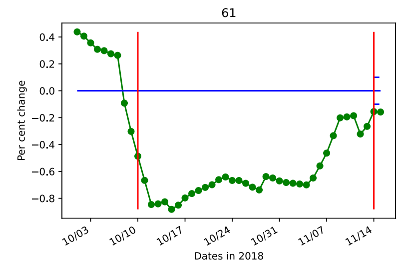
Panama City	Panama City Beach	Lynn Haven
		
Preparation: 0 Impact: -14.592 Residual effect: -0.185	Preparation: 0 Impact: -8.356 Residual effect: -0.421	Preparation: 0 Impact: -21.796 Residual effect: -0.157

Figure 3.8: NAICS 61 “Educational Services” pattern

NAICS 61 sector consists of elementary and secondary schools, colleges, universities, and professional schools and institutions, as well as educational support services. The NAICS 61 sector is related to the human rights of receiving education. It is found from Figure 3.8 that visits to this sector in the three cities all recovered below normal. Educational services are more flexible in a disaster context since students can take courses online instead of going to school in person. The residual effect indicator reflects the policies of educational institutions after a disaster. The policy can be adjusted swiftly in a disaster context, such as continue taking courses online after a disaster. Values of the residual effect indicator indicate that a disaster might have a long-term impact on the education sector. The development of remote education has significantly changed the way people receive education, and the disaster accelerates the progress in deploying online educational services.

(8) NAICS 62 “Health Care and Social Assistance” sector:

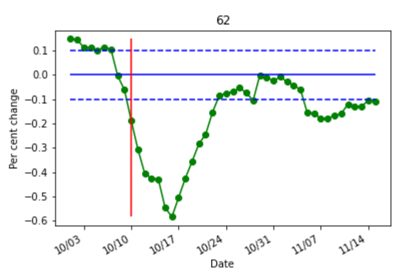
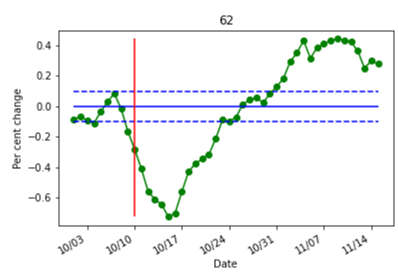
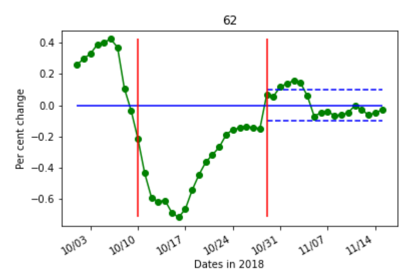
Panama City	Panama City Beach	Lynn Haven
		
Impact: -4.844 Residual effect: -0.093	Impact: -6.162 Residual effect: 0.224	Impact: -7.369 Residual effect: 0.013

Figure 3.9: NAICS 62 “Health Care and Social Assistance” pattern

NAICS 62 sector includes ambulatory health care services, hospitals, nursing care facilities, and social assistance. The NAICS 62 sector is related to human rights of physical and mental health. It is found from Figure 3.9 that this sector in Panama City has the highest value of impact indicator and the smallest value of residual effect indicator. Visits to this sector in Panama City Beach recovered beyond normal, and visits to this sector in the other two cities recovered to normal. The impact indicator and residual effect indicator both reflect the vulnerability of residents. The higher the impact indicator and residual effect indicator, the more vulnerable residents in a city. Table 3.10 shows the percentage of vulnerable groups across the three cities (US Census Bureau 2019d). Residents with disabilities, unemployed residents, and residents aged over 65 can be considered vulnerable groups. It can be seen from the table that Panama City has the highest percentage of vulnerable groups, while Lynn Haven has the smallest percentage of vulnerable groups. This might be a reason to explain the high impact value in Panama City and the high residual effect value in Panama City Beach. Vulnerable residents in Panama City showed more needs for health care and social assistance during a hurricane, and vulnerable residents in Panama City Beach showed more needs after the hurricane. As a result, decision-makers should provide medical and social resources to vulnerable groups when appropriate, based on the values of the impact indicator and residual effect indicator.

Table 3.10: Percentage of vulnerable groups across three cities

	Panama City	Panama City Beach	Lynn Haven
With any disability	22.1%	15.0%	14.2%
Unemployment for 24-64 aged groups	28.0%	21.0%	6.0%
Aged 65 and above	18.5%	18.4%	15.2%

(9) NAICS 72 "Accommodation and Food Services" sector:

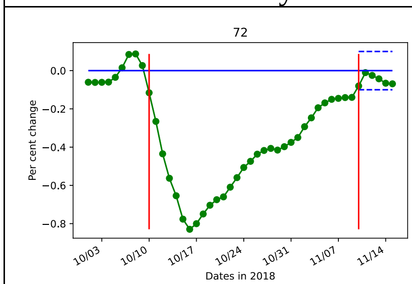
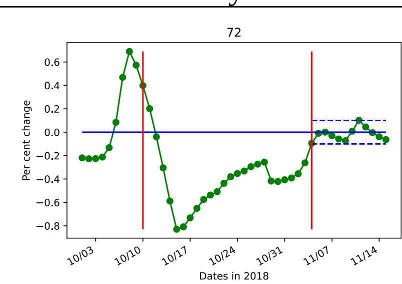
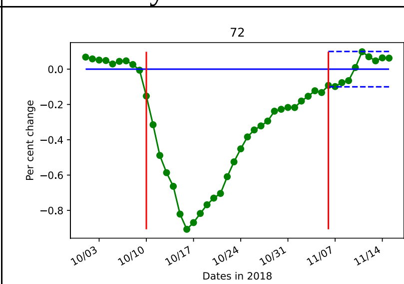
<table>
<tr><th>Panama City</th><th>Panama City Beach</th><th>Lynn Haven</th></tr>
<tr><td>
</td><td>
</td><td>
</td></tr>
<tr><td>Preparation: 0.213
Impact: -13.655
Residual effect: -0.049</td><td>Preparation: 1.815
Impact: -9.557
Residual effect: -0.018</td><td>Preparation: 0.247
Impact: -12.242
Residual effect: 0.002</td></tr>
</table>

Figure 3.10: NAICS 72 "Accommodation and Food Services" pattern

NAICS 72 sector includes "accommodation" and "food services and drinking places". Most accommodation and food services-related POIs belong to the "food services and drinking places" subsector for the three cities,. The NAICS 72 sector is related to the economic and lifestyle well-being of residents. It is found from Figure 3.10 that Panama City Beach has both the highest values of preparation indicator and impact indicator, and Panama City is the opposite. Visits to this sector in all three cities recovered to normal. The preparation indicator reflects the consumption desire before the disaster. Such desire usually appears to increase before a disaster since residents would like to consume in advance for the anticipation that they have to stay at home for a while during and after a disaster. The impact indicator reflects the resilience of this sector in a city. The higher the impact value, the more resilient the sector in a city. Typically, the residents' economic and well-being is positively related to their income level. Panama City Beach has the highest income level, while Panama City has the lowest income level. It might explain that Panama City Beach has the highest preparation and impact values. The residual effect reflects the degree that residents return to a normal lifestyle. NAICS 72 sector in all three cities shows a recovery-to-normal pattern, which indicates that residents returned to a normal lifestyle after the hurricane.

Chapter 4. Discussion

Based on the relationship between sector function and disaster, NAICS sectors can be classified into 4 categories:

(1) Sectors related to disaster preparedness (e.g., NAICS 44-45 “Retail Trade” sector). The preparation indicator of disaster preparedness-related sectors typically means the awareness of preparation. The impact indicator represents the resilience of residents in a city, and it is positively related to the preparation indicator. The more awareness of preparation, the more resilient these residents are.

(2) Sectors related to disaster recovery (e.g., NAICS 23 “Construction” sector, and NAICS 42 “Wholesale Trade” sector). There is a lack of disaster preparedness in the disaster recovery-related sectors. The impact indicator represents the severity of infrastructure damage in a city. The residual effect indicator represents the preparation for future disasters, as the renewed infrastructures are more resilient to cope with the following disasters.

(3) Sectors related to human rights in a disaster context. For most human rights-related sectors, the preparation indicator has no special meaning. The impact indicator represents resilience or vulnerability based on different sector functions.

There are two sectors where the impact indicator reflects resilience, and the impact indicator is positively related to the residual effect indicator. First, NAICS 31-33 “Manufacturing” sector, the residual effect indicator in this sector represents the employment status after a disaster. The more resilient the sector, the more job opportunities are offered after a disaster. Second, in NAICS 52 “Finance and Insurance” sector, the residual effect indicator represents the awareness of property protection and insurance. The more awareness of property protection and insurance residents have, the more resilient these residents are. For both sectors where the impact indicator reflects resilience, Panama City Beach has the highest impact value, and Panama City has the smallest impact value. The result is consistent with the ranking of impact values in NAICS 44-45 “Retail Trade” sector (the impact indicator also reflects resilience in this sector).

There is one sector (i.e., NAICS 62 “Health Care and Social Assistance” sector) where the impact indicator reflects vulnerability. The residual effect indicator in this sector also reflects vulnerability. Therefore, the impact indicator is also positively related to the residual effect indicator.

(4) Sectors are related to the economic and lifestyle well-being of residents in a disaster context (e.g., NAICS 72 “Accommodation and Food Services” sector). The preparation indicator of economic and lifestyle-related sectors typically means the consumption desire before a disaster. The impact indicator represents the resilience of residents in a city, and the ranking of impact values across three cities is consistent with sectors where the impact indicator also represents resilience. The residual effect indicator represents the degree that residents return to a normal lifestyle.

Based on different categories of NAICS sectors, as well as specific meanings of three indicators in each sector, decision-makers can identify the vulnerability in a city by comparing the values of indicators in a specific sector. For example, the city with the least resilient residents can be identified by comparing impact values in sectors where the impact indicator represents resilience (e.g., NAICS 44-45 “Retail Trade” sector, NAICS 31-33 “Manufacturing” sector, NAICS 52 “Finance and Insurance” sector, and NAICS 72 “Accommodation and Food Services” sector). With the information in NAICS 31-33 “Manufacturing” sector as well as unemployment information, decision-makers in Panama City should create more job opportunities for those unemployed residents to recover from the disaster. With information in NAICS 52 “Finance and Insurance” sector, decision-makers in Panama City are encouraged to promote the benefits of getting insured for health and property.

The city that has the most severe infrastructure damage can be identified by looking at impact values in sectors that are related to disaster recovery (e.g., NAICS 23 “Construction” sector, and NAICS 42 “Wholesale Trade” sector). Decision-makers should invest more construction resources in seriously damaged cities to make sure these infrastructures can be more resilient to cope with future disasters.

The city with more vulnerable groups (e.g., residents with a disability, unemployment groups, and aged groups) can be identified by looking at impact and residual effect values in NAICS 62 “Health Care and Social Assistance” sector. A high value of the impact indicator indicates that vulnerable residents have more needs to seek health care and social assistance during a disaster, while a high value of the residual effect indicator indicates that vulnerable residents have more needs after a disaster. Decision-makers should provide medical and social resources to vulnerable groups in a timely manner based on the values of the impact indicator and residual effect indicator.

Chapter 5. Conclusion and Future Work

This study proposed a method to build a comprehensive understanding of human mobility patterns under a natural disaster using mobility data. The proposed method was implemented in a case study of four cities, including Panama City, Panama City Beach, Lynn Haven, and Tallahassee, under Hurricane Michael. First, this study compared human mobility patterns across different cities with different levels of disaster severity. It shows that values of impact indicator of all NAICS sectors in a city moderately affected by hurricane are significantly smaller than those in cities strongly affected by hurricane. In addition, most NAICS sectors in the city moderately affected by hurricane show (1a) "with preparation, recovery beyond normal" pattern and (2b) "no preparation, recovery to normal" pattern. Second, three metrics, including the preparation indicator, the impact indicator, and the residual effect indicator were proposed to measure unique characteristics of human mobility patterns in specific NAICS sectors under disaster. Third, relationships between the NAICS sector function, the preparation indicator, the impact indicator, and the residual effect indicator were investigated. Different categories of NAICS sectors, as well as specific meanings of three indicators in each sector, can help decision-makers to make informed decisions regarding disaster preparation, response, and recovery. As of future work, we plan to implement the method in more case studies and develop a more comprehensive theory of disaster resilience based on human mobility data.

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