Center for Advanced Multimodal Mobility Solutions and Education

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Disaster Resilience through Diverse Evacuation and Emergency Transportation Systems

Final Report

by

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Table of Contents

List of Figures

List of Tables

EXCUTIVE SUMMARY

Multimodal transportation systems, including automobile, different forms of public transportation, walking, cycling, and ridesharing, have a significant impact on people's travel behaviors. Under disaster conditions, multimodal transportation could help move people away from high-risk areas to safer areas. Multimodal transportation systems could provide more opportunities for the protection of life, especially for certain populations such as carless individuals. In order to enhance disaster resilience, it is critical to have effective multimodal transportation systems.

Therefore, the objective of this study is to gain a better understanding on the diversity level of multimodal transportation systems and investigate the impact of the level of diversity on travel and evacuation behaviors during disasters. To this end, metrics and methods to quantify the diversity of transportation systems were proposed and tested in a case study of the city of Hartford. Smartphone location data (SLD) were collected to quantify the mobility change in the city of Hartford during two natural disasters. The potential relationship between disaster mobility and transportation infrastructure diversity was explored. Stakeholders from various agencies (e.g., DOT, emergent management office) can benefit from this study by better assessing and improving the diversity level of transportation systems, and making informed decisions in coping with disasters considering the transportation system characteristics.

Chapter 1. Introduction

1.1 Problem Statement

Disasters, whether natural (e.g., earthquakes, hurricanes, floods, wild fires) or man-made (e.g., terrorist attacks, chemical spills, nuclear power plant explosions), are occurring at an alarming rate in recent years, causing sudden disruptions to human life. The Federal Emergency Management Agency (FEMA) disaster database shows that in the past decade (i.e., 2008-2018), a total of 1,343 disaster declarations were issued requiring evacuation in the United States (FEMA 2019). Transportation system, as one of the critical infrastructure systems, also recognized as “lifelines”, plays a crucial role for a region in disaster response and recovery. There is an urgent need to develop resilient transportation infrastructure systems that can better serve communities both under business-as-usual and emergency conditions.

In recent studies, multimodal emergency transportation has drawn more and more attention. Multimodal transportation systems have various travel modes and services, including automobile, different forms of public transportation (bus, train, ferry, etc.), walking, cycling, ridesharing, and mobility substitutes such as telework and delivery services (Litman 2018). In real world, people are very likely to choose different ways to move to safe areas based on their own conditions in the face of disasters. For example, in a typical community, 20-40% of the total population, and 10-20% of adolescents and adults, cannot drive due to disability, economic, age constraints, or vehicle failures (Litman 2017). These carless people will need to rely on other approaches other than driving for evacuation. Also, in some conditions (e.g., chemical spill, earthquake, terrorist attacks), evacuation on foot is a vital mode and could be the only possible mode of escape. Therefore, it is critical to have a diverse multimodal transportation system in order to enhance the disaster resilience of people.

1.2 Objectives

The hypothesis of this study is that the diversity of multimodal transportation systems would affect travelers’ behaviors and potentially evacuation choices during disasters. Specifically, three research objectives are proposed:

Objective 1: Quantify the level of diversity of infrastructures in a multimodal transportation system. Specifically, six types of transportation modes are considered in this study: auto, bus, rail, bike, walking, and ridesharing;
Objective 2: Quantify the level of diversity in travel behaviors. Compare the infrastructure diversity and travel behavior diversity of the same transportation system, and explore the reasons for divergence if any;
Objective 3: Investigate the potential influences of transportation infrastructure diversity on travelers’ behaviors during disasters.

1.3 Expected Contributions

The potential benefits of the projects are twofold. First, it creates metrics and methods to assess the level of diversity of multimodal transportation systems from both the infrastructure perspective and the travel behavior perspective. The methods and metrics can help quantify the level of diversity of different transportation systems and identify improvement needs. Second, it investigates the relationships between travel behaviors during disasters and transportation infrastructure diversity. The relationship can help decision makers to make informed decisions in transportation planning as well as disaster preparation and response.

1.4 Report Overview

Chapter 2 presents the proposed method for assessing multimodal transportation system diversity based on the physical infrastructure characteristics and a case study. Chapter 3 presents the proposed method for assessing multimodal transportation system diversity based on travel behavior surveys and a case study. Chapter 4 summarizes and compares the results from the case studies. Chapter 5 presents the proposed method for quantifying human mobility change during disasters and explores its relationships with transportation infrastructure diversity.

Chapter 2. Transportation Infrastructure Diversity Assessment

2.1 Literature Review

Physical infrastructure diversity is used to measure the quantity and distribution of different transportation modes available in a region. The diversity of a multimodal transportation system has been studied from the physical infrastructure perspective using different methods (Rahimi-Golkhandan et al. 2019; Su et al. 2014). In this study, the approach proposed by Rahimi-Golkhandan et al. (2019) in assessing the diversity of transportation infrastructure systems using the ecological concepts of functional richness and evenness was followed.

An ecological system contains many different species that interact with each other as well as with their surrounding environment (Machado-León and Goodchild 2017). The ecological system diversity is defined as the abundance and distribution of different species in the functional space of a given area. Functional richness and functional evenness are two measures that can be used together to quantify the ecological system diversity (Mason et al. 2005; Mouillot et al. 2013). An analogy can be made between ecologic systems and multimodal transportation systems based on their similarity in certain attributes (Amoaning-Yankson and Amekudzi-Kennedy 2017). Therefore, the concept of ecological systems diversity, functional richness, and functional evenness can be translated into the context of multimodal transportation systems.

2.2 Methodology

2.2.1 Functional Richness

Functional richness in an ecological system is defined as the volume occupied by all species within its functional space of a given area (Mouillot et al. 2013). In multimodal transportation systems, functional richness can be translated as the abundance of all transportation modes in a given area. Therefore, the abundance of each transportation mode needs to be quantified first. Then, the abundance of different transportation modes needs to be aggregated to represent the overall functional richness of the transportation system in the area.

The abundance of a certain transportation mode can be defined as the amount of service it provides per unit area. The functional richness of roadways, bus routes, railways, sidewalks, and bike routes can be calculated as the length of routes per unit area in a region, as shown in equation (1):

$$Richness = \frac{L}{A} \tag{1}$$

L: the total length of a transportation mode mentioned above;

A: the size of an area.

For the ridesharing mode, the functional richness can be calculated as the number of ridesharing providers (i.e., individual drivers who provide ridesharing services) available per unit area, as shown in equation (2):

$$Richness = \frac{n_{RS}}{A} \tag{2}$$

n_{RS}: the number of ridesharing providers available;

A: the size of an area.

2.2.2 Functional Evenness

Functional evenness is related to the regularity of the distribution of all species within the functional space of an ecological system (Mouillot et al. 2013). This concept can be used to measure the distribution of transportation modes in a region (Rahimi-Golkhandan et al. 2019). If all travelers have the same accessibility to one transportation mode across a region, the functional evenness of that transportation mode is high. While if only a few people have easy access to a transportation mode, the functional evenness of that transportation mode is low.

In order to quantify the functional evenness of each transportation mode, a concept of functional regularity index (FRO) is introduced (Bulla, 1994). The basic idea of FRO is to compare the actual distribution of species' traits with the perfect even distribution of the traits (Mouillot et al. 2005; Villéger et al. 2008). Following the idea of FRO, the functional evenness of a multimodal transportation system can be assessed. First, census blocks of an area, as the smallest geographic units used by the United States Census Bureau are identified. Then, the accessibility from a census block centroid (i.e., a point located in the geographic center of the polygon) to a transportation mode is captured. For roadways, bike routes, and sidewalks, the accessibility is measured as the shortest distance of a census block centroid to the nearest roadway, bike route or sidewalk. For the bus and rail transit modes, the accessibility is measured as the distance of a census block centroid to the nearest bus stop or railway station. For the ridesharing mode, the accessibility is defined as the number of ridesharing providers available within a selected distance of a census block centroid. The closer the accessibility values across different census blocks, the higher the functional evenness value. If the accessibility values to one transportation mode for all the census block centroids in a region are identical, the functional evenness of that transportation mode has its maximum value of 1.

The functional evenness of a transportation mode can be quantified using equation (3):

$$Evenness = \frac{\sum_{i=1}^{n} \min\left(\frac{d_i}{\sum_{i=1}^{n} d_i}, \frac{1}{n}\right) - \frac{1}{n}}{1 - \frac{1}{n}} \tag{3}$$

n: the number of census block centroids in a region;

d_i: the accessibility of the i^{th} centroid to a certain transportation mode.

2.2.3 Physical Infrastructure Diversity

After the quantification of functional richness and evenness of each transportation mode in a region, entropy weight method (EWM) is adopted to aggregate these individual metrics into one diversity metric. This diversity metric can represent the level of diversity of a multimodal transportation system from the physical infrastructure perspective.

EWM is an objective weighting method that can be used to integrate different indicators into one single index by assigning weights to the indicators (He et al. 2016). The weights are determined based on the degree of differentiation among values of indicators. In this study, since six transportation modes are considered and each mode has a functional richness value and a functional evenness value, 12 indicators in total needs to be integrated for each area. For each indicator, its values across different areas will be evaluated. If the values show a large variance, a higher weight will be given to the indicator (Zhu et al. 2020). This is because a higher level of variation in the values implies that more information is included in an indicator. The equation and steps for calculating physical infrastructure diversity based on EWM are provided below.

The physical infrastructure diversity of a multimodal transportation system is shown in equation (4).

$$D_{PI} = \sum_{i=1}^{n} \left(W_{R_i} Richness_i + W_{E_i} Evenness_i \right) \tag{4}$$

D_{PI}: the value of physical infrastructure diversity;

$Richness_i$: the richness value for the i^{th} transportation mode;

W_{R_i}: the weight for the corresponding richness indicator;

$Evenness_i$: the evenness value for the i^{th} transportation mode;

W_{E_i}: the weight for the corresponding evenness indicator;

n: the total number of transportation modes considered.

The sum of the weights of all the indicators in equation (4) must equal one. The weights of the indicators in equation (4) can be determined using the following steps:

Step 1: The values of each indicator are mapped into (0, 1] through data normalization. Data normalization is performed by dividing the original value of an indicator by the maximum value of this indicator among all regions studied, as shown in equation (5). Data normalization eliminates the units of measurement, and enables the comparison and integration of different indicators.

$$x_{ij} = \frac{a_{ij}}{\max(a_j)} \ (i = 1,2,\cdots,m; j = 1,2,\cdots,2n) \tag{5}$$

m: the number of regions studied;

n: the number of transportation modes considered for each region;

a_{ij}: the original value of the j^{th} indicator in the i^{th} region;

a_j: all the original values of the j^{th} indicator among all regions.

x_{ij}: the value of the j^{th} indicator in the i^{th} region after data normalization.

Step 2: Calculate the entropy value of each indicator. To determine the entropy value, the ratio of the j^{th} indicator of the i^{th} region to the sum of all the j^{th} indicators of all regions is first calculated as shown in equation (6). Then the entropy value of the j^{th} indicator can be calculated using equation (7). If the values of an indicator across all the regions studied are close to each other, the entropy value of this indicator would be large, since entropy essentially measures uncertainty.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{6}$$

$$E_j = -\frac{\sum_{i=1}^{m} p_{ij} \ln p_{ij}}{\ln m} \tag{7}$$

p_{ij}: the ratio of the value of the j^{th} indicator for the i^{th} region to the sum of all values of the j^{th} indicator among all regions;

E_j: the entropy value of the j^{th} indicator;

m: the total number of regions.

Step 3: Generate the entropy weight of each indicator, as shown in equation (8). Entropy weight measures the amount of information contained in an indicator. A larger entropy value implies a high level of similarity in all values of an indicator across different regions. As a result, less information is contained in the indicator, and the entropy weight of this indicator is low.

$$W_j = \frac{1 - E_j}{2n - \sum_{j=1}^{2n} E_j} \tag{8}$$

W_j: the weight of the j^{th} indicator;

n: the number of transportation modes in a region.

2.3 Case Study

A case study of the capital city of Connecticut, Hartford was conducted to assess its transportation infrastructure diversity. The size of the city of Hartford is 17.3 square miles

(Connecticut Department of Economic Community Development, 2016). It has a population of 124,390, with 53,696 housing units (U.S. Census Bureau 2018). Six zip code areas of the city of Hartford (i.e., 06103, 06105, 06106, 06112, 06114, and 06120) were chosen as the study regions. Using the method introduced above, the diversity of the multimodal transportation systems in the six zip code areas, including roadways, bus routes, railways, sidewalks, bike routes, and ridesharing were quantified.

In order to quantify the physical infrastructure diversity in the six zip code areas, infrastructure data were collected from Hartford GIS Data (City of Hartford 2019), which included ArcGIS data of various transportation infrastructures such as roadways, bus routes and stops, railways, bike routes, and sidewalks. The functional richness and evenness of these transportation modes were calculated using the ArcGIS data. For the ridesharing mode, data were obtained from the CT rides website, which is a GIS-based website that helps commuters find ridesharing providers (CTrides 2019). Through the website, a commuter can input his/her address and find out the number of ridesharing providers within a certain distance range. In this study, a search on the number of ridesharing providers in the six zip code areas was conducted in October 2019. The number of ridesharing providers available was used to calculate the functional richness of ridesharing in each zip code area. The functional evenness of ridesharing in each zip code area was calculated based on the number of ridesharing providers available within a certain distance (0.5 mile) of each census block centroid. For a specific zip code area, if the number of ridesharing providers in different census blocks is close, the functional evenness is considered to be high.

The GIS maps of different transportation infrastructures in the case study are shown in Figure 2.1 - Figure 2.5. Data for the functional richness calculation of each transportation mode in the six zip code areas are summarized in Table 2.1.

Table 2.1: Data for the functional richness calculation of each transportation mode in the six zip code areas

Zip code	Roadway length (miles)	Bus route length (miles)	Railway length (miles)	Bike route length (miles)	Sidewalk length (miles)	# of ridesharing providers available	Area (square miles)
06103	20.90	79.35	1.25	2.18	41.13	93	0.54
06105	41.25	44.79	3.22	8.49	91.70	239	2.27
06106	86.19	83.69	4.21	17.87	200.84	238	4.30
06112	53.13	20.48	3.06	10.54	116.07	81	3.04
06114	62.97	44.87	5.82	6.84	99.58	75	4.05
06120	44.06	48.10	17.05	9.60	81.33	59	3.97

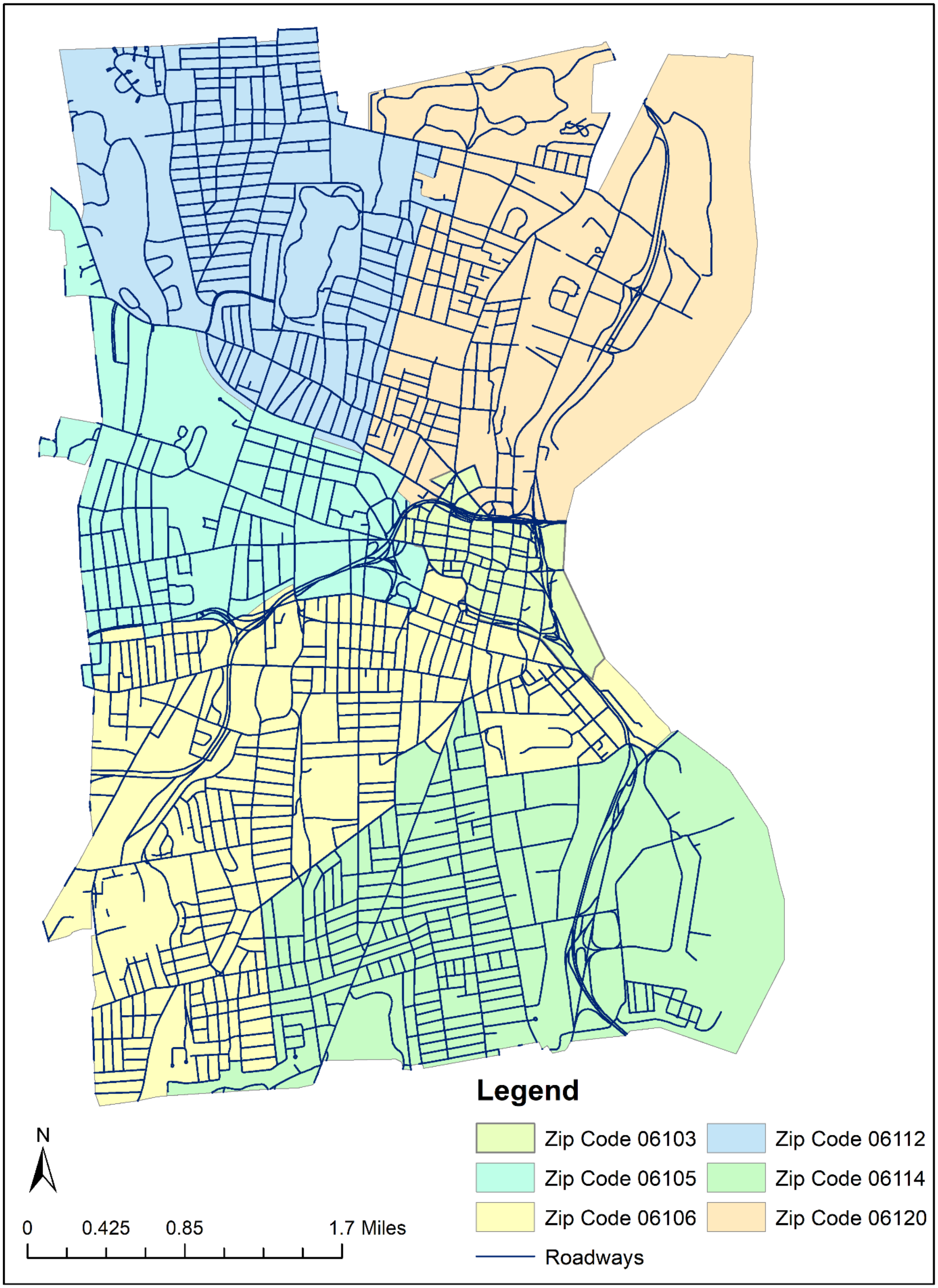

Figure 2.1: The overview of roadways in six zip code areas in the city of Hartford

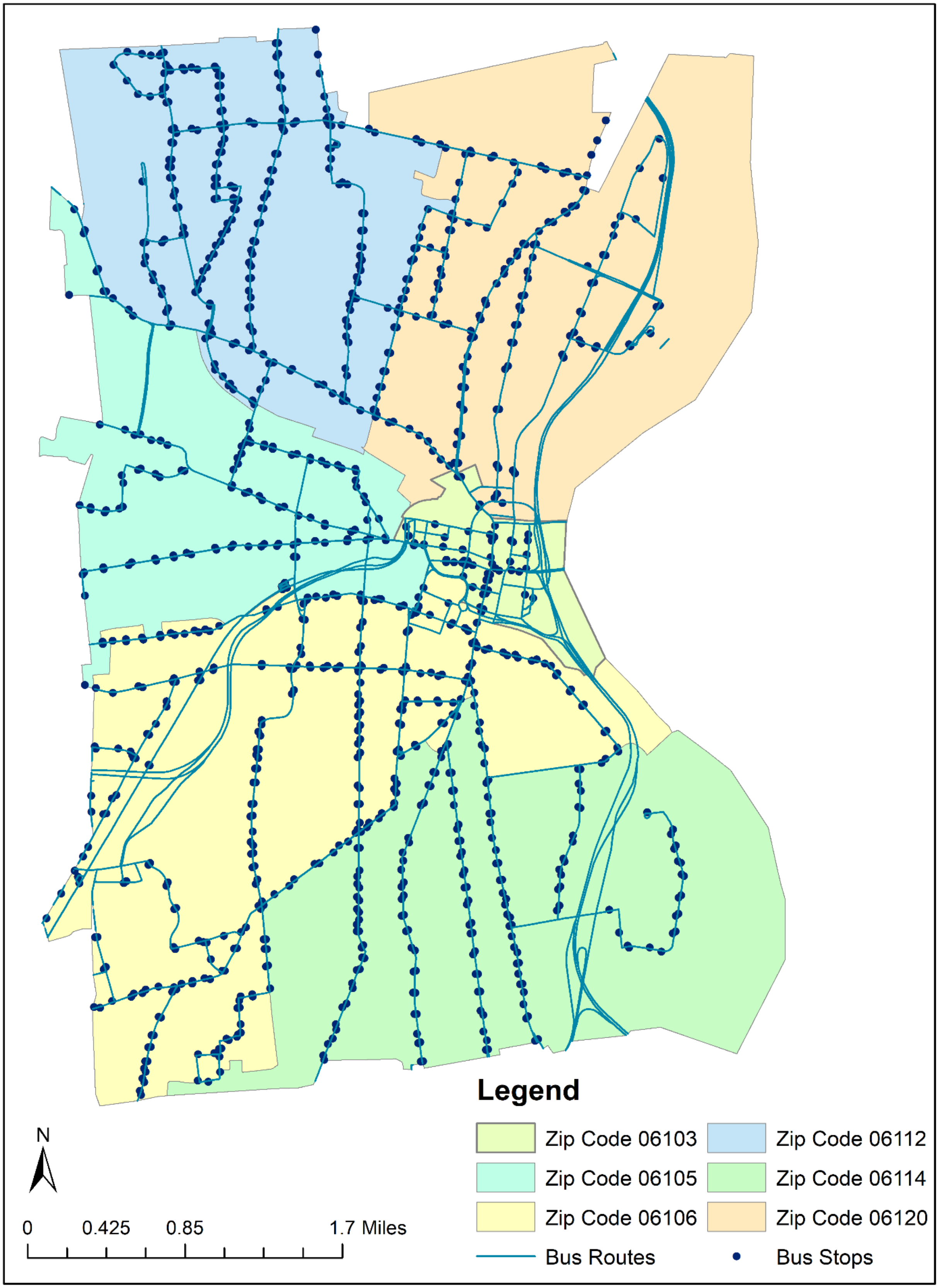

Figure 2.2: The overview of bus routes and stops in six zip code areas in the city of Hartford

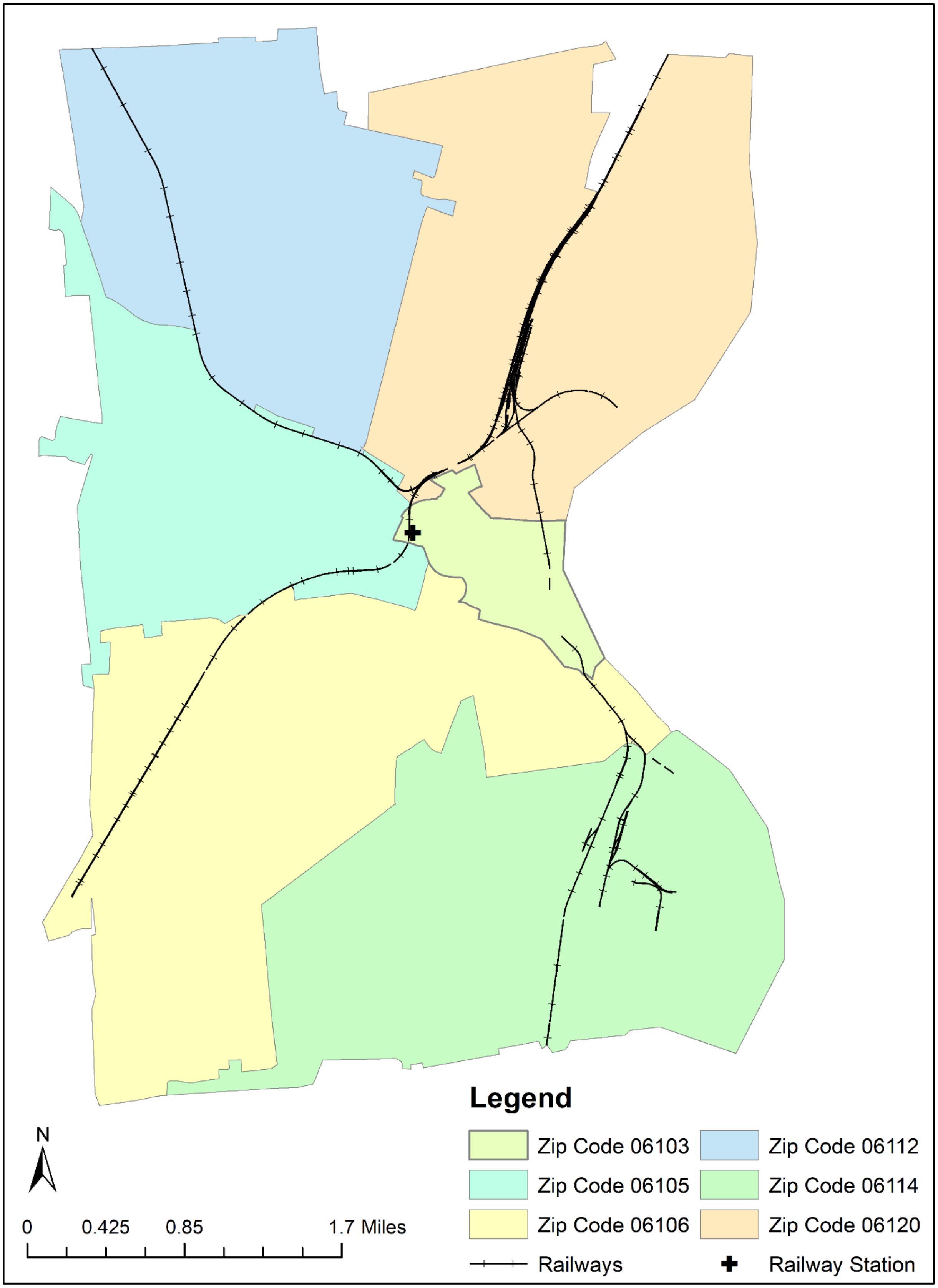

Figure 2.3: The overview of railways in six zip code areas in the city of Hartford

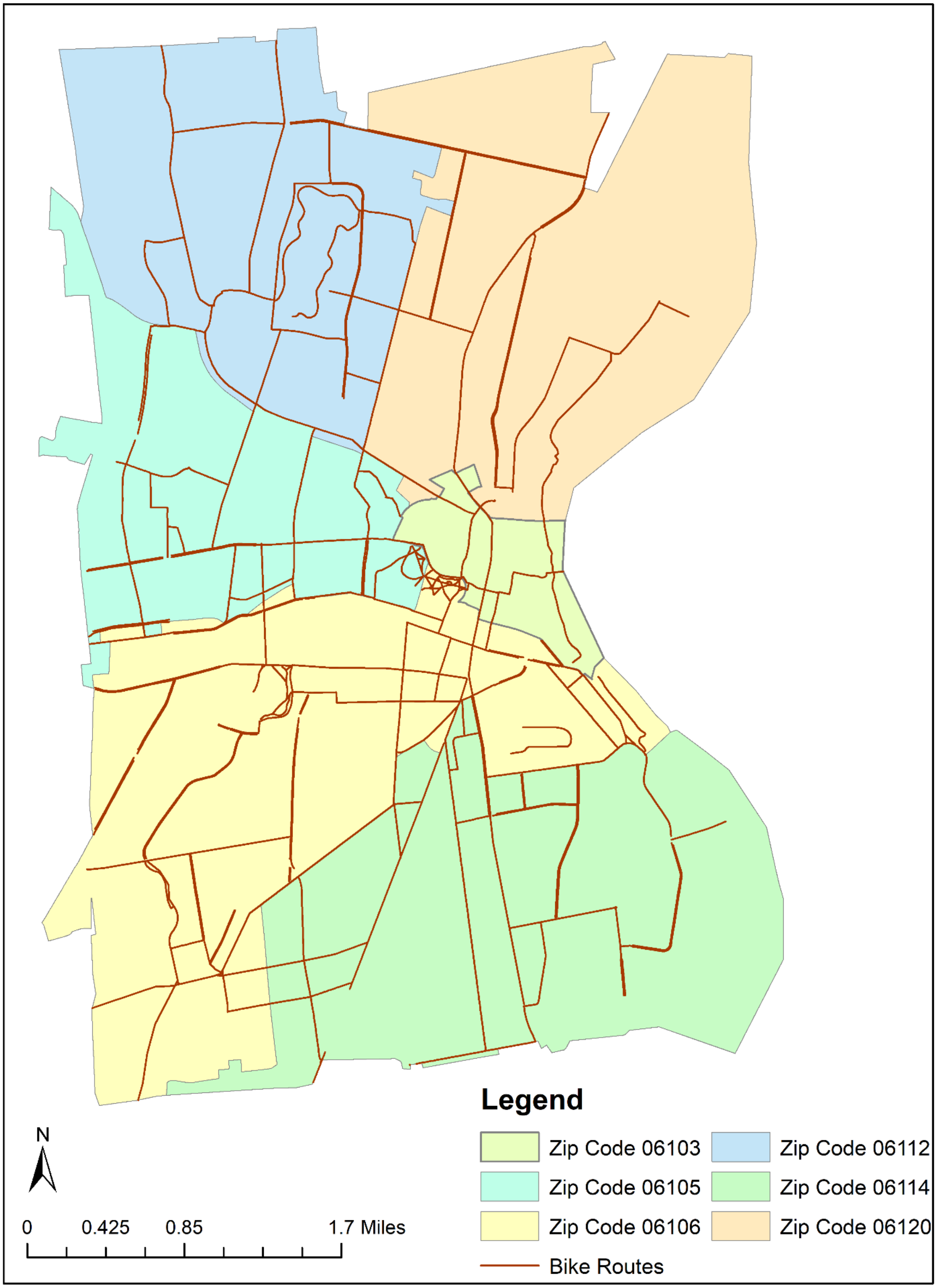

Figure 2.4: The overview of bike routes in six zip code areas in the city of Hartford

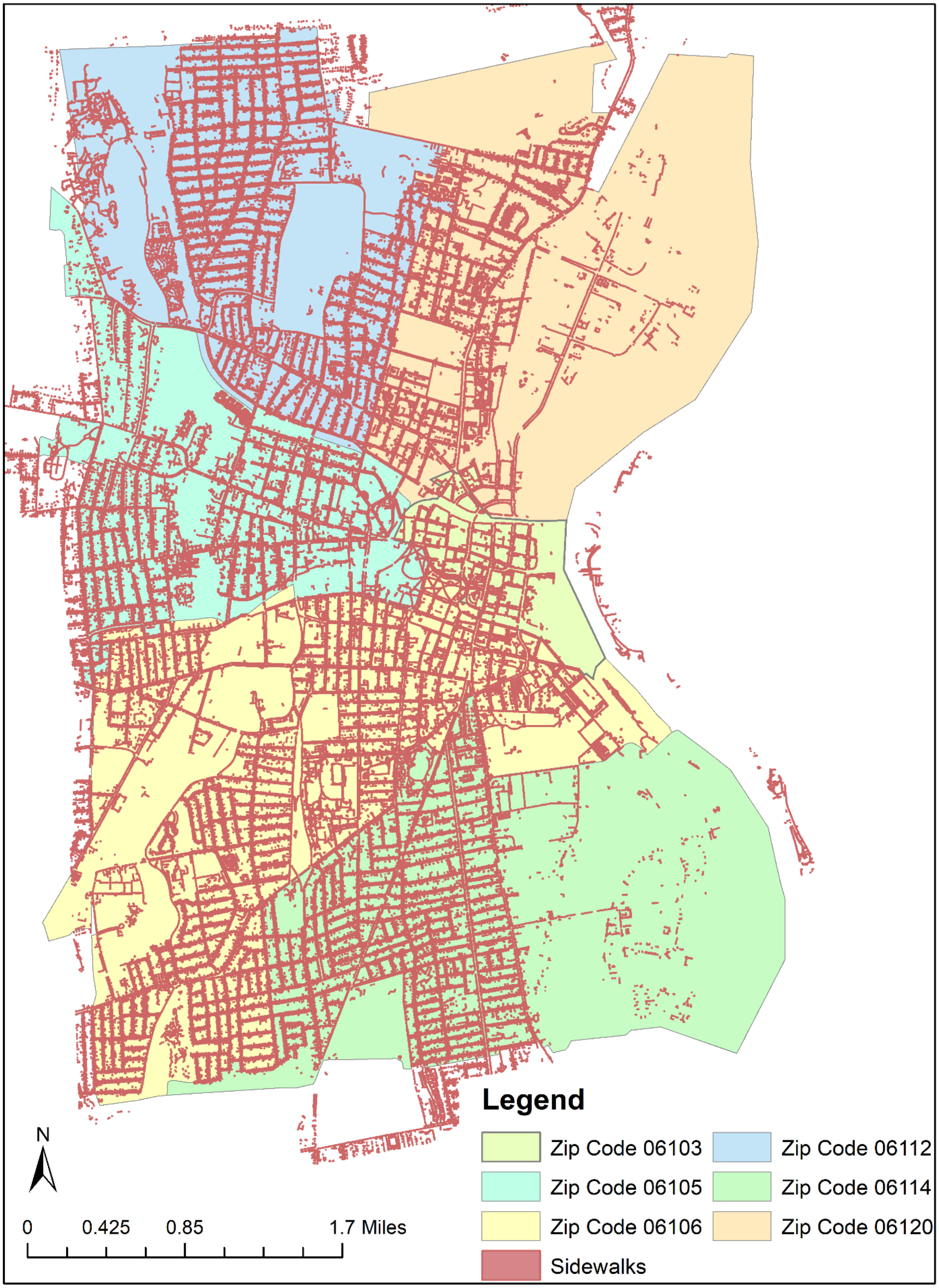

Figure 2.5: The overview of sidewalks in six zip code areas in the city of Hartford

Using the data above, the functional richness of each transportation mode in six zip code areas can be calculated. For example, the total length of bus routes in zip code area 06103 is 79.35 miles, and the area size of this zip code area is 0.54 square miles. As a result, the functional richness of bus routes in 06103 is:

$$R_{BS} = \frac{L}{A} = \frac{79.35}{0.54} = 146.950$$

The results of richness calculation (original results and normalized results) are summarized in Table 2.2. Python codes of the functional richness calculation is attached in Appendix A.

Table 2.2: The functional richness of each transportation mode in six zip code areas (before data normalization)

Zip code	R_{RN}		R_{BS}		R_{RT}		R_{BR}		R_{WW}		R_{RS}	
	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD
06103	38.711	1.000	146.950	1.000	2.306	0.537	4.033	0.970	76.171	1.000	172.222	1.000
06105	18.171	0.469	19.731	0.134	1.417	0.330	3.738	0.900	40.394	0.530	105.286	0.611
06106	20.043	0.518	19.463	0.132	0.980	0.228	4.155	1.000	46.707	0.613	55.349	0.321
06112	17.477	0.451	6.738	0.046	1.008	0.235	3.467	0.834	38.182	0.501	26.645	0.155
06114	15.548	0.402	11.078	0.075	1.437	0.334	1.689	0.406	24.588	0.323	18.519	0.108
06120	11.098	0.287	12.115	0.082	4.295	1.000	2.419	0.582	20.485	0.269	14.861	0.086

(Note: RN for roadways, BS for bus routes, RT for railways, BR for bike routes, WW for sidewalks, RS for ridesharing, ORIG for original, NORMD for normalized)

When calculating the functional evenness of each transportation mode in each zip code area, the shortest distance from each census block centroid to the nearest transportation infrastructure was generated through the proximity function in ArcGIS. The detailed information is shown in Figure 2.6 - Figure 2.10. Accessibility values from each census block centroid to each transportation mode in six zip code areas are summarized in Table 2.3 - Table 2.8.

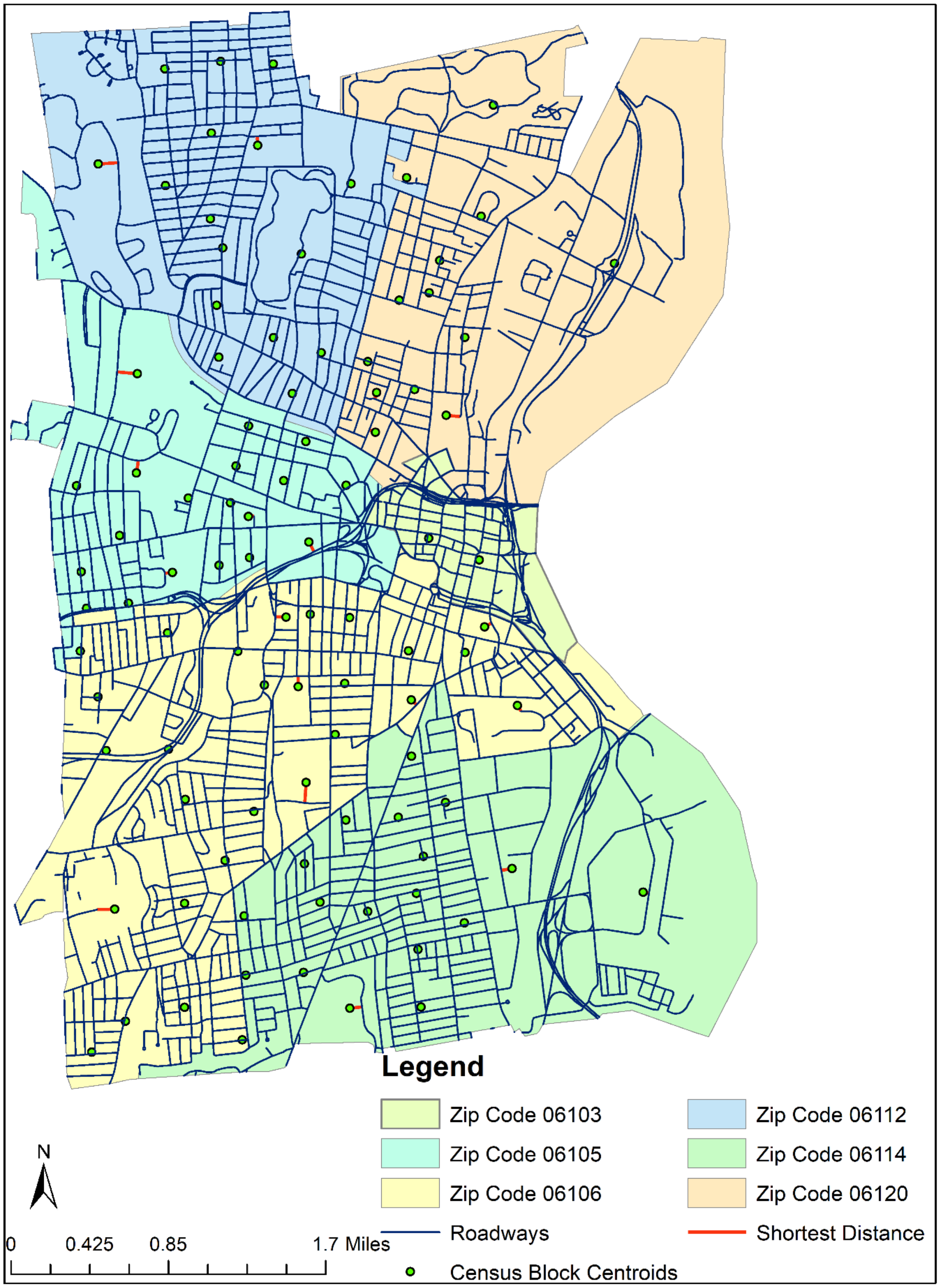

Figure 2.6: The overview of the shortest distance from each census block centroid to the nearest roadway in six zip code areas in the city of Hartford

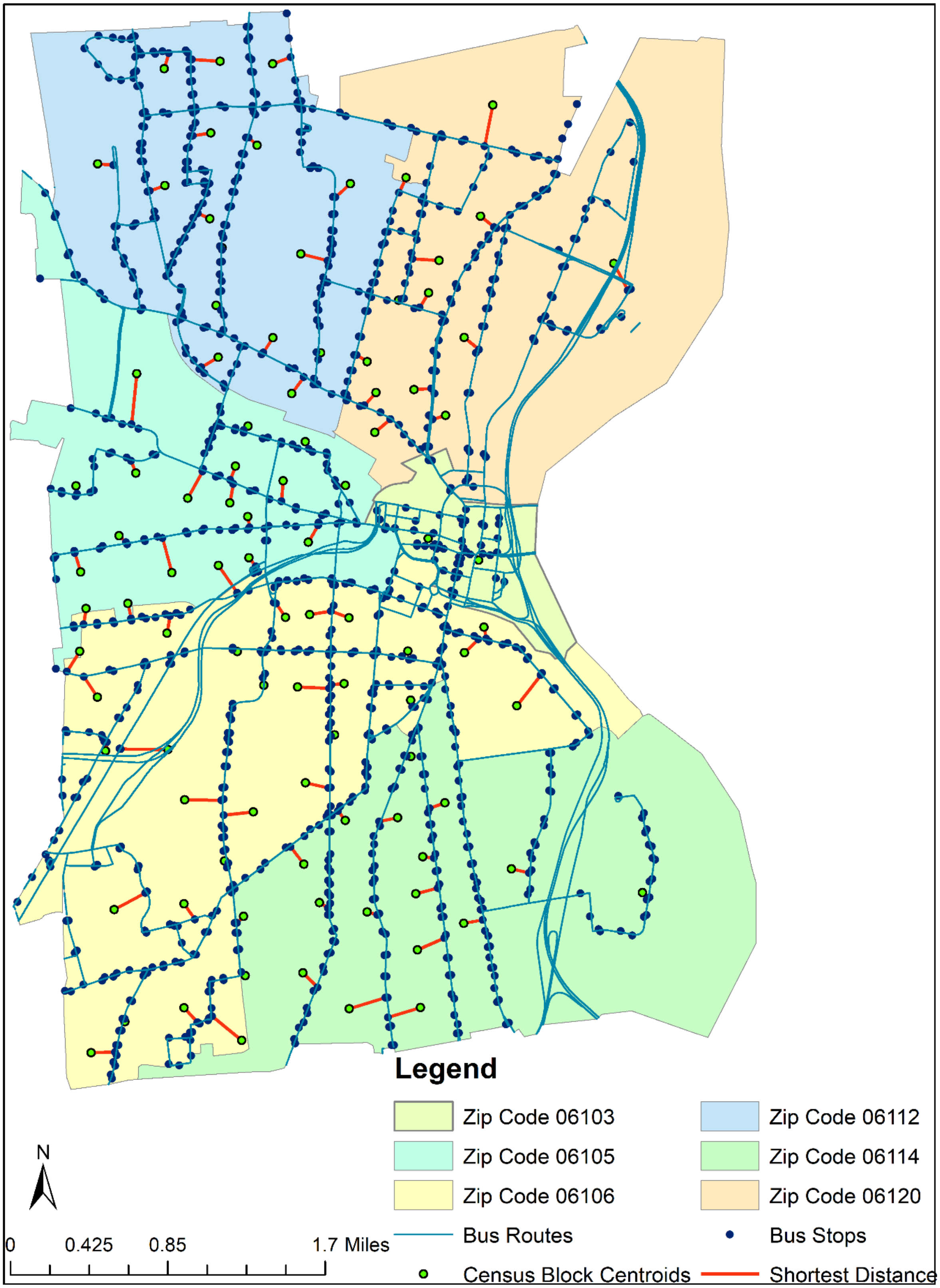

Figure 2.7: The overview of the shortest distance from each census block centroid to the nearest bus stop in six zip code areas in the city of Hartford

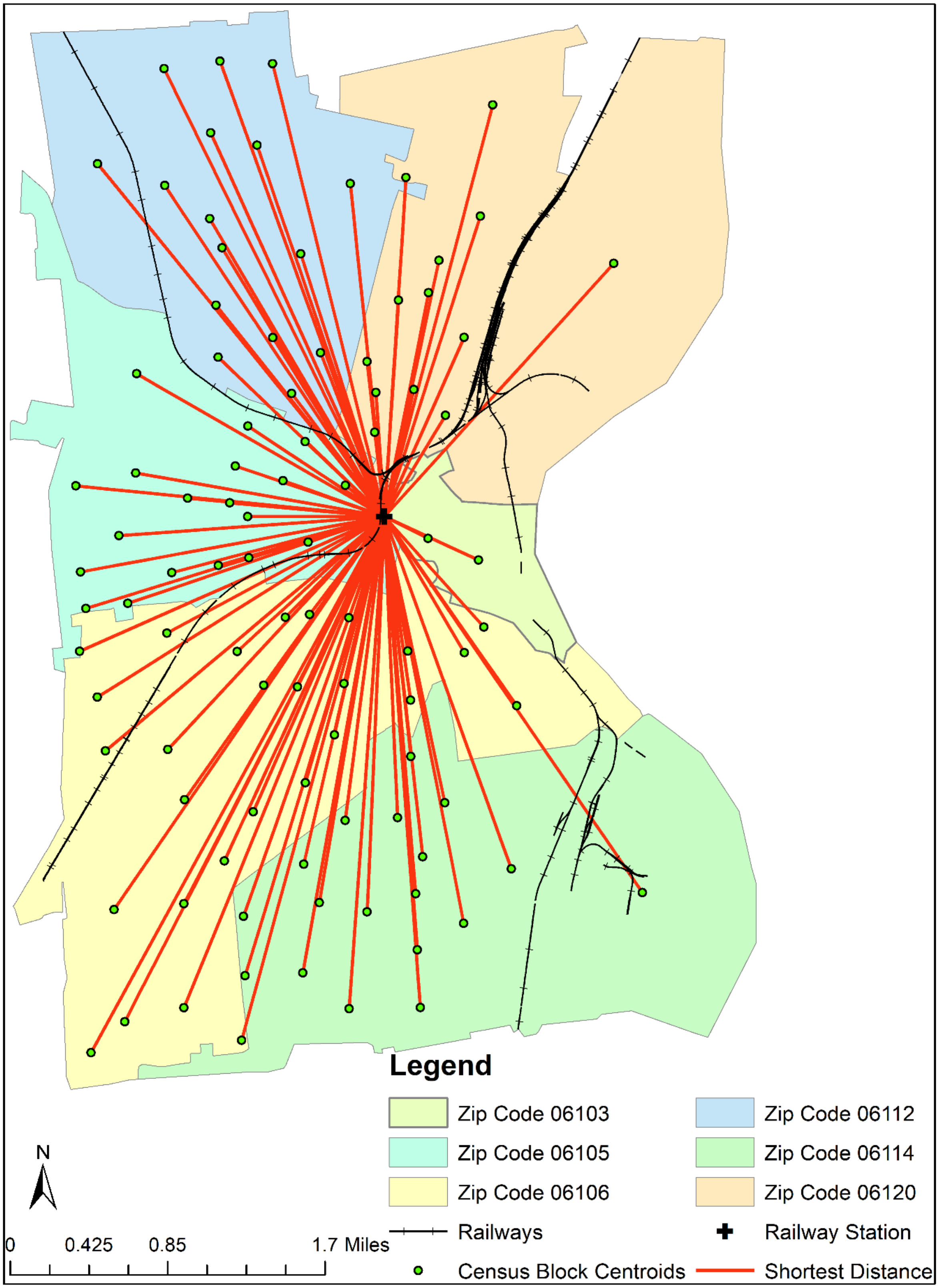

Figure 2.8: The overview of the shortest distance from each census block centroid to the nearest railway station in six zip code areas in the city of Hartford

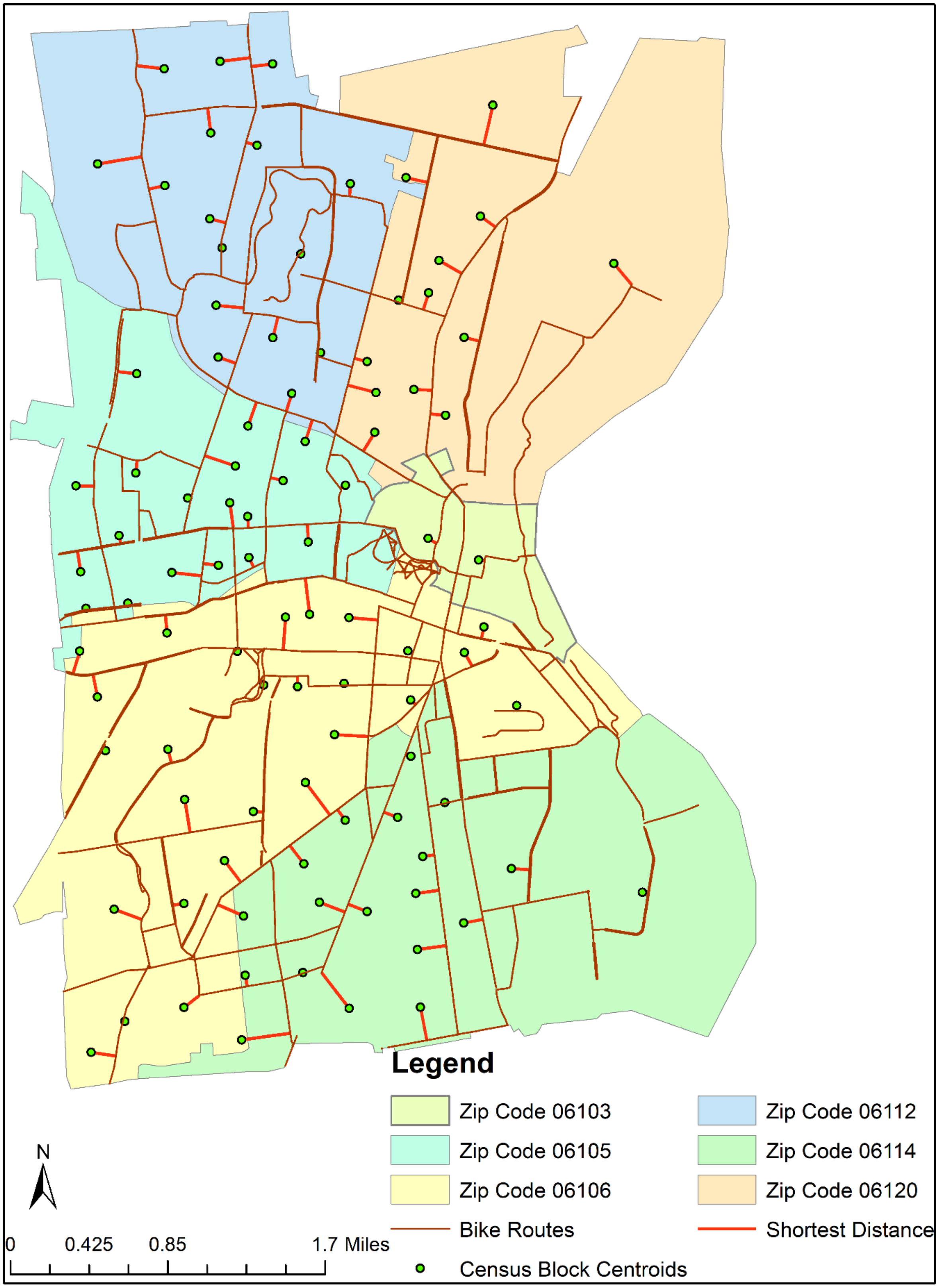

Figure 2.9: The overview of the shortest distance from each census block centroid to the nearest bike route in six zip code areas in the city of Hartford

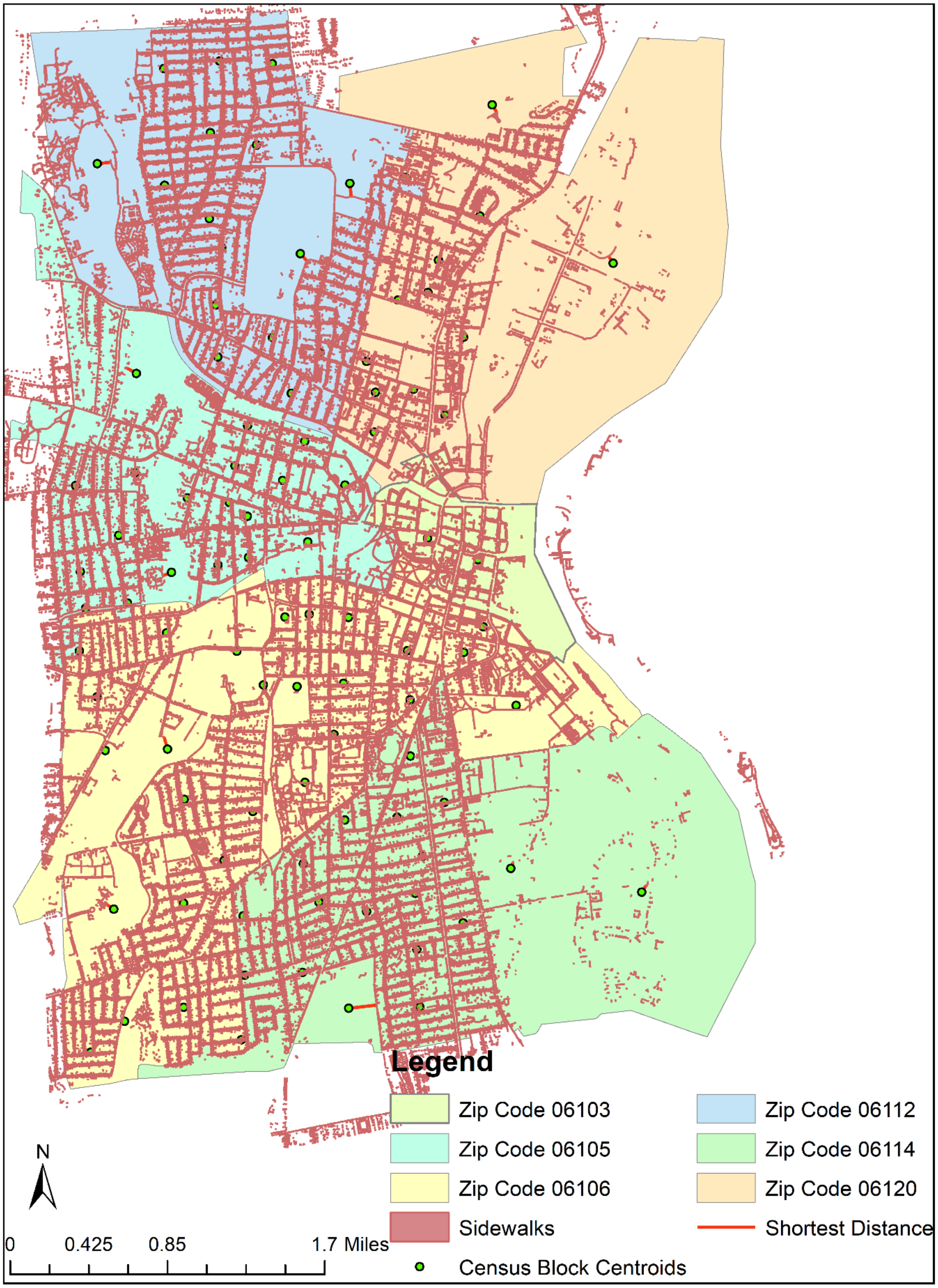

Figure 2.10: The overview of the shortest distance from each census block centroid to the nearest sidewalk in six zip code areas in the city of Hartford

Table 2.3: Accessibility from each census block centroid to each transportation mode in the 06103 zip code area

Centroid number	Roadways (feet)	Bus stops (feet)	Railway stations (feet)	Bike routes (feet)	Sidewalks (feet)	Ridesharing
1	114.87	212.33	2960.87	168.94	43.05	43
2	48.95	218.49	1396.52	658.30	37.92	57

Table 2.4: Accessibility from each census block centroid to each transportation mode in the 06105 zip code area

Centroid number	Roadways (feet)	Bus stops (feet)	Railway stations (feet)	Bike routes (feet)	Sidewalks (feet)	Ridesharing
1	44.67	437.69	7725.99	54.53	11.95	18
2	59.63	556.53	4430.03	712.97	30.15	32
3	226.40	1025.70	6272.40	1040.67	246.20	30
4	23.97	418.53	4489.12	1776.96	0.00	33
5	163.17	312.30	3902.45	656.73	65.33	32
6	128.46	588.87	3067.40	2009.84	75.05	32
7	49.34	230.63	8844.68	509.91	20.23	15
8	35.05	567.03	8808.75	588.89	8.81	22
9	75.82	246.40	1421.94	1127.70	44.30	20
10	311.91	562.34	2288.63	783.26	64.57	43
11	95.95	878.56	5634.35	930.70	3.53	25
12	16.40	940.38	4934.14	924.17	3.16	27
13	49.72	313.28	4038.34	844.79	1.19	25
14	21.37	166.75	4671.84	2299.75	0.00	23
15	163.11	230.69	3113.24	1733.91	85.96	26
16	584.90	1449.15	8156.34	551.82	325.05	4
17	356.94	376.09	7199.02	1201.82	9.39	21
18	135.59	269.89	7589.74	216.57	95.81	27
19	51.23	456.86	8907.70	41.12	6.47	20
20	23.37	686.12	9505.17	660.71	5.19	18

Table 2.5: Accessibility from each census block centroid to each transportation mode in the 06106 zip code area

Centroid number	Roadways (feet)	Bus stops (feet)	Railway stations (feet)	Bike routes (feet)	Sidewalks (feet)	Ridesharing
1	152.36	558.17	15141.67	1733.04	98.20	5
2	583.83	675.02	7924.71	1171.04	15.98	32
3	96.29	100.87	6388.06	1912.20	5.06	8
4	31.91	86.50	16208.31	2682.68	64.42	2
5	191.05	1112.15	6590.20	152.16	121.56	10
6	110.58	1051.74	9889.70	1092.25	57.26	3
7	503.71	1013.27	13610.67	949.72	249.77	2
8	62.88	133.69	10835.28	1042.45	10.60	7
9	136.57	544.32	12439.12	321.07	82.26	5
10	56.17	683.22	17437.77	3973.90	17.00	3
11	12.72	1089.73	15490.79	3155.15	11.67	2
12	19.48	1346.37	9076.56	386.09	362.10	32
13	69.69	358.20	4905.45	1824.13	27.55	12
14	294.13	905.94	5454.68	534.95	164.72	17
15	70.53	142.80	5696.47	60.37	15.34	11
16	306.17	478.03	4033.22	1013.87	87.41	29
17	12.45	224.26	5919.52	94.06	14.81	15
18	156.91	223.45	3895.70	1343.95	0.43	32
19	203.11	187.95	5294.04	1040.96	37.61	27
20	225.22	327.97	4244.80	327.45	15.93	49
21	91.23	554.94	4504.96	431.89	50.92	28
22	128.55	547.39	3059.90	1043.41	94.43	26
23	0.30	617.15	3515.68	1047.41	11.84	24
24	74.54	498.04	7036.81	506.15	37.15	9
25	17.44	703.79	9673.73	647.96	1.07	7
26	104.82	260.44	10396.23	100.44	84.12	32
27	54.39	845.89	9221.91	272.02	4.37	8

Table 2.6: Accessibility from each census block centroid to each transportation mode in the 06112 zip code area

Centroid number	Roadways (feet)	Bus stops (feet)	Railway stations (feet)	Bike routes (feet)	Sidewalks (feet)	Ridesharing
1	563.17	454.78	12976.40	1270.84	381.48	1
2	59.30	505.49	6015.22	1059.05	0.17	12
3	90.34	118.29	5018.12	75.89	1.57	24
4	266.79	329.28	11204.08	893.47	10.43	8
5	50.64	453.80	11338.14	468.96	5.19	3
6	84.01	587.68	4394.74	748.65	21.35	22
7	144.73	562.39	6573.01	2088.43	52.05	8
8	136.86	194.85	7710.93	1060.48	40.78	5
9	103.92	515.50	12017.65	1652.44	29.53	9
10	73.90	462.80	14244.08	802.89	13.71	7
11	90.71	575.19	9554.74	436.88	381.96	10
12	58.70	793.13	7868.07	19.61	279.17	12
13	29.72	806.01	13814.52	1756.12	5.46	13
14	118.55	546.87	13311.38	1176.16	45.90	13
15	31.34	54.83	8962.31	923.98	0.00	3
16	112.92	375.65	9852.74	1420.12	77.15	3

Table 2.7: Accessibility from each census block centroid to each transportation mode in the 06114 zip code area

Centroid number	Roadways (feet)	Bus stops (feet)	Railway stations (feet)	Bike routes (feet)	Sidewalks (feet)	Ridesharing
1	87.36	532.56	8603.82	1893.42	7.80	13
2	313.93	518.28	10688.68	511.87	181.05	1
3	27.21	460.18	8350.81	478.06	4.87	13
4	87.05	264.90	12094.73	1209.51	18.70	11
5	21.33	151.74	13688.45	1972.11	6.11	10
6	130.68	341.88	8740.98	2340.17	49.91	10
7	160.64	122.48	6885.10	1296.47	116.53	20
8	349.46	1087.15	14081.65	4809.83	798.35	1
9	31.86	298.09	11293.31	3304.05	0.88	9
10	27.40	585.41	13231.46	3301.11	9.61	9
11	22.88	840.24	12399.76	3437.97	7.84	4
12	149.09	961.74	14052.58	4311.43	24.96	3
13	65.36	653.71	10798.12	3023.82	17.99	9
14	59.32	550.18	11825.56	1924.92	17.21	6
15	17.85	318.84	9768.82	2001.01	1.11	8
16	166.83	233.15	13016.17	154.20	226.66	0
17	15.70	626.14	10184.44	1129.89	19.09	11
18	121.33	285.65	11171.97	1980.05	9.13	11

Table 2.8: Accessibility from each census block centroid to each transportation mode in the 06120 zip code area

Centroid number	Roadways (feet)	Bus stops (feet)	Railway stations (feet)	Bike routes (feet)	Sidewalks (feet)	Ridesharing
1	68.04	91.08	6191.91	92.61	4.55	14
2	45.66	493.25	6515.49	671.74	5.67	9
3	399.46	388.35	3374.12	553.84	13.81	2
4	47.80	862.58	9749.14	2864.07	243.62	0
5	72.31	549.81	5600.49	432.00	18.60	3
6	89.73	508.06	9003.90	810.23	10.35	6
7	75.79	1196.86	12150.52	1154.37	248.30	2
8	142.03	477.20	9695.82	620.90	23.18	8
9	14.54	756.23	7479.90	770.21	2.68	10
10	196.94	579.73	2421.66	2223.97	46.99	22
11	15.94	355.85	4448.85	1422.62	2.14	14
12	187.14	488.19	3548.03	1748.61	0.13	11
13	85.76	494.31	3725.89	1464.41	37.73	8

Using the data above, the functional evenness of each transportation mode in the six zip code areas were calculated. For example, there are in total 20 census blocks in zip code area 06105. The distance values from each census block centroid to the nearest bus stop were identified and summarized in Table 2.4. The functional evenness of bus routes in 06105 was calculated using equation (3):

$$E_{BS} = \frac{\sum_{i=1}^{20} \min\left(\frac{d_i}{\sum_{i=1}^{20} d_i}, \frac{1}{20}\right) - \frac{1}{20}}{1 - \frac{1}{20}} = 0.761$$

The results of evenness calculation (original results and normalized results) are summarized in Table 2.9. Python codes of the functional evenness calculation is attached in Appendix A.

Table 2.9: Evenness values of each transportation mode in six zip code areas (before data normalization)

Zip code	E_{RN}		E_{BS}		E_{RT}		E_{BR}		E_{WW}		E_{RS}	
	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD	ORIG	NORMD
06103	0.598	0.881	0.986	1.000	0.641	0.697	0.408	0.537	0.937	1.000	0.860	0.988
06105	0.587	0.866	0.761	0.772	0.805	0.876	0.737	0.969	0.454	0.484	0.870	1.000
06106	0.625	0.921	0.740	0.751	0.781	0.849	0.667	0.876	0.545	0.582	0.644	0.740
06112	0.678	1.000	0.821	0.833	0.853	0.928	0.761	1.000	0.374	0.399	0.728	0.836
06114	0.617	0.910	0.768	0.779	0.920	1.000	0.747	0.982	0.313	0.334	0.752	0.864
06120	0.638	0.940	0.825	0.837	0.795	0.865	0.705	0.927	0.356	0.381	0.705	0.810

(Note: RN for roadways, BS for bus routes, RT for railways, BR for bike routes, WW for sidewalks, RS for ridesharing, ORIG for original, NORMD for normalized)

With all the functional richness and evenness of each transportation mode in six zip code areas calculated, the weight of each indicator was obtained using equations (5)-(8). The results are summarized in Table 2.10.

Table 2.10: Weight of each richness and evenness indicator

Indicator	R_{RN}	R_{BS}	R_{RT}	R_{BR}	R_{WW}	R_{RS}
Weight	0.055	0.445	0.104	0.028	0.061	0.232
Indicator	E_{RN}	E_{BS}	E_{RT}	E_{BR}	E_{WW}	E_{RS}
Weight	0.001	0.003	0.004	0.012	0.052	0.004

(Note: RN for roadways, BS for bus routes, RT for railways, BR for bike routes, WW for sidewalks, RS for ridesharing)

The physical infrastructure diversity of each zip code area was then calculated using equation (4). For example, the physical infrastructure diversity in the 06103 zip code area was calculated as follows:

$$\begin{aligned} D_{PI} &= \sum_{i=1}^{6} \left(W_{R_i} Richness_i + W_{E_i} Evenness_i\right) \\ &= 0.055 \times 1.000 + 0.445 \times 1.000 + 0.104 \times 0.537 + 0.028 \times 0.970 + 0.061 \times 1.000 \\ &\quad + 0.232 \times 1.000 + 0.001 \times 0.881 + 0.003 \times 1.000 + 0.004 \times 0.697 + 0.012 \times 0.537 \\ &\quad + 0.052 \times 1.000 + 0.004 \times 0.988 \\ &= 0.945 \end{aligned}$$

Following the same steps, the physical infrastructure diversity of other zip code areas was calculated. The physical infrastructure diversity values of all the six zip code areas and their normalized values are summarized in Table 2.11. As shown in Table 2.11, the 06103 zip code area is the most diverse and the 06114 zip code area is the least diverse in terms of physical transportation infrastructures.

Table 2.11: Values of the physical infrastructure diversity in six zip code areas

Zip code	06103	06105	06106	06112	06114	06120
Physical infrastructure diversity	0.945	0.367	0.301	0.203	0.186	0.250
Physical infrastructure diversity-Normalized	1.000	0.388	0.319	0.214	0.197	0.265

Chapter 3. Travel Behavior Diversity Assessment

3.1 Literature Review

Assessing transportation system diversity from the physical infrastructure perspective could provide useful insights on transportation infrastructure. However, it may lack consideration of the human aspects of transportation. Studying the characteristics of physical transportation infrastructures only reflects the transportation design and planning intention, while failing to reflect the actual performance of multimodal transportation systems from the travelers' perspective. The complex human-infrastructure interactions could not be captured if only focusing on the physical aspects of multimodal transportation systems.

Aiming at capturing the human aspects in multimodal transportation system assessment, existing studies have used subjective rating and expert opinions. For example, a "Transportation for Everyone" rating system was developed by Litman (2017) to assess whether travelers are satisfied with the existing mobility options. Feng and Hsieh (2009) also studied transportation diversity from the views of various transportation stakeholders. Despite the efforts, an objective quantification method to assess the level of travel diversity based on actual human behavior is still missing. In this study, an entropy-based method to quantify transportation system diversity based on travel behavior survey is proposed.

3.2 Methodology

Transportation system diversity assessment from the travel behavior perspective reflects how diversely travelers are using different transportation modes in a region. In this study, the number of trips made by travelers using a specific mode during a given time period is used to quantify the usage of the mode. Entropy is calculated based on the deviation from a perfectly equal distribution of the usage of all transportation modes. A higher entropy value means that travelers are using diverse types of transportation modes in their daily lives.

The entropy-based travel behavior diversity is determined using the following steps:

Step 1: The percentage of trips made by each transportation mode in a region is calculated:

$$p_{ij} = \frac{N_{ij}}{\sum_{i=1}^{n} N_{ij}} \; (i = 1,2,\cdots,n;\; j = 1,2,\cdots,m) \tag{9}$$

p_{ij}: the percentage of trips made by the i^{th} transportation mode in the total number of trips in the j^{th} region during the given period of time;

N_{ij}: the number of trips using the i^{th} transportation mode in the j^{th} region during the given period of time;

m: the number of regions studies;

n: the number of transportation mode considered.

Step 2: Based on the percentages of trips made by different modes obtained in Step 1, the entropy value of a region regarding its residents' diverse travel behaviors can be calculated, as shown in equation (10):

$$E_j = -\frac{\sum_{i=1}^{n} p_{ij} \ln p_{ij}}{\ln n} \ (j = 1,2,\cdots,m) \tag{10}$$

E_j: the entropy value of the j^{th} region.

In equation (10), if all p_{ij} values of the j^{th} region are equal to each other, which means $p_{ij} = {}^{1}/_{n}$, $-\sum_{i=1}^{n} p_{ij} \ln p_{ij}$ equals to $\ln n$ and the entropy value will be 1. This means that this region has the most diverse possible travel behavior pattern. The entropy value decreases when the differences in p_{ij} values increases.

Step 3: Data normalization is conducted to obtain the travel behavior diversity of the j^{th} region:

$$D_{TR,j} = \frac{E_j}{\max(E)} \ (j = 1,2,\cdots,m) \tag{11}$$

E: the entropy values of all regions;

$D_{TR,j}$: the normalized travel behavior diversity of the j^{th} region.

3.3 Case Study

The method for calculating travel behavior diversity was also implemented in the same case study of the city of Hartford, Connecticut. The data used for quantifying the travel behavior diversity in six zip code areas in the city of Hartford were mainly from a statewide travel behavior survey conducted in Connecticut in 2016 (Konduri et al. 2017). Survey invitations were mailed to 153,649 households living in Connecticut to understand their travel behaviors. Targeted oversampling and up-sampling methods were used to ensure a good representation of different households in Connecticut, especially the transit-using and zero-vehicle households, as well as the households in hard-to-reach communities (Konduri et al. 2017). In total, 8,403 households responded and participated in the survey. For the purpose of this study, 2,631 household responses from the city of Hartford were used for analysis.

The travel behavior survey was broken down into two distinct parts: the recruit survey and the travel diary survey. In the recruit survey, basic background information regarding household characteristics was collected. Data collected in the recruit survey included household information (e.g., household composition, household demographics, current home location, number of household vehicles), personal information (e.g., person-level demographics, typical commute behavior), and vehicle information. In the travel diary survey, details regarding all trips completed by household members over a pre-assigned 24-hour period were collected. The households invited to the survey were randomly assigned one of 30 weekday "travel dates", spread over ten weeks in March, April, and May 2016. All travel dates were on a Tuesday, Wednesday, or Thursday, due to the focus on typical weekday travel of residents. Travel dates were pre-assigned to households and invitations were evenly distributed over all the dates. The travel diary survey collected details about each individual trip, such as the main purpose of the trip, the start and arrived time of the trip, the location of the trip origin and destination, and the transportation mode used during the trip.

Based on the travel behavior survey data, the number of trips of different transportation modes made by residents in the six zip code areas in the city of Hartford was captured and used for data analysis. While processing the survey data, some trip legs were required to be consolidated into a single travel journey using trip linking (Konduri et al. 2017). Trip linking was needed, since some survey respondents reported individual trip segments of travel occurrence as separate trips when not necessary. For example, an individual going back home from office may have been reported walking to the parking lot and driving home as two separate trips. Considering the main trip purpose, it should have been reported as a single trip using the auto mode. Without trip linking, the trip rates will be inflated, and subsequent travel analyses will be erroneous.

The travel behavior diversity in the six zip code areas in the city of Hartford was quantified using the following steps: first, trips made by residents in each of the six zip code areas were identified according to the trip originate location. Second, the number of trips made by each transportation mode in each zip code area was identified. Finally, equations (9)-(11) were used to calculate the travel behavior diversity for each zip code area. The number of trips for each transportation mode and the original entropy values of the six zip code areas are summarized in Table 3.1. The normalized values of the travel behavior diversity in six zip code areas are summarized in Table 3.2. As shown in Table 3.2, zip code area 06103 is the most diverse from the travel behavior perspective, while zip code area 06114 is the least diverse from the travel behavior perspective.

Table 3.1: Aggregated number of trips for each transportation mode and the original entropy values in six zip code areas

Zip code	Aggregated number of trips for each transportation mode						Total number of trips	Entropy (original)
	Driving	Bus system	Rail transit	Cycling	Walking	Ridesharing		
06103	194	70	1	3	132	4	404	0.624
06105	449	74	1	16	181	2	723	0.550
06106	528	108	0	7	105	10	758	0.504
06112	130	45	0	4	22	0	201	0.523
06114	226	60	0	0	30	0	316	0.435
06120	147	42	0	422	20	2	633	0.512

Table 3.2: Values of the travel behavior diversity in six zip code areas

Zip code	06103	06105	06106	06112	06114	06120
Travel behavior diversity	1.000	0.881	0.808	0.838	0.696	0.820

Chapter 4. Comparison of Physical Infrastructure Diversity and Travel Behavioral Diversity

4.1 Comparison of Diversity

The values of physical infrastructure diversity and travel behavior diversity in the six zip code areas in the city of Hartford are shown in Figure 4.1 and Figure 4.2. Diversity values from the physical infrastructure and travel behavior perspectives cannot be directly compared, since they are quantified through different methods. Instead, the rankings of the two diversity indicators are compared. The results are discussed in detail in section 4.2.

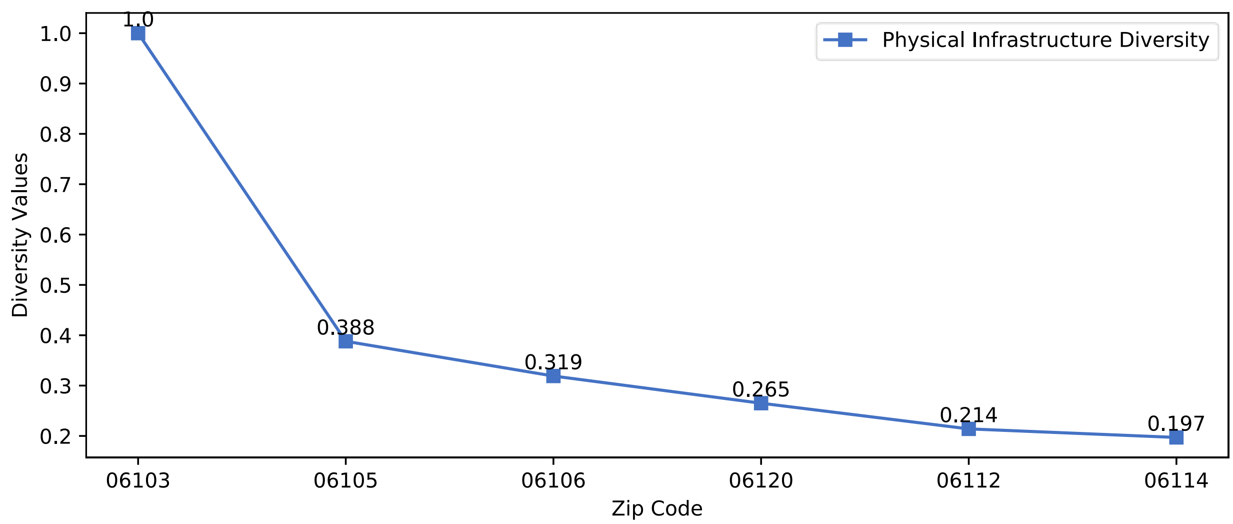

Figure 4.1: Ranking of the physical infrastructure diversity in six zip code areas

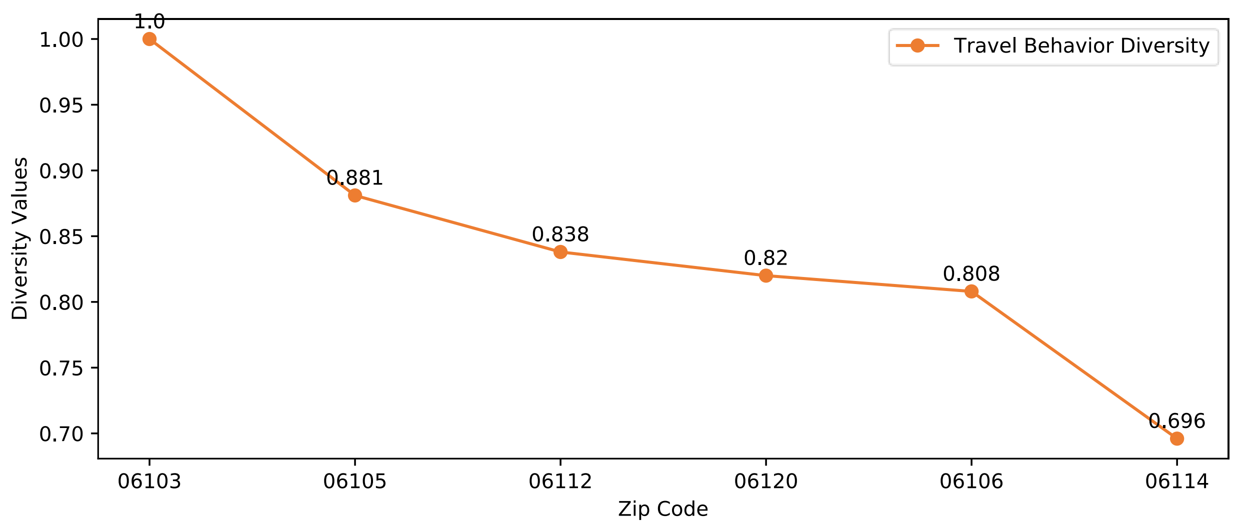

Figure 4.2: Ranking of the travel behavior diversity values in six zip code areas

4.2 Results and Findings

There are several interesting findings from the comparison between the physical infrastructure diversity and travel behavior diversity. First, the rankings show similar trends in the six zip code areas from both the physical infrastructure and travel behavior perspectives. For both infrastructure diversity and travel behavior diversity, zip code area 06103 has the highest values among all the zip code areas studied, followed by zip code area 06105. Zip code area 06114 has the lowest values in terms of both indicators. This finding indicates that the travel behavior diversity and physical infrastructure diversity are highly correlated. In order for residents to travel using alternative transportation modes, certain infrastructures need to be in place. This finding is consistent with research findings from Heinen et al. (2015) and Lin et al. (2017), which pointed out that an improvement of the diversity of transportation infrastructures could help improve residents' diverse travel mode choices.

Second, although residents' diverse mode choices are highly dependent on the physical infrastructure diversity conditions, their diverse travel behavior might also be affected by other internal and external factors, which would moderate the constraints of transportation infrastructures. Examples of internal factors include people's intrinsic social values of using multiple travel options, as well as their socio-demographic backgrounds. Examples of external factors include encouraging residents to use diverse travel options through social media or community engagement activities. In the case study, the 06103 zip code area has both the highest physical infrastructure diversity and travel behavior diversity. From the physical infrastructure perspective, all other zip code areas have much lower diversity values. For example, the 06105 zip code area, which has the second highest physical infrastructure diversity, has only around 40% level of diversity compared to the 06103 zip code area. The 06114 zip code area, which has the lowest physical infrastructure diversity, has only around 20% level of diversity compared to the 06103 zip code area. However, from the travel behavior perspective, there is not much difference between different zip code areas studied. For example, the 06114 zip code area, which has the lowest travel behavior diversity, still has around 70% level of diversity compared to the 06103 zip code area. Other four zip code areas have more than 80% level of diversity compared to the 06103 zip code area. This finding implies that the internal and external factors mentioned above could have significant impacts on residents' travel behaviors. Even when the physical infrastructure diversity is not ideal, it is still possible that people are choosing alternative transportation modes actively.

Third, potential effects of different socio-demographic factors have on people's travel behavior diversity were investigated. In the case study, among the six zip code areas, the 06112 zip code area ranked the fifth in terms of the physical infrastructure diversity, but ranked the third in terms of travel behavior diversity. In order to explain the inconsistency in the rankings in the 06112 zip code area, four zip code areas (i.e., 06106, 06112, 06114 and 06120) that have similar levels of physical infrastructure diversity were further investigated in terms of their socio-demographic factors and potential impacts. The information regarding a list of socio-demographic factors including gender, age, race, education level, and household income level in these four zip code areas was collected from the 2013-2017 American Community Survey (ACS) 5-Year Estimates (U.S. Census Bureau 2018) and summarized in Table 4.1.

Table 4.1: Distributions of residents' socio-demographic characteristics in four zip code areas in the city of Hartford

Zip code	06106	06112	06114	06120
Gender				
Male	48.7%	44.0%	49.1%	48.0%
Female	51.3%	56.0%	50.9%	52.0%
Age				
Under 15	19.8%	19.8%	22.2%	28.0%
15-24	19.0%	21.6%	19.7%	17.9%
24 plus	61.2%	58.6%	58.1%	54.1%
Race				
White	15.8%	7.6%	13.3%	3.9%
Hispanic	59.6%	12.7%	63.4%	47.3%
Asian	2.5%	0.3%	3.5%	0.4%
Black	19.6%	77.3%	17.0%	46.6%
Other	2.5%	2.1%	2.8%	1.8%
Education level				
Less than high school graduate	47.1%	33.0%	30.4%	50.8%
High school graduate or equivalent	24.2%	18.7%	21.1%	26.0%
Some college or associate degree	20.6%	16.1%	18.3%	24.8%
Bachelor's degree or higher	9.3%	5.0%	16.0%	20.7%
Household income level				
Less than $10,000	16.3%	14.1%	10.0%	19.6%
$10,000 to $14,999	10.3%	7.5%	11.3%	9.8%
$15,000 to $24,999	15.2%	13.0%	14.6%	20.3%
$25,000 to $34,999	10.7%	11.8%	12.3%	14.9%
$35,000 to $49,999	14.1%	15.5%	16.5%	16.2%
$50,000 to $74,999	15.5%	16.7%	17.0%	9.6%
$75,000 to $99,999	8.3%	9.6%	9.5%	4.4%
$100,000 to $149,999	6.6%	7.2%	5.5%	4.4%
$150,000 to $199,999	2.1%	2.8%	2.2%	0.6%
$200,000 or more	0.8%	1.7%	1.0%	0.0%

Through a close examination, it was found out that three socio-demographic factors (gender, age, and race) might be able to explain the fact that a higher rank of travel behavior diversity compared with its physical infrastructure diversity in 06112.

(1) Gender

According to Table 4.1, 06112 has a female percentage of 56.0%, which is higher than the other three zip code areas. Some studies pointed out that due to the natural attributes of trips made by females (e.g., shorter travel distance, shorter trip duration), females would show more tendency to low-carbon transportation modes (e.g., public transit, cycling, and walking) (Li et al. 2018; Ng and Acker 2018). Therefore, the higher percentage of female population might be one reason that 06112 shows a more diverse travel pattern under the similar infrastructure diversity level with the other three zip code areas.

(2) Age

According to Table 4.1, 06112 has 21.6% of population in the age group of 15-24, while the other three zip code areas have less than 20% of population in this age group. Studies have found out that younger workers in this age group are more likely to choose non-motorized commuting modes (e.g., public transit, cycling, and walking), due to their better physical abilities and lower income levels (Martin et al. 2016; McKenzie 2014). Therefore, age might be another factor to explain why residents in the 06112 zip code area tend to show more diverse travel behaviors.

(3) Race

Previous studies indicate that Hispanic, Asian, and Black residents tend to use alternative transportation modes more, while white residents usually use private cars as their major mode option (Martin et al. 2016). As shown in Table 4.1, in zip code areas 06112 and 06120, there is a large percentage of residency of Hispanic, Asian, and Black races, and a low percentage of residency of white race. Especially in the 06112 zip code area, Black residents occupy an very high percentage of the population. This might also contribute to the fact that residents in zip code area 06112 are using more diverse transportation modes compared to the other three zip code areas.

Chapter 5. Impacts of Transportation Infrastructure Diversity on Travel Behaviors during Disasters

5.1 Transportation Mobility and Evacuation Planning

When natural disasters happen, evacuations move people away from high-risk areas to safer areas for the protection of life using transportation systems. However, natural disasters can cause failures in a transportation system, which can affect mobility and other economic activities in a community. An important aspect of designing and executing evacuation plans is identifying how humans react and move to safe places during a disaster. Human mobility prediction in disaster scenarios is crucial for various recovery efforts, including the planning of locations and capacities of evacuation shelters, and the allocation of various emergency supplies. A detailed understanding of mobility pattern is a major need for emergency responders and in general for decision makers such as the federal and state governments. Despite the importance of predicting evacuation mobility dynamics after natural disasters for effective first response and disaster relief, the general understanding of evacuation mobility behavior of impacted people remains limited because of the lack of empirical evidence across multiple disaster instances. What's more, little is known about the impacts of diverse multimodal transportation systems on human evacuation and travel behaviors in disasters.

In existing literature there are two major categories of studies that have investigated people's mobility during and after evacuation. The distinction among these two categories primarily lies in the types of data (i.e., survey data and location-based data) that are used to analyze the mobility trend. These two categories of studies are briefly discussed below.

5.1.1 Survey-based studies

Traditionally, survey has been the key method to investigate people's evacuation behaviors. Although survey-based studies mostly do not explicitly discuss the mobility change phenomenon, the outcomes of these studies can be interpreted to determine the mobility behavior during natural disasters. These studies either interviewed a sample population after a natural disaster impacted them or interviewed the population potentially to be impacted in case of a disaster (Murakami et al. 2014; Dostal 2015). For example, Wong et al. (2018) studied the evacuation behavior of victims of Hurricane Irma via an online survey data. Authors found that factors such as destination of evacuation, transportation mode, household income, and length of residence significantly affect the travel behavior. Mongold et al. (2021) conducted survey with coastal and inland population after hurricanes Florence, Michael, Barry, and Dorian to compare the differences in evacuation decisions and timing. Evacuation orders (issuance and receiving of orders) and population factors (e.g., friends, neighbors, and acquaintances) were found to significantly contribute to the inland-coastal difference in evacuation rates. Elliott and Pais (2006) used survey data collected from Hurricane Katrina survivors to examine the influences of race and class on evacuation behavior. Xu et al. (2016) developed an ordered probity model based on the demographic features (e.g., race, gender, education) from survey that could be used for predicting evacuation rates in future. It was observed that although the survey data provided key insights on the variables that affect evacuation behaviors of people during a disaster, it is challenging and expensive to conduct these surveys due to low sample sizes. Also, the statistical models developed based on these surveys have often been found to lack accuracy for prediction and are often challenged when applied to new events (Xu et al. 2016; Henley et al. 2020).

5.1.2 Location-based studies

With the popularization and wide application of positioning technologies, more and more location-based data have been applied in evacuation mobility-related studies. These data make it possible to study human mobility patterns based on spatiotemporal location points. Specifically, smartphone location data (SLD) using Global Position System (GPS) and social media data are currently being widely used to generate key insights on human mobility trend during business-as-usual and disaster impacted periods.

With the ubiquitous use of social media platforms (e.g., Twitter, Facebook etc.), a massive volume of real-time data is available. Such data can provide valuable insights on individual behavior during extreme events. Most of the research utilizing social media data during emergency situations belong to one of the two categories: 1) using social media posts' text to assess the users' reaction to the emergency (Ross et al. 2018) or 2) mining the spatiotemporal variations of the geotagged posts to understand human mobility during extreme events (Roy and Hasan 2021;Wang et al. 2017). For example, Martín et al. (2020) and Wang and Taylor (2014, 2016) studied how severe natural disasters could influence human mobility patterns in coastal urban populations using individuals' movement data collected from Twitter. They analyzed the human movement data before, during, and after each event, comparing the perturbed movement data to movement data from business-as-usual conditions. The results suggested that natural disasters can significantly perturb human movements by changing travel frequencies and displacement. Leveraging the location, time and text of the geo-tagged Tweets, by evacuees prior, during and post-hurricane, Kumar and Ukkusuri (2018) found large variations in the users' evacuation patterns, most likely due to lack of previous experience of users to cope with large scale natural disaster. Although having geotagged social media data is significant for addressing longstanding problems of data availability and reliability, there are a few problems associated with it. Only 1-2% of tweets are geo-tagged and the location information is of low reliability (Tasse et al. 2017; Priedhorsky et al. 2014). Thus, this type of data may not truly reflect the mobility behavior during evacuation for the larger population.

With the development of various mobile positioning technologies, the use of smartphone location data (SLD) for mobility and evacuation research has been gaining tractions that typically provide a larger sample size. The essence of the SLD is the large-scale spatiotemporal data collected from different apps in the phone or from network carriers that track call placements of its users. Both the spatial and temporal information can be leveraged to obtain users trip information. For example, Song et al. (2013, 2014) constructed a large human mobility database that stored GPS records from mobile devices before, during, and after two major natural disasters (the Great East Japan Earthquake and Fukushima nuclear accident). They also developed a probabilistic inference model based on the dataset to predict the short-term and long-term evacuation behaviors for individuals throughout Japan. Ultimately, the authors built an intelligent system, namely, DeepMob, for understanding and predicting human evacuation behavior and mobility following different types of natural disasters (Song et al. 2017). Using the GPS location and number of calls made by the users, Lu et al. (2012) investigated to what extent the chaotic conditions after a natural disaster influenced the disorder and unpredictability of the population's movements, and the dynamics of the population flows out of and back into the region of study. In general, SLD data has been used to investigate the mobility trend during evacuation due to its relative abundance and higher degree of granularity (i.e., more information per data point). Due to such benefits, SLD data were used for this study to analyze mobility during natural disasters and identify potential relationships with transportation diversity. While doing so, the following assumptions are made in this study: (1) in an evacuation scenario, people will have access to their mobile phones with signals not being subject to serious interference, and (2) SLD data can accurately reflect human mobility distributions in fine spatiotemporal granularities.

5.2 Methodology

The research methodology primarily consists of three steps: data Collection, data pre-processing, and mobility analysis.

5.2.1 Data collection

In the data collection step, SLD mobility data are collected from a third-party provider. There are different data providers that provide access to aggregated and privacy-safe mobility data (e.g., Streetlight, Cuebic, SafeGraph). These data are collected from anonymized users who have opted-in to provide access to their location data anonymously, through the General Data Protection Regulation (GDPR)-compliant framework. Although majority of these data providers provide similar mobility data; the country/region of data origin, aggregation level, and data collection period may vary. In this study, the main data used is a smartphone location dataset provided by SafeGraph, a location intelligence and measurement platform (SafeGraph 2021). SafeGraph provides data of Point of Interest (POI) which is defined as "a place you spend time or money". POIs are typically used in maps or geo-datasets to represent a particular feature, as opposed to linear features like roads or areas of land-use (Novack et al. 2018). SafeGraph collected and anonymized POI data from USA, Canada, and UK from various sources (e.g., third-party data partners such as mobile application developers) (Dargin et al. 2021). The data in general reveals trends in visits to POIs, including total visits over a given period, the number of visits each day, and the overall visitors to POIs from different geographic areas. SafeGraph POI visitation data, which is made available for academic research free of charge in aggregated form, can be a useful source of information for studying certain aspects of urban dynamics and travel behavior.

SafeGraph provides POI via three primary datasets, i.e., Core places, Geometry, and Patterns. Core places datasets contains base information such as location name, category, and brand association for POIs where consumers spend time or business operations take place. Geometry datasets provide POI footprints with spatial hierarchy metadata depicting when child polygons (e.g., restaurant) are contained by parents (e.g., shopping mall) or when two children (e.g., restaurant and clothing store) share the same polygon (e.g., shopping mall). Finally, Patterns datasets provide place, traffic, and demographic aggregations that answer: how often people visit, how long they stay, where they came from, where else they go, and more. Overall, the POI data for over 400 categories are available that include industrial, healthcare, retail, parks, leisure sectors and more. This allows analysts to gain detailed insight into mobility behavior in a geographic region over time.

5.2.2 Data pre-processing

After collecting the data, pre-processing will be conducted to transform it into suitable format for mobility analysis. Pre-processing will be conducted in two steps. First, relevant mobility data will be identified with respect to selected natural disasters. Second, these data will also be categorized according to different zip codes to better capture the mobility trend in specific localized areas. This will ultimately result in smaller datasets with more streamlined information with regards to mobility behavior of people in specific localized areas during natural disasters that will significantly reduce the computational complexity and computation time.

5.2.3 Mobility analysis

The goal of mobility analysis is to investigate (1) whether there is any difference in people's mobility during natural disasters, and (2) whether transportation diversity has any impacts on people's mobility during natural disasters. After pre-processing the datasets, the mobility change during a natural disaster will be calculated using equation (12).

$$\text{Mobility change} = \frac{(\text{Observed mobility during disaster day} - \text{Observed average mobility during other same days within the same month})}{\text{Observed average mobility during other same days within the same month}} \quad (12)$$

A positive value of mobility change indicates that mobility increased during the disaster day and negative value indicates otherwise. If applicable, similar analysis will also be conducted for the day before and after the disaster day as well. People may move to shelters or other safe areas if they are aware that their homes are potentially to be impacted by the disaster. People may also move to other areas during the day when disaster hit or the day after their homes are structurally damaged or due to loss of key services (e.g., lack of water and electricity) to their homes.

5.3 Case Study

In the case study, mobility data during two natural disasters were collected and analyzed for the six zip codes in the city of Hartford. The mobility results were compared with the transportation infrastructure diversity values obtained in Chapter 2 to understand the transportation infrastructure impacts on disaster mobility.

5.3.1 Data description

In the context of this study, only the Patterns datasets from SafeGraph have been chosen as they provide aggregated raw counts of visits to different POIs in Connecticut. An aggregated value to different POIs provides a better estimation of the total traffic experienced by them. The patterns POI datasets have 28 attributes that provide details information of different POIs. Appendix B shows the description, data type, and a sample coding example of different attributes in the pattern's datasets.

5.3.2 Identifying natural disasters

Two natural disasters were identified in the state of Connecticut to investigate the mobility pattern during natural disasters. The first natural disaster considered was a thunderstorm with four tornadoes and widespread swath of damaging straight-line winds that occurred on May 15, 2018; which produced one of the most severe weather events in Connecticut in decades (NOAA 2021). It caused about $23.7 million in damage and clean-up costs for state and local governments in Connecticut (Hladky 2019). The second natural disaster selected was tropical storm Isaias that impacted Connecticut on August 4, 2020 which resulted in the first tornado on record in Connecticut to be associated with a tropical storm or hurricane (Latto et al. 2020). Approximately 9,000 trees fell into power lines, street and homes, more than 90 state roads were closed, along with hundreds of local streets (Corcoran 2021). The grand total in damages to public and private infrastructure was approximately $230 million in Connecticut (Corcoran 2021; Eversource 2020). Figure 5.1 and Figure 5.2 show the severity of these natural disasters on different parts of Connecticut. These two natural disasters were chosen due to their large magnitude and observed effects on human life. In addition, tropical storms and tornadoes are two different types of natural disasters. People usually have days to weeks to prepare for a tropical storm, while the lead time for tornado warning is much shorter. Comparing the results from the two natural disasters could provide additional insights on disaster mobility.

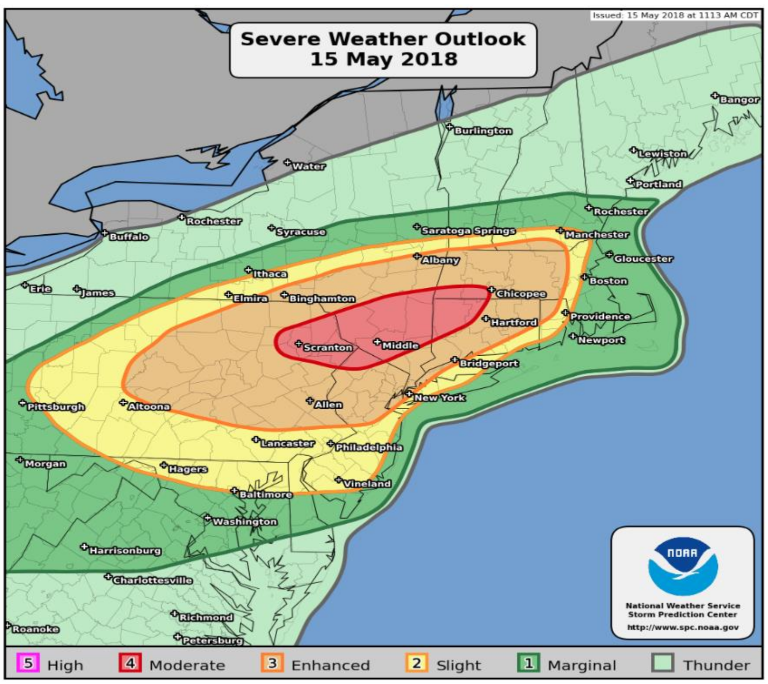

Figure 5.1: Severity of thunderstorm in May 15, 2018 (NWS 2018)

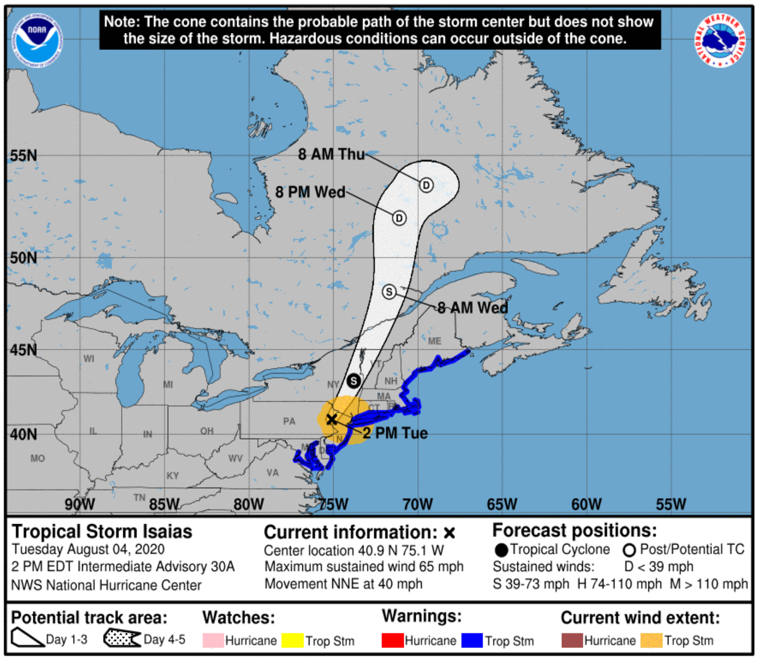

Figure 5.2: Severity of tropical storm Isaias in August 4, 2020 (Tomlinson and O'Neill 2020)

5.3.3 Data preprocessing

Patterns data were collected for two months (i.e., May 2018 and August 2020) across different zip codes (i.e., postal_code in Appendix B) in Connecticut. As the transportation diversity values were assessed only for six zip codes in Hartford, Connecticut (i.e., 06103, 06105, 06106, 06112, 06114, and 06120), other zip codes data were removed from the datasets. Each of the six zip codes had multiple POIs, and each POI had a number of visits per day (i.e., visits_by_day in Appendix B). As the number of visits per day is provided in a matrix format, pre-processing was conducted to divide the matrix data into daily visit counts. This results in 31 daily visit counts for all six zip codes in the months of May 2018 and August 2020, respectively (Table 5.1 and able 5.2). Results showed that there were more data points available for the month of May in 2018 (Table 5.1) compared to August 2020 (able 5.2). There might be multiple reasons behind this, such as the impact of COVID-19. This phenomenon will not have any significant effects on the accuracy of the analysis as the available data for each day and each zip code are higher than the minimum acceptable sample threshold (i.e., >=30) (Johanson and Brooks 2010).

Table 5.1: Observed mobility for May, 2018

	Zip codes					
Day	**06103**	**06105**	**06106**	**06112**	**06114**	**06120**
	Total visits					
1	2684	2586	6457	1654	2641	1901
2	2653	2279	5739	1463	2262	1726
3	3071	2088	5302	1307	2187	1582
4	2846	2222	5574	1511	2546	1924
5	2272	1473	4225	1327	2257	1532
6	927	1273	3547	1076	1813	1263
7	2772	2188	5579	1508	2300	1748
8	2829	2382	5415	1499	2362	1764
9	2583	2231	5358	1460	2323	1728
10	2371	2107	4799	1300	1961	1572
11	2390	2332	5589	1748	2467	2012
12	1041	1230	3590	1111	1887	1500
13	707	1017	2847	892	1465	1244
14	2405	2226	5094	1263	2123	1882
15	2874	2063	4583	1170	1873	1825
16	2378	1983	4772	1295	2047	1814
17	2515	2096	5091	1377	2282	1834
18	2904	2240	5392	1592	2502	3364
19	2241	1452	4230	2021	2291	1685
20	1153	1504	4007	1353	2376	1620
21	3042	2333	5224	1430	2442	1788
22	2546	2275	4894	1757	2339	1932
23	2391	2247	5091	2153	2593	2212
24	2445	2170	5275	1878	2847	2036
25	1911	2174	5294	2129	2897	3631
26	1137	1349	3813	1511	2688	1618
27	775	1346	3514	1443	2175	1353
28	537	1138	3168	1405	2031	1575
29	2364	2280	5178	2041	2825	2061
30	2609	2235	5062	2738	2987	1932
31	2854	2394	5414	2557	3260	1909

able 5.2: Observed mobility for August, 2020

Day	Zip codes					
	06103	06105	06106	06112	06114	06120
	Total visits					
1	401	823	3421	1033	1984	1008
2	308	751	3555	753	1725	818
3	729	1252	3587	916	1933	1144
4	629	1124	3495	759	1893	998
5	854	1201	3585	898	1902	994
6	921	1205	3957	908	1996	1213
7	896	1160	3913	898	1966	1263
8	456	794	3487	778	1658	1001
9	378	674	2308	578	1210	571
10	720	1031	3394	741	1713	990
11	724	1103	3261	1723	1735	1025
12	756	1037	2922	3151	1718	1020
13	692	1065	3188	3676	1824	1042
14	636	1032	3323	3875	1937	1076
15	366	772	2984	3734	1667	911
16	276	613	2322	3644	1286	657
17	624	1002	3016	3649	1796	990
18	689	1144	3551	1177	4291	1009
19	688	934	2953	933	3365	963
20	719	1196	3215	1065	3755	1228
21	875	1337	3793	1292	4129	1338
22	518	1075	2909	1135	3545	1072
23	312	655	2278	799	2154	608
24	657	929	2786	869	2616	978
25	743	991	2847	804	1994	870
26	769	1020	3038	812	1968	916
27	691	990	2837	738	1995	853
28	737	1039	3151	739	1982	988
29	394	739	2584	727	1742	811
30	261	597	2049	603	1470	595
31	715	1079	3034	749	1901	961

5.3.4 Mobility analysis

The path and potential extent of damage by tropical storm Isaias was predicted by a number of agencies such as The National Oceanic and Atmospheric Administration (NOAA). People who were living in the potentially affected areas could have evacuated prior to the day when the tropical storm Isaias based on the available information. Therefore, mobility data with regards to the tropical storm Isaias were collected for the six zip codes on the day prior to the disaster (08/03/2020: Monday), on the day of the disaster (08/04/2020: Tuesday), and the day after the disaster (08/05/2020: Wednesday). On the other hand, the warning for the four tornadoes and widespread swath of damaging straight-line winds that occurred on May 15, 2018 was issued only a couple of hours before the disaster impacted the region (Hanrahan 2018). People could not have evacuated to safer areas due to the unexpected nature of the disaster. Therefore, mobility data for the thunderstorm were collected for the six zip codes only on the day of the disaster (08/15/2018: Tuesday) and the day after the disaster (08/16/2018: Wednesday).

The results of mobility change during tropical storm Isaias are summarized in Table 5.3. Results showed that mobility increased for the zip codes 06103, 06105, 06106, and 06120 on the days before and after the disaster. For example, mobility increased by 23.92% and 20.46%, respectively for zip code 06105 on the days before and after the disaster, respectively. It must be noted that zip codes 06103, 06105, 06106, and 06120 were previously observed to have higher levels of transportation infrastructure diversity. The results implied that if the transportation infrastructure diversity is comparatively higher, there is a higher possibility for people to evacuate or carry out their natural activities even in disaster times due to ease of access to different transportation modes. Another key observation was that despite having the most diverse transportation infrastructure, mobility increase was not the highest for zip code 06103 on the days before and after the disaster. This may be attributed to other factors such as potentially higher structural resilience of homes in zip code 06103. However, on the disaster day, zip code 06103 saw a decrease in mobility change by 12.47%. This might because that people already found shelter beforehand due to better transportation infrastructure and staying there till the disaster tapers off. Mobility was observed to decrease for 06112 and 06114 for the days before, during, and after the disaster. This shows that people living in areas with lower levels of transportation infrastructure diversity may be stuck despite facing significant challenges from natural disasters. If any of the existing transportation infrastructures is disrupted in those areas, the challenge for people moving in and out of these areas increases, causing a decrease in the disaster resilience of residents.

With regards to the thunderstorm, mobility was observed to increase only in zip code 06103 on disaster day by 10.29%. Even though people could not anticipate the disaster, they could evacuate to safe areas more easily due to more diverse transportation infrastructures in zip code 06103. On the day after the disaster, mobility decreased in all zip codes. For example, mobility decreased by 10.17% and 4.50% for zip codes 06106 and 06120, respectively on the day after the disaster. Another significant observation was that the mobility decreases on zip codes 06103, 06105, 06106, and 06120 was lower compared to zip codes 06112 and 06114. This reinforced the insights of the findings from tropical storm Isaias that higher transportation infrastructure diversity results in comparatively lower effects on mobility. This means that people living in areas with higher transportation infrastructure diversity levels are potentially more resilient to disasters.

Table 5.3: Mobility change during hurricane Isaias

	Zip Codes					
Day before (08/03/2020: Monday)	**06103**	**06105**	**06106**	**06112**	**06114**	**06120**
Observed Mobility	729	1252	3587	916	1933	1144
Other Monday within this month (Avg.)	679	1010.25	3057.5	1502	2006.5	979.75
Mobility change (%)	7.36	23.92	17.31	-39.01	-3.66	16.76
	Zip Codes					
Disaster day (08/04/2020: Tuesday)	**06103**	**06105**	**06106**	**06112**	**06114**	**06120**
Observed Mobility	629	1124	3495	759	1893	998
Other Tuesday within this month (Avg.)	718.66	1079.33	3219.66	1234.66	2673.33	968
Mobility change (%)	-12.47	4.13	8.55	-38.52	-29.19	3.09
	Zip Codes					
Day after (08/05/2020: Wednesday)	**06103**	**06105**	**06106**	**06112**	**06114**	**06120**
Observed Mobility	854	1201	3585	898	1902	994
Other Wednesday within this month (Avg.)	737.66	997	2971	1632	2350.3	966.33
Mobility change (%)	15.77	20.46	20.66	-44.97	-19.07	2.86

Table 5.4: Mobility change during thunderstorm wind

	Zip Codes					
Disaster day (5/15/2018: Tuesday)	**06103**	**06105**	**06106**	**06112**	**06114**	**06120**
Observed	2874	2063	4583	1170	1873	1825
Other Tuesday within this month	2605.75	2380.75	5486	1737.75	2541.75	1914.5
Mobility change (%)	10.29	-13.34	-16.46	-32.67	-26.31	-4.67
	Zip Codes					
Day after (5/16/2018: Wednesday)	**06103**	**06105**	**06106**	**06112**	**06114**	**06120**
Observed	2378	1983	4772	1295	2047	1814
Other Wednesday within this month	2559	2248	5312.5	1953.5	2541.25	1899.5
Mobility change (%)	-7.07	-11.78	-10.17	-33.71	-19.44	-4.50

Chapter 6. Conclusion and Future Work

This study explored the diversity of multimodal transportation systems and its impact on travel behaviors, especially during disasters. The proposed methods were implemented in a case study of the city of Hartford, Connecticut. By calculating and comparing the physical infrastructure diversity and travel behavior diversity of multimodal transportation systems in the six zip code areas in Hartford, it was found out that a higher level of physical infrastructure diversity could promote a higher level of diversity in travel behaviors. However, the travel behavior diversity variation across different zip code areas is not as significant as the variation in their physical infrastructure diversity levels. It implied that humans are resourceful in using existing multimodal transportation systems, and measures can be taken to enhance the diversity of travel behaviors even if the infrastructure diversity level is not ideal. For example, advertising the availability and benefits of multiple transportation options through various channels such as community engagement activities and social media could help residents adopt alternative transportation modes. In addition, social-economic factors (i.e., gender, age, and race) and their impacts on travel behavior diversity in the case study were discussed. Smartphone location data (SLD) were used to understand human mobility during two disasters in the city of Hartford. The results suggested that if the transportation infrastructure diversity is comparatively higher, there is a higher possibility for people to better cope with disasters due to ease of access to different transportation modes.

Transportation and urban planners could use the proposed methods and results to obtain a holistic understanding of a multimodal transportation system, and better guide the planning and design of multimodal cities. First, investment on diverse physical infrastructures such as bus routes and bike routes should be considered, since an improvement of physical infrastructure diversity could help improve travel behavior diversity. Second, in regions where resource is limited for directly improving physical infrastructure, other measures can be taken such as community engagement and social network influence to prompt the use of alternative transportation modes. Third, there is no "one-size-fits-all" solution for different multimodal transportation systems in different regions. Socio-demographic backgrounds of the travelers should be carefully incorporated into consideration when planning and designing a multimodal transportation system.

The existing study has several limitations. First, the scope of case study is limited. The observations from the case study might not be true for other areas. In order to develop general findings and theories, more case studies are required in future work. Second, currently the disaster mobility is investigated at the aggregate level. The potential impacts of transportation infrastructure diversity on individual disaster evacuation behaviors and mobility changes need to be further studied in the future through other methods such as interview and survey.

References

1. Amoaning-Yankson, S., and Amekudzi-Kennedy, A. (2017). “Transportation system resilience: Opportunities to expand from principally technical to sociotechnical approaches.” *Transportation Research Record*, 2604(1), 28–36.
2. Bulla, L. (1994). “An index of evenness and its associated diversity measure.” *Oikos*, JSTOR, 167–171.
3. City of Hartford. (2019). “Hartford Data.” <https://openhartford-hartfordgis.opendata.arcgis.com> (Oct. 16, 2019).
4. Connecticut Department of Economic Community Development (DECD). (2016). “Connecticut Population, Land Area and Density by Location.” <https://portal.ct.gov/DECD/Content/About_DECD/Research-and-Publications/01_Access-Research/Population-Data> (Aug. 21, 2020).
5. Connecticut Department of Transportation (CTDOT). (2020). “Transit-Oriented Development.” <https://portal.ct.gov/DOT/Transit-Oriented-Development/Transit-Oriented-Development-Home-Page> (Aug. 21, 2020).
6. Corcoran, D. (2021). “One Year Later: The Lasting Impacts of Tropical Storm Isaias.” <https://www.nbcconnecticut.com/news/local/one-year-later-the-lasting-impacts-of-tropical-storm-isaias/2552629/>.
7. CTrides. (2019). “Ways to Commute.” <https://ctrides.com/ways-to-commute/carpool> (Oct. 25, 2019).
8. Dargin, J. S., Li, Q., Jawer, G., Xiao, X., and Mostafavi, A. (2021). “Compound hazards: An examination of how hurricane protective actions could increase transmission risk of COVID-19.” *International Journal of Disaster Risk Reduction*, Elsevier, 102560.
9. Dostal, P. J. (2015). “Vulnerability of urban homebound older adults in disasters: a survey of evacuation preparedness.” *Disaster medicine and public health preparedness*, Cambridge University Press, 9(3), 301–306.
10. Elliott, J. R., and Pais, J. (2006). “Race, class, and Hurricane Katrina: Social differences in human responses to disaster.” *Social science research*, Elsevier, 35(2), 295–321.
11. Eversource. (2020). *30-Day Event Report: Tropical Storm Isaias*.
12. FEMA. 2019. “Disaster Declarations by Year.” https://www.fema.gov/disasters/year?field_dv2_declaration_type_value=All&=Apply (July 7, 2019).
13. Feng, C. M., and Hsieh, C. H. (2009). “Implications of transport diversity for quality of life.” *Journal of Urban Planning and Development*, 135(1), 13–18.
14. Hanrahan, R. (2018). “May 15, 2018 Tornadoes And Damaging Wind.” <https://www.ryanhanrahan.com/2018/05/20/may-15-2018-tornadoes-and-damaging-wind/>.
15. He, Y., Guo, H., Jin, M., and Ren, P. (2016). “A linguistic entropy weight method and its application in linguistic multi-attribute group decision making.” *Nonlinear Dynamics*, Springer Netherlands, 84(1), 399–404.

16. Heinen, E., Panter, J., Mackett, R., and Ogilvie, D. (2015). "Changes in mode of travel to work: A natural experimental study of new transport infrastructure." *International Journal of Behavioral Nutrition and Physical Activity*, International Journal of Behavioral Nutrition and Physical Activity, 12(1), 1–10.
17. Henley, S. S., Golden, R. M., and Kashner, T. M. (2020). "Statistical modeling methods: challenges and strategies." *Biostatistics \& Epidemiology*, Taylor \& Francis, 4(1), 105–139.
18. Hladky, G. B. (2019). "Connecticut Still Recovering From Savage May 2018 Tornadoes." *Hartford Courant*.
19. Johanson, G. A., and Brooks, G. P. (2010). "Initial scale development: sample size for pilot studies." *Educational and psychological measurement*, SAGE Publications Sage CA: Los Angeles, CA, 70(3), 394–400.
20. Konduri, K. C., Ritter, C., Lynch, J., Lownes, N. E., and Greene, E. (2017). *Connecticut Statewide Transportation Study*.
21. Kumar, D., and Ukkusuri, S. V. (2018). "Utilizing geo-tagged tweets to understand evacuation dynamics during emergencies: A case study of Hurricane Sandy." *Companion Proceedings of the The Web Conference 2018*, 1613–1620.
22. Latto, A., Hagen, A., and Berg, R. (2020). "National Hurricane Center Tropical Cyclone Report."
23. Li, J., Lo, K., and Guo, M. (2018). "Do socio-economic characteristics affect travel behavior? A comparative study of low-carbon and non-low-carbon shopping travel in Shenyang City, China." *International Journal of Environmental Research and Public Health*, 15(7).
24. Lin, T., Wang, D., and Guan, X. (2017). "The built environment, travel attitude, and travel behavior: Residential self-selection or residential determination?" *Journal of Transport Geography*, Elsevier, 65(October), 111–122.
25. Litman, T. (2017). *Evaluating Transportation Diversity*. Victoria Transport Policy Institute.
26. Litman, T. 2018. *Evaluating Transportation Diversity: Multimodal Planning for Efficient and Equitable Communities*. Victoria, BC, Canada.
27. Lu, X., Bengtsson, L., and Holme, P. (2012). "Predictability of population displacement after the 2010 Haiti earthquake." *Proceedings of the National Academy of Sciences*, National Acad Sciences, 109(29), 11576–11581.
28. Machado-León, J. L., and Goodchild, A. (2017). "Review of performance metrics for community-based planning for resilience of the transportation system." *Transportation Research Record*, 2604(1), 44–53.
29. Martín, Y., Cutter, S. L., Li, Z., Emrich, C. T., and Mitchell, J. T. (2020). "Using geotagged tweets to track population movements to and from Puerto Rico after Hurricane Maria." *Population and Environment*, Springer, 42(1), 4–27.
30. Martin, E., Shaheen, S., Zohdy, I., Chan, N., Bansal, A., Bhattacharyya, A., Tawfik, A., Yelchuru, B., Finson, R., and Wah, C. Y. Y. (2016). "Understanding Travel Behavior: Research Scan." *U.S. Department of Transportation. Federal Highway Administration*.

31. Mason, N. W. H., Mouillot, D., Lee, W. G., and Wilson, J. B. (2005). “Functional richness, functional evenness and functional divergence: The primary components of functional diversity.” *Oikos*, 111(1), 112–118.
32. McKenzie, B. (2014). “Modes Less Traveled: Commuting by Bicycle and Walking in the United States, 2008–2012.” *American Community Survey Reports, ACS-26, U.S. Census Bureau, Washington, DC*, (May), 2008–2012.
33. Mongold, E., Davidson, R. A., Trivedi, J., DeYoung, S., Wachtendorf, T., and Anyidoho, P. (2021). “Hurricane evacuation beliefs and behaviour of inland vs. coastal populations.” *Environmental Hazards*, Taylor \& Francis, 20(4), 363–381.
34. Mouillot, D., Graham, N. A. J., Villéger, S., Mason, N. W. H., and Bellwood, D. R. (2013). “A functional approach reveals community responses to disturbances.” *Trends in Ecology and Evolution*, 28(3), 167–177.
35. Mouillot, D., Mason, W. H. N., Dumay, O., and Wilson, J. B. (2005). “Functional regularity: A neglected aspect of functional diversity.” *Oecologia*, 142(3), 353–359.
36. Murakami, H., Yanagihara, S., Goto, Y., Mikami, T., Sato, S., and Wakihama, T. (2014). “Study on casualty and tsunami evacuation behavior in Ishinomaki City: Questionnaire survey for the 2011 Great East Japan Earthquake.” *Tenth US National Conference on Earthquake Engineering Frontiers of Earthquake Engineering*.
37. Ng, W.-S., and Acker, A. (2018). “Understanding urban travel behaviour by gender for efficient and equitable transport policies.”
38. NOAA. (2021). “Storm Events Database.” <http://www.ncdc.noaa.gov/stormevents/>.
39. Novack, T., Peters, R., and Zipf, A. (2018). “Graph-based matching of points-of-interest from collaborative geo-datasets.” *ISPRS International Journal of Geo-Information*, Multidisciplinary Digital Publishing Institute, 7(3), 117.
40. NWS. (2018). “May 15, 2018 Severe Weather Outbreak.” <https://www.weather.gov/okx/SevereEvent051518>.
41. Priedhorsky, R., Culotta, A., and Del Valle, S. Y. (2014). “Inferring the origin locations of tweets with quantitative confidence.” *Proceedings of the 17th ACM conference on Computer supported cooperative work \& social computing*, 1523–1536.
42. Rahimi-Golkhandan, A., Garvin, M. J., and Brown, B. L. (2019). “Characterizing and measuring transportation infrastructure diversity through linkages with ecological stability theory.” *Transportation Research Part A: Policy and Practice*, Elsevier, 128(August 2018), 114–130.
43. Rahimi Golkhandan, A. (2020). “Characterization and Assessment of Transportation Diversity: Impacts on Mobility and Resilience Planning in Urban Communities.” Virginia Tech.
44. Ross, B., Potthoff, T., Majchrzak, T. A., Chakraborty, N. R., Ben Lazreg, M., and Stieglitz, S. (2018). “The diffusion of crisis-related communication on social media: an empirical analysis of Facebook reactions.” *Proceedings of the 51st Hawaii International conference on system sciences*.

45. Roy, K. C., and Hasan, S. (2021). “Modeling the dynamics of hurricane evacuation decisions from twitter data: an input output hidden markov modeling approach.” *Transportation research part C: emerging technologies*, Elsevier, 123, 102976.
46. SafeGraph. (2021). “Places Data for Innovative Teams.” <https://www.safegraph.com/>.
47. Song, X., Shibasaki, R., Yuan, N. J., Xie, X., Li, T., and Adachi, R. (2017). “DeepMob: learning deep knowledge of human emergency behavior and mobility from big and heterogeneous data.” *ACM Transactions on Information Systems (TOIS)*, ACM New York, NY, USA, 35(4), 1–19.
48. Song, X., Zhang, Q., Sekimoto, Y., Horanont, T., Ueyama, S., and Shibasaki, R. (2013). “Modeling and probabilistic reasoning of population evacuation during large-scale disaster.” *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, 1231–1239.
49. Song, X., Zhang, Q., Sekimoto, Y., and Shibasaki, R. (2014). “Prediction of human emergency behavior and their mobility following large-scale disaster.” *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, 5–14.
50. Su, S., Xiao, R., Li, D., and Hu, Y. (2014). “Impacts of transportation routes on landscape diversity: A comparison of different route types and their combined effects.” *Environmental Management*, 53(3), 636–647.
51. Tasse, D., Liu, Z., Sciuto, A., and Hong, J. (2017). “State of the geotags: Motivations and recent changes.” *Proceedings of the International AAAI Conference on Web and Social Media*.
52. Tomlinson, P., and O’Neill, T. (2020). “Low-end’ Hurricane Could Impact Connecticut Next Week.”
53. U.S. Census Bureau. (2018). “2013-2017 American Community Survey (ACS) 5-Year Estimates, Table DP05 ‘ACS DEMOGRAPHIC AND HOUSING ESTIMATES.’” <https://data.census.gov/cedsci/table?q=Hartford city, Connecticut&g=1600000US0937000&tid=ACSDP5Y2017.DP05> (Aug. 21, 2020).
54. Villéger, S., Mason, N. W. H., and Mouillot, D. (2008). “New multidimensional functional diversity indices for a multifaceted framework in functional ecology.” *Ecology*, 89(8), 2290–2301.
55. Wang, Q., and Taylor, J. E. (2014). “Quantifying, Comparing Human Mobility Perturbation during Hurricane Sandy, Typhoon Wipha, Typhoon Haiyan.” *Procedia Economics and Finance*, Elsevier B.V., 33–38.
56. Wang, Q., and Taylor, J. E. (2016). “Patterns and limitations of urban human mobility resilience under the influence of multiple types of natural disaster.” *PLoS one*, Public Library of Science San Francisco, CA USA, 11(1), e0147299.
57. Wang, Y., Wang, Q., and Taylor, J. E. (2017). “Aggregated responses of human mobility to severe winter storms: An empirical study.” *PloS one*, Public Library of Science San Francisco, CA USA, 12(12), e0188734.

58. Wong, S., Shaheen, S., and Walker, J. (2018). “Understanding evacuee behavior: a case study of hurricane Irma.”
59. Xu, K., Davidson, R. A., Nozick, L. K., Wachtendorf, T., and DeYoung, S. E. (2016). “Hurricane evacuation demand models with a focus on use for prediction in future events.” *Transportation Research Part A: Policy and Practice*, Elsevier, 87, 90–101.
60. Zhu, Y., Tian, D., and Yan, F. (2020). “Effectiveness of Entropy Weight Method in Decision-Making.” *Mathematical Problems in Engineering*, 2020, 1–5.

Appendix A: Python Code for Functional Richness and Evenness Calculation

```
import pandas as pd
import numpy as np
df=pd.read_excel('Hartford Infrastructural Data.xlsx',skiprows=1,sheet_name='Data Collection')

#Richness calculation
R_RN=df['roadway lengths']/df['area SQMI']
R_BS=df['bus route lengths']/df['area SQMI']
R_RT=df['railway lengths']/df['area SQMI']
R_BR=df['bike lane lengths']/df['area SQMI']
R_WW=df['sidewalk lengths']/5/5280/df['area SQMI']
R_RS=df['Ridesharers that live in zip code']/df['area SQMI']
result1=pd.DataFrame({'R_RN':R_RN,'R_BS':R_BS,'R_RT':R_RT,'R_BR':R_BR,'R_WW':R_W
W,'R_RS':R_RS})
result1.to_excel('output_richness.xlsx', sheet_name='Sheet1')

#Evenness calculation
df1=pd.read_excel('Hartford Infrastructural Data.xlsx','06103')
df2=pd.read_excel('Hartford Infrastructural Data.xlsx','06105')
df3=pd.read_excel('Hartford Infrastructural Data.xlsx','06106')
df4=pd.read_excel('Hartford Infrastructural Data.xlsx','06112')
df5=pd.read_excel('Hartford Infrastructural Data.xlsx','06114')
df6=pd.read_excel('Hartford Infrastructural Data.xlsx','06120')

#Evenness of roadways
sum1=0
for i in range(len(df1)):
    sum1+=min(df1['Roadway'][i]/df1['Roadway'].sum(),1/len(df1))
sum2=0
for i in range(len(df2)):
    sum2+=min(df2['Roadway'][i]/df2['Roadway'].sum(),1/len(df2))
sum3=0
for i in range(len(df3)):
    sum3+=min(df3['Roadway'][i]/df3['Roadway'].sum(),1/len(df3))
sum4=0
for i in range(len(df4)):
    sum4+=min(df4['Roadway'][i]/df4['Roadway'].sum(),1/len(df4))
sum5=0
for i in range(len(df5)):
    sum5+=min(df5['Roadway'][i]/df5['Roadway'].sum(),1/len(df5))
sum6=0
for i in range(len(df6)):
    sum6+=min(df6['Roadway'][i]/df6['Roadway'].sum(),1/len(df6))
```

```
E_RN=pd.Series([(sum1-1/len(df1))/(1-1/len(df1)),(sum2-1/len(df2))/(1-1/len(df2)),(sum3-
1/len(df3))/(1-1/len(df3)),(sum4-1/len(df4))/(1-1/len(df4)),(sum5-1/len(df5))/(1-
1/len(df5)),(sum6-1/len(df6))/(1-1/len(df6))])

#Evenness of bus routes
sum1=0
for i in range(len(df1)):
    sum1+=min(df1['Bus Stop'][i]/df1['Bus Stop'].sum(),1/len(df1))
sum2=0
for i in range(len(df2)):
    sum2+=min(df2['Bus Stop'][i]/df2['Bus Stop'].sum(),1/len(df2))
sum3=0
for i in range(len(df3)):
    sum3+=min(df3['Bus Stop'][i]/df3['Bus Stop'].sum(),1/len(df3))
sum4=0
for i in range(len(df4)):
    sum4+=min(df4['Bus Stop'][i]/df4['Bus Stop'].sum(),1/len(df4))
sum5=0
for i in range(len(df5)):
    sum5+=min(df5['Bus Stop'][i]/df5['Bus Stop'].sum(),1/len(df5))
sum6=0
for i in range(len(df6)):
    sum6+=min(df6['Bus Stop'][i]/df6['Bus Stop'].sum(),1/len(df6))
E_BS=pd.Series([(sum1-1/len(df1))/(1-1/len(df1)),(sum2-1/len(df2))/(1-1/len(df2)),(sum3-
1/len(df3))/(1-1/len(df3)),(sum4-1/len(df4))/(1-1/len(df4)),(sum5-1/len(df5))/(1-
1/len(df5)),(sum6-1/len(df6))/(1-1/len(df6))])

#Evenness of railways
sum1=0
for i in range(len(df1)):
    sum1+=min(df1['Railroad Station'][i]/df1['Railroad Station'].sum(),1/len(df1))
sum2=0
for i in range(len(df2)):
    sum2+=min(df2['Railroad Station'][i]/df2['Railroad Station'].sum(),1/len(df2))
sum3=0
for i in range(len(df3)):
    sum3+=min(df3['Railroad Station'][i]/df3['Railroad Station'].sum(),1/len(df3))
sum4=0
for i in range(len(df4)):
    sum4+=min(df4['Railroad Station'][i]/df4['Railroad Station'].sum(),1/len(df4))
sum5=0
for i in range(len(df5)):
    sum5+=min(df5['Railroad Station'][i]/df5['Railroad Station'].sum(),1/len(df5))
sum6=0
for i in range(len(df6)):
    sum6+=min(df6['Railroad Station'][i]/df6['Railroad Station'].sum(),1/len(df6))
```

```
E_RT=pd.Series([(sum1-1/len(df1))/(1-1/len(df1)),(sum2-1/len(df2))/(1-1/len(df2)),(sum3-
1/len(df3))/(1-1/len(df3)),(sum4-1/len(df4))/(1-1/len(df4)),(sum5-1/len(df5))/(1-
1/len(df5)),(sum6-1/len(df6))/(1-1/len(df6))])

#Evenness of bike routes
sum1=0
for i in range(len(df1)):
    sum1+=min(df1['Bike Path'][i]/df1['Bike Path'].sum(),1/len(df1))
sum2=0
for i in range(len(df2)):
    sum2+=min(df2['Bike Path'][i]/df2['Bike Path'].sum(),1/len(df2))
sum3=0
for i in range(len(df3)):
    sum3+=min(df3['Bike Path'][i]/df3['Bike Path'].sum(),1/len(df3))
sum4=0
for i in range(len(df4)):
    sum4+=min(df4['Bike Path'][i]/df4['Bike Path'].sum(),1/len(df4))
sum5=0
for i in range(len(df5)):
    sum5+=min(df5['Bike Path'][i]/df5['Bike Path'].sum(),1/len(df5))
sum6=0
for i in range(len(df6)):
    sum6+=min(df6['Bike Path'][i]/df6['Bike Path'].sum(),1/len(df6))
E_BR=pd.Series([(sum1-1/len(df1))/(1-1/len(df1)),(sum2-1/len(df2))/(1-1/len(df2)),(sum3-
1/len(df3))/(1-1/len(df3)),(sum4-1/len(df4))/(1-1/len(df4)),(sum5-1/len(df5))/(1-
1/len(df5)),(sum6-1/len(df6))/(1-1/len(df6))])

#Evenness of sidewalks
sum1=0
for i in range(len(df1)):
    sum1+=min(df1['Sidewalk'][i]/df1['Sidewalk'].sum(),1/len(df1))
sum2=0
for i in range(len(df2)):
    sum2+=min(df2['Sidewalk'][i]/df2['Sidewalk'].sum(),1/len(df2))
sum3=0
for i in range(len(df3)):
    sum3+=min(df3['Sidewalk'][i]/df3['Sidewalk'].sum(),1/len(df3))
sum4=0
for i in range(len(df4)):
    sum4+=min(df4['Sidewalk'][i]/df4['Sidewalk'].sum(),1/len(df4))
sum5=0
for i in range(len(df5)):
    sum5+=min(df5['Sidewalk'][i]/df5['Sidewalk'].sum(),1/len(df5))
sum6=0
for i in range(len(df6)):
    sum6+=min(df6['Sidewalk'][i]/df6['Sidewalk'].sum(),1/len(df6))
```

```
E_WW=pd.Series([(sum1-1/len(df1))/(1-1/len(df1)),(sum2-1/len(df2))/(1-1/len(df2)),(sum3-
1/len(df3))/(1-1/len(df3)),(sum4-1/len(df4))/(1-1/len(df4)),(sum5-1/len(df5))/(1-
1/len(df5)),(sum6-1/len(df6))/(1-1/len(df6))])

#Evenness of ridesharing
sum1=0
for i in range(len(df1)):
    sum1+=min(df1['Ridesharers (live, 0.5mi)'][i]/df1['Ridesharers (live,
0.5mi)'].sum(),1/len(df1))
sum2=0
for i in range(len(df2)):
    sum2+=min(df2['Ridesharers (live, 0.5mi)'][i]/df2['Ridesharers (live,
0.5mi)'].sum(),1/len(df2))
sum3=0
for i in range(len(df3)):
    sum3+=min(df3['Ridesharers (live, 0.5mi)'][i]/df3['Ridesharers (live,
0.5mi)'].sum(),1/len(df3))
sum4=0
for i in range(len(df4)):
    sum4+=min(df4['Ridesharers (live, 0.5mi)'][i]/df4['Ridesharers (live,
0.5mi)'].sum(),1/len(df4))
sum5=0
for i in range(len(df5)):
    sum5+=min(df5['Ridesharers (live, 0.5mi)'][i]/df5['Ridesharers (live,
0.5mi)'].sum(),1/len(df5))
sum6=0
for i in range(len(df6)):
    sum6+=min(df6['Ridesharers (live, 0.5mi)'][i]/df6['Ridesharers (live,
0.5mi)'].sum(),1/len(df6))
E_RS=pd.Series([(sum1-1/len(df1))/(1-1/len(df1)),(sum2-1/len(df2))/(1-1/len(df2)),(sum3-
1/len(df3))/(1-1/len(df3)),(sum4-1/len(df4))/(1-1/len(df4)),(sum5-1/len(df5))/(1-
1/len(df5)),(sum6-1/len(df6))/(1-1/len(df6))])

result2=pd.DataFrame({'E_RN':E_RN,'E_BS':E_BS,'E_RT':E_RT,'E_BR':E_BR,'E_WW':E_W
W,'E_RS':E_RS})
result2.to_excel('output_evenness.xlsx', sheet_name='Sheet1')
```

Appendix B: Description of Pattern Datasets

Table B.1: Description of pattern datasets

Column Name	Description	Type	Example
placekey	Unique and persistent ID tied to this POI.	String	222-222@222-222-222
parent_placekey	If place is encompassed by a larger place (e.g., mall, airport), this lists the placekey of the parent place; otherwise, null.	String	223-223@222-222-222
location_name	The name of the place of interest.	String	Salinas Valley Ford Lincoln
street_address	Street address of the place of interest.	String	1100 Auto Center Circle
city	The city of the point of interest.	String	Irvine
region	The state, province or county of the place of interest.	String	CA
postal_code	The postal code of the place of interest.	String	92602
safegraph_brand_ids	Unique and consistent ID that represents this specific brand.	List	SG_BRAND_59dcabd7cd2395a2, SG_BRAND_8310c2e3461b8b5a
brands	If this POI is an instance of a larger brand that we have explicitly identified, this column will contain that brand name.	List	ford, lincoln
date_range_start	Start time for measurement period in ISO 8601 format of YYYY-MM-DDTHH:mm:SS±hh:mm (local time with offset from GMT).	String	2020-03-01T00:00:00-06:00
date_range_end	End time for measurement period in ISO 8601 format of YYYY-MM-DDTHH:mm:SS±hh:mm (local time with offset from GMT). The end time will be the last day of the month at 12 a.m. local time.	String	2020-03-31T00:00:00-06:00
raw_visit_counts	Number of visits in our panel to this POI during the date range.	Integer	1542
raw_visitor_counts	Number of unique visitors from our panel to this POI during the date range.	Integer	1221
visits_by_day	The number of visits to the POI each day (local time) over the covered time period.	JSON [Integer]	[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_cbg	The census block group the POI is located within.	String	560610112022

Column Name	Description	Type	Example
visitor_home_cbgs	The number of visitors to the POI from each census block group based on the visitor's home location.	JSON {String: Integer}	{"360610112021": 603, "460610112021": 243, "560610112021": 106, "660610112021": 87, "660610112021": 51}
visitor_home_aggregation	The number of visitors to the POI from each census tract based on the visitor's home location.	JSON {String: Integer}	{"17031440300": 1005, "18089021500": 522, "17197883516": 233, "17031826402": 5, "17031826301": 4, "04013115802": 4}
visitor_daytime_cbgs	The number of visitors to the POI from each census block group based on primary daytime location between 9 am - 5 pm.	JSON {String: Integer}	{"360610112030": 9872, "880610112021": 8441, "569610112020": 5671, "160610112041": 2296, "980610112021": 1985}
visitor_country_of_origin	The number of visitors to the POI from each country based on visitor's home country code.	JSON {String: Integer}	{"US": 98,"CA": 12}
distance_from_home	Median distance from home travelled by visitors (of visitors whose home we have identified) in meters.	Integer	1211
median_dwell	Median minimum dwell time in minutes.	Double	5
bucketed_dwell_times	The distribution of visit dwell times based on pre-specified buckets. Key is the range of dwell time in minutes and value is number of visits that were within that range.	JSON {String: Integer}	{ "<5": 40, "5-20": 22, "21-60": 45, "61-240": 3, ">240": 5}
related_same_day_brand	Other brands that the visitors to this POI visited on the same day as the visit to this POI.	JSON {String: Integer}	{"mcdonalds": 7,"amc": 5,"target": 3}
related_same_month_brand	Other brands that the visitors to this POI visited in the same month as the visit to this POI.	JSON {String: Integer}	{"mcdonalds": 7,"amc": 5,"target": 3}
popularity_by_hour	The number of visits in each hour over the course of the date range, in local time. First element in the array corresponds to the hour of midnight to 1 am, second is 1am to 2am, etc.	JSON [Integer]	[0, 0, 0, 0, 0, 0, 0, 222, 546, 444, 333, 232, 432, 564, 456, 345, 678, 434, 545, 222, 0, 0, 0, 0]
popularity_by_day	The number of visits in total on each day of the week (in local time) over the course of the date range.	JSON {String: Integer}	{"Monday": 3300,"Tuesday": 1200,"Wednesday": 898,"Thursday": 7002,"Friday": 5001,"Saturday": 5987,"Sunday": 0}

Column Name	Description	Type	Example
device_type	The number of visitors to the POI that are using Android vs. iOS.	JSON {String: Integer}	{"android": 6, "ios": 8}
carrier_name	The number of visitors to the POI based on the wireless carrier of the device.	JSON {String: Integer}	{"Verizon": 342, "T-Mobile": 288, "AT&T": 265}