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Urban Accessibility Measurement and Visualization — A Big Data Approach

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URBAN ACCESSIBILITY MEASUREMENT AND VISUALIZATION
– A BIG DATA APPROACH

by

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DEDICATION

To my parents, Jian Jiang and Mei Shen.

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ABSTRACT

Accessibility measurement has always been an important question in different areas including transportation, urban planning, politics, and sociology. However, how to measure transportation accessibility in different areas have been limited to data availability and technology. Recently, with increasing availability in public transportation data, we found a gap between current methods and large volume of data now available. This thesis developed a new method to measure multi-mode transportation data, including taxi, bus, and subway. Based on this measurement, we can visualize and understand the spatiotemporal patterns of accessibility in New York City (NYC). With historical travel records and public transit schedule, Relative Index (RI) is developed in this thesis to measure and compare the differences in the accessibility in NYC. RI distribution patterns during different time periods were also compared and analyzed for more information about transportation in NYC. By the end of this thesis, a practical application that measured accessibility for nine major hospitals in NYC was provided. Results in this thesis showed that subways have more impacts about accessibility than bus. Also, service frequency during different time of a day has affect accessibility.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Accessibility is a term commonly used in geographical research, transportation and urban planning, which has been studied for decades and its definition varies in different research situations, including “interactions between human and lands” (Hansen, 1959), “the ease or difficulty for people to reach their opportunities or services” (Wachs & Kumagai, 1973), and “the benefits provided by a transportation/land-use system” (Ben-Akiva & Lerman, 1979). Consequently, the exact measurement of accessibility also varies according to different circumstances. Traditional accessibility was measured by generating a static travel scenario or by using self-reported travel dairy. Those methods not only lack accuracy but also involve subjective bias due to limited samples. Recently, many public transportation companies, including taxi, bus, and subway companies, have released their transportation data, which potentially can provide new and more accurate information for accessibility measurement. However, there is a gap in current literature between available transportation data and methodologies that are able to process, analyze, and model information from such travel data.

In this research I propose to develop an approach to the measurement and visualization of driving accessibility, with big data of taxi trips and public transit uses (including both bus and subway) in New York City (NYC). Specifically, a relative access index will be developed and subsequent analyses will be carried out to (1) integrate multiple transportation modes and big data of daily mobility, and (2) visualize and understand the spatiotemporal distribution of accessibility patterns in NYC.

Public transit usually refers to buses and subway systems in urban areas. Accessibility of public transit has drawn intensive attention in transportation research from different perspectives. As an environment-friendly commuting and travel mode, public transportation can help reduce greenhouse gas emissions, traffic congestion, car accidents, and oil price vulnerability (Litman, 2003). Research also found that public transportation users have lower obesity rate and present better physical and mental health (Sallis et al., 2004). Moreover, accessibility of public transportation can be used as an indicator to measure social equality. For example, accessibility measurements of public transportation helped researchers to identify socially disadvantaged groups in gender (M.-P. Kwan et al., 2003; M. P. Kwan, 1999), age (Hess, 2009), socio-economic status (Niedzielski & Eric Boschmann, 2014), races (Tribby & Zandbergen, 2012), and disability (Church & Marston, 2003). Traditionally, public transit accessibility was measured by service frequency estimation or travel situation simulation. Recently, the increasing availability of public transit usage data opens the possibility to measure public transit accessibility accurately and dynamically with a big data approach.

Taxis, unlike buses or subways, provide private and convenient location-to-location transportation services. In the past few years, taxi companies worldwide have installed Global Positioning System (GPS) equipment in taxicabs. In general, two types of travel data can be collected from in-car GPS. The first type of data has the entire route recorded with GPS positions regularly sampled at a certain time interval. The second type of data only contains information on the origin (pick-up location) and destination (drop-off location) of each taxi trip, and the travel distance, duration, and cost, without the actual driving route of each trip.

Both public transit accessibility and taxi trip data have been studied to reveal different urban characteristics. Public transit data have been used to analyze job opportunities (T. Lei, Chen, & Goulias, 2012), food deserts (Burns & Inglis, 2007; Paez et al., 2010), and activity-based research (Mavoa et al., 2012). Continuous taxi data have been used for travel condition monitoring and road network analysis (Veloso et al., 2011). Trip-based taxi data is useful for urban land use and human mobility analysis (Peng et al., 2012). However, few studies have integrated more than one type of transportation modes in accessibility measurements.

This project will develop a methodology to quantify and visualize the integrated accessibility of both taxi and public transit (combining buses and subways) in New York City, based on big data of public transit uses and taxi trips. Public transit timetable was provided by the Metropolitan Transportation Authority (MTA) in the General Transit Feed Specification (GTFS) format. On an average weekday, there are more than 5 million riders for subway systems and more than 2 million for public buses. For each trip, GTFS data includes service date, route, stations, departure and arrival time at each station. Based on this information, the public transit travel time for each origin and destination pair for given departure time can be calculated. Historical taxi trip data are provided by the New York City Taxi & Limousine Commission, which is the largest taxi company that operates the yellow cabs in NYC. For the year of 2013, there were more than 170 millions (173,179,759) taxi trips recorded. Each taxi trip includes information on pick-up date and time, drop-off date and time, passenger count, trip time in second, trip distance, pick-up location (latitude and longitude), drop-off location (latitude and longitude), payment type, fare amount, surcharge, MTA tax, toll amount, and the total amount.

CHAPTER 2

RESEARCH OBJECTIVES

- Develop a new measurement of accessibility with multi-mode transportation data including taxi, bus and subway;
- Visualize and understand the spatiotemporal patterns of accessibility in NYC, defined with different type of destinations (or origins) for different applications.

CHAPTER 3

LITERATURE REVIEW

3.1 Accessibility

In general, the word “accessibility” means “capable of being reached, thus, implying a measure of the proximity between two points” (Ingram, 1971). In the simplest case, two places (or points) are connected, which means accessibility exists between these two places. Measurements of accessibility can be as simple as the length of the straight line between two points. Considering transportation road network, accessibility between two places can be measured as the length of road, or the travel time that connect the two places.

When measuring accessibility from a social or economic perspective, an “attraction” variable is often added into a distance decay function. Hansen (1959) introduced a gravity model in accessibility and land-use. For example, as the distance between home and a shopping center increases, the possibility for one to go to that shopping center decreases. Different functional forms can be applied to calculate the distance decay between two locations, including power, exponential, and Gaussian (Scott & Horner, 2008).

Accessibility in transportation research generally measures how easy, or how difficult, for people to get to their opportunities or services (Wachs & Kumagai, 1973). Based on different applications, Geurs and van Wee (2004) grouped accessibility into four groups: 1) infrastructure-based accessibility, 2) location-based accessibility, 3) person-based accessibility, and 4) utility-based accessibility. Infrastructure-based accessibility measures the performance of road network, such as travel speed and congestion condition. Location-based accessibility measures places of interest can be reached, given the original location. Person-based accessibility comes from space-time geography, which measures places can be reached given individual's time and space constraints (M. P. Kwan, 1999; Miller, 1991). Utility-based accessibility measures the usage of certain transportation mode or the market share of one transportation mode (Ben-Akiva & Lerman, 1979).

Based on different data types used in accessibility measurements, Páez, Scott, and Morency (2012) grouped accessibility measurements into two categories: normative measurement and positive measurement. *Normative measurements* do not use behavior data and considers only the performance of transportation. Larsen and Gilliland (2008) measured food deserts in urban London, ON, Canada, based on walking and public transit accessibility. Farber, Morang, and Widener (2014) used public transit data to study the temporal variability of public transportation. *Positive measurements* use people's travel behavior data, which come from survey or behavioral models. For examples, Minocha et al. (2008) used local trip data to estimate demand factors. Pasch et al. (2009) surveyed teenagers to study the association between teenagers' alcohol use and alcohol outlet locations. Scott and Horner (2008) conducted a travel diary survey for urban opportunity accessibility.

Accessibility in urban areas has been studied for many applications using different types of data. Here, I review three major areas of urban accessibility. The first area includes studies related to *public transit accessibility*. Each public transit trip can be divided into three segments: from one's origin to transit network, travel inside transit network, and from transit network to destination. Because of this division, public transit accessibility has two sub-areas: to/from transit network and in transit network. Researches in both sub-areas will be reviewed in Section 3.2. The second major area of research involves *taxi travels*. Taxi travel data is a direct indicator of accessibility in terms of monetary or time cost, but more complicated and meaningful information can be retrieved from taxi travel data. A detailed review of taxi travel data analysis can be found in section 3.3. The third major area focuses on *relative accessibility*, which includes comparison among more than one type of accessibility measurements. Such comparison can be conducted between accessibility using different transportation modes, during different time periods, or for different groups of public transit users. Section 3.4 reviews relative accessibility researches.

3.2 Accessibility in public transit

Accessibility measurements in public transit can be further grouped into two categories: to/from transit network, and in transit network. To/From transit network accessibility measures the destination people travel from their original location to transit stop and travel from the last transit stop to their final destination. The in-transit-network accessibility considers the travel time on buses or subways, transfer time among different lines, etc.

3.2.1. To/From Transit Network

This type of accessibility measures the physical access to transportation network, defined as how far one person needs to travel to a transit stop, either a bus stop or a subway station (Currie, 2010). It is also called *service area* of a transit stop in many studies. There are two traditional methods to measure service areas: circular buffer analysis and road network analysis. However, buffer analysis is rarely used due to overestimation of service areas and served population. Guti and Garc (2008) and Biba, Curtin, and Manca (2010) compared service area and population inside service areas using circular buffer analysis and road network analysis. Their results showed that buffer zone overestimates one-third to half of service areas and served population. Range of this variance is due to different density of road network. Studies also showed that individuals' walking speed and maximum tolerant walking distance affect accessibility of public transit accessibility by changing threshold of service area (El-Geneidy, Tetreault, & Surprenant-Legault, 2010; Hess, 2009; Mavoa et al., 2012). In addition, other factors, such as safety, weather, infrastructure (Walton & Sunseri, 2010) and even individual's social identity (Murtagh, Gatersleben, & Uzzell, 2012) also affect accessibility to/from public transit network.

3.2.2. In Transit Network

Slightly different from the general definition of accessibility, public transit accessibility measures the ease, or difficulty, for passengers to get to their destinations using public transit systems. The measurement of travel cost varies in different applications and different research preferences. The most straightforward measurement is the travel distance, or the length of public transit route between the origin and the destination, which can be calculated with road network data (Liu & Zhu, 2004). These measurements, however, often assume that the travel speed in the network is constant, which is not true with real transportation conditions.

Compared to the route length, the travel time is a more commonly used in measurements for travel cost. O'Sullivan, Morrison, and Shearer (2000) developed a tool to draw isochrones lines for public transit accessibility. Given an original point, their tool can draw accessible areas that can be reached within a given time threshold using public transit. Their travel time estimation is based on average travel speed along road network. Travel-time-based accessibility measurement did not have significant development until lately due to the lack of data availability. Later studies implemented public transit timetable into their travel time calculation models to increase accuracy. For example, Cheng and Agrawal (2010) developed a query-based tool called Time-based Transit Service Area Tool (TTSAT). Users can set preferred waiting time, maximum transfers, and time budget. TTSAT will generate accessible areas based on user-preferences and public transit timetable. T. L. Lei and Church (2010) developed a dynamic model, which, based on bus timetable, can calculate both accessibility from given origin to all possible destinations, and accessibility from all possible origins to given destination.

Another important development in accessibility measurement is to measure accessibility for different time periods of a day. Polzin, Pendyala, and Navari (2002) included supply and demand during different time periods in one day. Based on the predicted ridership and available public transit service, their model calculates the availability regarding the daily trips per capita. Chen et al. (2011) applied temporal component in job-based accessibility. They used the percentage of reachable workers for different types of industrial working places during different time periods in one day. Their model is able to map accessibility at the block level.

3.3 Taxi Travel Data Analysis

Taxis in urban areas provide convenient and private location-to-location transportation services based on customers' request. In the last decade, with the increasing global positioning system (GPS) technology, many taxi companies have installed in-car GPS trackers in taxicabs. This tracking data not only helped track taxicabs' movements for better navigation and dispatching but also guaranteed a safer environment for taxi drivers. Taxi data have been used for different research objectives in different cities all over the world, including San Francisco, USA (Herring et al., 2010; Hoque, Hong, & Dixon, 2012; Hunter et al., 2009), Lisbon, Portugal (Veloso et al., 2011), Shanghai, China (Peng et al., 2012), Stockholm, Sweden (Jenelius & Koutsopoulos, 2013), and Delft, Netherlands (Zheng & Van Zuylen, 2013).

Taxi data can be grouped into two categories: tracing data and origin-destination (OD) data. Tracing data consists of taxi trajectories obtained from GPS devices that record taxi locational information at a certain time interval, usually at 30 seconds or 60 seconds. They are very useful to monitor road network condition and are commonly used to measure infrastructure-based accessibility. Researchers first plotted locations onto road network map, then processing data by projecting any off-road points onto road networks. Based on continuous changes in location, driving speed can be inferred and thus travel time can be predicted. Hunter et al. (2009) used about 60,000 observations from 50 taxicabs in San Francisco to calculate travel time. Herring et al. (2010) used a probabilistic model to estimate arterial traffic condition from 500 taxicabs in San Francisco. Veloso et al. (2011) used Gamma distribution to model taxicabs' distribution over Lisbon, Portugal area. Jenelius and Koutsopoulos (2013) used data from 1500 vehicles in Stockholm, Sweden to estimate travel time between any two points on the road network. Zheng and Van Zuylen (2013), based on probe cars, created a three-layer neural network to simulate travel conditions in Delft, Netherlands.

3.4 Relative Accessibility

Relative accessibility compares different accessibility measures. These comparisons can be between poverty and non-poverty (Niedzielski & Eric Boschmann, 2014), personal identities (Murtagh, Gatersleben, & Uzzell, 2012), genders (M. P. Kwan, 1999), and age groups (Hess, 2009). The most commonly compared pair in transportation and planning research is between public transportation and private car driving. The travel time for car-based accessibility uses similar methods as used in infrastructure-based accessibility measurements and public transit-based accessibility measurements have been reviewed in section 3.2. In this section, I will review research work on relative accessibility between public transit and private vehicle.

Implemented from O'Sullivan, Morrison, and Shearer (2000), mapping service areas from a given location of public transit and driving provides the most direct comparison between accessibility measurements. Besides visual comparison, travel time ratio and location-based accessibility measurements are commonly used to quantify differences in accessibility.

Mapping the ratio of travel time between public transit and private vehicle is one of the common methods. Hess (2005) focused on low-wage job accessibility for low-income adults in the Buffalo-Niagara region. From centroid of each neighborhood, they calculated a 30-minute travel buffer for automobile driving and public transit riding, respectively. Their job accessibility measurements were the summations of jobs within 30-minute travel time. They used the ratio of automobile and public transit job accessibility in each neighborhood. Their results showed that automobile drivers have 2-3 times more job accessibility than public transit users. Salonen and Toivonen (2013) used travel time ratio of public transit to car to map accessibility to public libraries in Greater Helsinki area, Netherland. They used three different models for public transit and driving: (1) a simple model that ignores congestion and parking, (2) an intermediate model that includes congestion but ignores parking, and (3) an advanced model considering both congestion and parking. In all three models, the average travel time for public transit is longer than average travel time for cars. In addition, public transit travel time to the closest destination is also longer than that for cars. However, this ratio measurement is calculated at the infrastructure level, by measuring how public transit and taxi are performing locally. Only one original location can be used at each time. When original location is determined, it measures accessibility as a property to all possible destinations.

There are studies on location-based accessibility measurements, which often employ an opportunity index to compare accessibility among different locations. Shen (2001) studied job opportunities differences between using public transit and driving. They defined an accessibility score as the ratio of the total number of opportunities to the total of opportunity seekers for each zone. They generated 775 transportation analysis zones in the Boston Metropolitan Area and calculated a job opportunity index for each zone using public transit and private cars. Their study showed that not many job opportunities exist if one only uses public transit. For these opportunity-based calculation methods, researchers need to arbitrarily assign a weight or score to different opportunity or activity types, or arbitrarily classify service or importance levels for different opportunities. Compared to ratio measurements, opportunity-based measurements consider accessibility as a property of original location, but these weights or classifications are usually based on self-understanding or survey results.

3.5 Applications with Accessibility Measurements

Location based accessibility measures the opportunity and convenience for people to get to their activity places, such as work places, healthcare facilities, supermarkets, educational resources, and other activity locations that are essential for people’s daily life. In the past, many researchers have used accessibility measurements as social indicators to study social inequality and to examine urban development and planning.

Shen (2001) and Hess (2005) used public transit accessibility to measure spatial distributions of job opportunities and poverty adults. Their studies identified the spatial mismatch between job opportunities and labor market. Kawabata and Shen (2007) and Tribby and Zandbergen (2012) used public transit accessibility to jobs to measure urban developments and public transportation planning. T. Lei, Chen, and Goulias (2012) and Chen et al. (2011) examined accessibilities in different types of working and identified workers in certain sectors to improve their commuting experiences. Niedzielski and Eric

Boschmann (2014) compared commuting accessibility for poverty workers and non-poverty workers.

Accessibility measurements are also important in health geography. Lovett et al. (2002) measured accessibility from each postcodes to local general practitioners. Burns and Inglis (2007) compared accessibilities to supermarkets (healthy food) and fast food outlets (unhealthy food) for people from different socio-economic status. Langford, Fry, and Higgs (2012) measured public transit to primary and secondary healthcare facilities.

CHAPTER 4

DATA AND STUDY AREA

4.1. Study Area: New York City

This research focuses on the New York City (NYC), which consists of five boroughs: Brooklyn, Queens, Manhattan, the Bronx, and Staten Island (Figure 4.1). Each of the five boroughs is a separate county of the state of New York. According to the U.S. Census Bureau, NYC has an estimated population of 8,491,079 in year 2014 and an area of about 800 km^2. Since Staten Island has a separate subway system that is not connected to the main subway system and has very limited bus routes connecting to the main areas of NYC, Staten Island is excluded in this study (Figure 4.1).

Figure 4.1: Study Area of NYC

NYC has the highest population density of all the major cities in the United States, which makes NYC an ideal study area for this research for two main reasons. First, the public transportation ridership is very high in NYC. Due to limited spaces and high land price, NYC has the lowest car ownership in the United States, with 66% households not having a private car (Salon, 2009). Therefore, residents' daily commuting and traveling rely heavily on public transportation. According to the data from Metropolitan Transportation Authority (MTA)'s ridership report in 2013, the annual ridership was more than 1.7 billion for subway and 0.67 billion for transit buses. On an average weekday, the ridership was about five million for subway and two million for transit buses. According to the data obtained from the New York City Taxi & Limousine Commission, there were more than 14 million taxi trips for each month in 2013, i.e., roughly half a million taxi trips per day.

Second, NYC has a very complex, dense and effective public transportation network and a large fleet of taxi cars. In the Manhattan area, bus stops or subway stations are within walking distance. In 2013, there were 13,437 taxicabs running in NYC. In addition, there are 21 subway routes with 494 subway stations in NYC. Transit bus network consists of 237 local routes and 65 express routes (MTA, 2013). Figure 4.2 is a demonstration of accessible areas of public transit system, assuming the willing walking distance is 500 meters. This high density of public transportation network and high diversity in transportation mode choices in NYC provide a strong necessity, an ideal test bed, and abundant data for the studying, understanding, and use of accessibility.

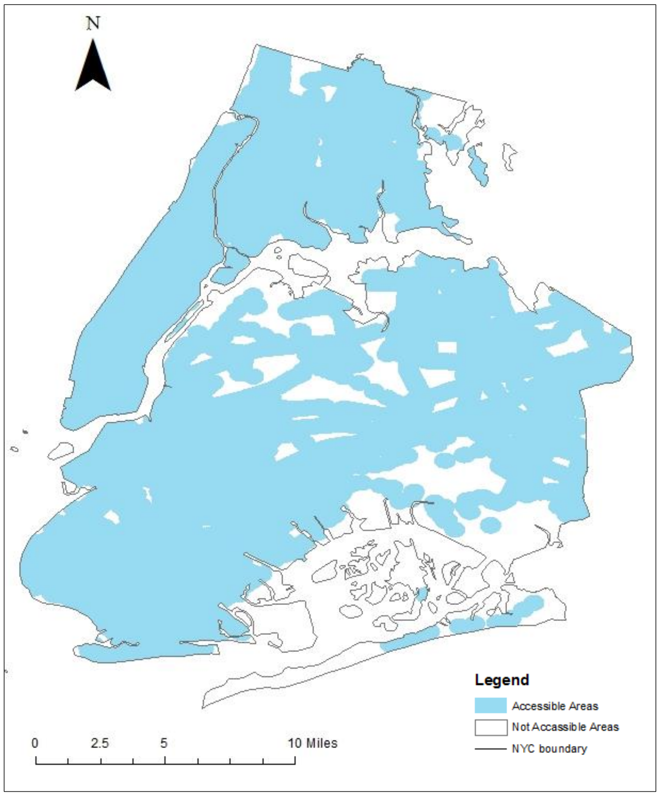


Figure 4.2 Public Transit Accessible Areas

4.2. Data

4.2.1. GIS Based Data

Basic geographical information data, including city and borough boundaries, are available from the New York State GIS Clearinghouse (https://gis.ny.gov/). Subway and transit bus routes are digitized and maintained by the City University of New York Mapping Service at the Center of Urban Research (http://www.gc.cuny.edu/CUR). Hospital data used in the application parts can be found from New York State Open Data – Health Data (https://health.data.ny.gov/Health/Health-Facility-Map/875v-tpc8). This dataset includes all types of healthcare facilities. For demonstration purpose, only hospital data were used in application in Section 6.2.2.

4.2.2. Taxi Trip Data

The New York City Taxi & Limousine Commission is one of the major taxi companies operating in NYC. Trip data are available for taxicabs holding license from the NYC Taxi & Limousine Commission. This research uses the taxi trip data for the entire year of 2013, which has 13,437 registered taxicabs and 173,179,759 taxi trips in 2013 (i.e. about half a million taxi rides each day), with a total of 1.99 billion dollars for taxi fare (tips were not included). Information associated with each trip includes: pick-up data and time, drop-off date and time, passenger count, trip time in second, trip distance, pick-up location (latitude and longitude), drop-off location (latitude and longitude), payment type, fare amount, surcharge, MTA tax, toll amount, and total amount. The average taxi trip time was 799 seconds (about 13 minutes), the average trip distance was 4.65 kilometers and the average fare for a taxi trip was 11.49 dollars.

In this research, it is assumed that that the actual driving route (which is not available in the data) of each recorded taxi trip is the shortest path (in terms of travel time) from the origin to the destination.

4.2.3. Public Transit Data

Public transit data for New York City subway and transit buses are published and maintained by the Metropolitan Transportation Authority (MTA), which is the company that operates NYC subways and major transit bus routes. The public transit data are in General Transit Feed Specification (GTFS) format, containing public transportation schedules and associated geographical information. The structure of GTFS data includes agency, routes, trips, stops, stop_times, and calendar. Detailed explanation of the GTFS data format can be found at https://developers.google.com/transit/gtfs/reference.

CHAPTER 5

METHODOLOGY

This research proposes a Relative Index to measure the relative accessibility between public transit and taxi. As reviewed in Section 3.4, there are two main approaches to measure relative accessibility: travel time ratio measurement and opportunity-based measurement. Travel time ratio is used to measure the relative performance between taxi and public transit and considers accessibility as a property of the connection between origin and destination (rather than a property of the location). Opportunity-based measurement, on the other hand, views accessibility as a property of the location (rather than the connection), which involves arbitrary decisions on different types of destinations.

Relative Index developed in this study has three innovations. First, it considers accessibility as a property of a location but derives the measure as the collective property of all connections that involve the location. The new measure is calculated with real and big travel records so that there are much less arbitrary decisions or biases involved compared to traditional methods. Second, the method uses historical taxi travel records and public transit timetables to accurately model travel time, rather than using road network and properties such as speed limit as previous studies do. Third, the new method and data can enable the measurement of accessibility at high spatiotemporal resolution, e.g., for different time periods of a day and different days of a week, based on big data of taxi trips and transit schedules (which, for example, differ significantly for weekdays and weekend days). As such, the new method can enable the analysis and understanding of dynamic accessibility patterns, with time-varying and multimodal accessibility measurements.

The proposed Relative Index (RI) measurement is derived with a regression approach. The RI for a given location is defined as the slope of the regression line, with public transit travel time on y-axis and taxi travel time on x-axis, for all (or a selected group of) destinations from the given location. This new method can enable both location-based measurement (by deriving a regression line with data for destinations) and connection-based measurement (by comparing the travel time ratio of the specific connection to the regression line), both of which can vary across space and time.

5.1 Public Transit Accessibility

Given an origin, a destination, and a departure time, the total travel time can be estimated based on the complete public transit schedule, with the arrival and departure time for each bus or subway train and the estimate of walk time for transfer connections within the network and to/from origin/destination. The Dijkstra shortest path algorithm is used to find the travel time using public transportation between the origin and the destination, including walking time to/from stations, waiting time, riding subways and/or buses, walking for transfers, and waiting time during transfer. I use the threshold of 500 meters to define a "walkable" distance from an origin location to a public transit and from the public transit to a destination, calculated using the Manhattan distance.

5.2 Taxi Accessibility

One of the contributions of this study is to use real big data of historical taxi trip records (instead of road networks) to estimate the actual travel time between a given origin and a destination for a specific departure time. As such, it implicitly considers traffic conditions and other unknown factors in calculating the driving time. Given an origin, a destination, and a departure time, related Taxi travel records will be retrieved and processed to estimate the travel time, which can be the average time of all taxi trips that started from the neighborhood of the origin around the given departure time and ended near the destination.

5.3 Relative Index (RI)

First, for each origin location, the travel time to each possible destination (i.e. other public transit stops in the transit network and out of the 500-meter buffer zone around the transit stop) is obtained with the shortest path algorithm and the public transit schedule. For each destination, the actual taxi trip time is also obtained from the taxi trips data, as explained in previous sections.

Then for the given origin, its public transit time and taxi time to each destination are plotted, with the taxi travel time on the x-axis and the public transit time on the y-axis. A regression analysis is used to derive a Relative Index between the public transit travel time and taxi travel time. Specifically, the Total Least Square regression method is used:

$$\boldsymbol{y = \alpha + \beta x} \qquad \textbf{Eq 5.1}$$

where the slope of this regression line, β, is an overall measurement of how efficient the public transit system is compared to taxi. Compared to the Ordinary Least Square regression (Figure 5.1 left), the Total Least Square regression (Figure 5.1 right) calculates residuals for both x and y. which allow us to treat α and β symmetrically (Golub & Van Loan, 1980). In this research, errors exist in both taxi and public transit measurements and thus the Total Least Square regression is more suitable for this case.

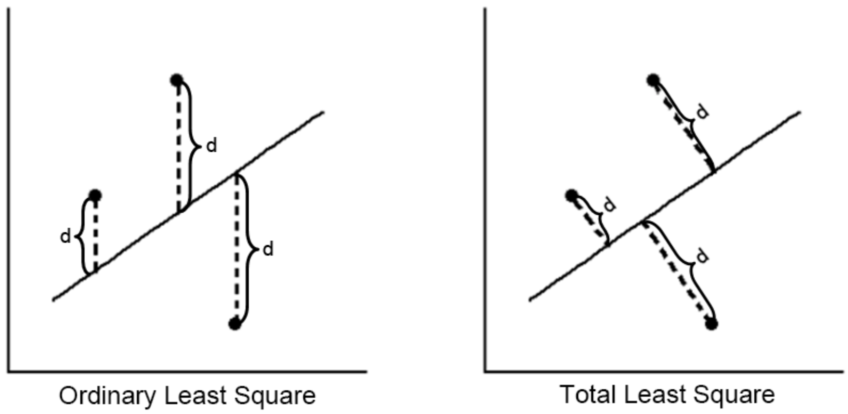


Figure 5.1: Comparison Between OLS and TLS Regression.

In Eq. 1, α (intercept with y-axis) can be understood as the walking time to public transit system and the waiting time for next bus or subway. Because taxi waiting time is not available, α is neglected in this measurement. The slope or this regression line, β, is defined as RI in this measurement.

For one location, RI means the expected change in travel time of public transit given travel time changes in taxi. For example, if one location has RI of 7.5, it means, for every minute increasing in taxi travel time, public transit riders should expect 7.5 minutes increasing using public transit. If one location has RI of 1, it means taxi and public transit have essentially similar performances. Therefore, high RI means this location has a low relative accessibility (i.e. not convenient for people to use public transit system compared to using taxi) and low RI means high relative accessibility, that public transit has similar performance with taxi (assuming no walking and waiting time). Figure 5.2 is an example of trips starting at Penn Station during 3 pm. Each point on this scatter plot represents one O-D pair. For this O-D pair, the origin is within 500-meter buffer zone around Penn Station and the destination is outside this 500-meter buffer zone. Location of the point in this coordinate system is determined by the travel time using taxi and public transit. The slope of the red line in Figure 5.2 is the RI for the cell containing Penn Station during 3 pm.

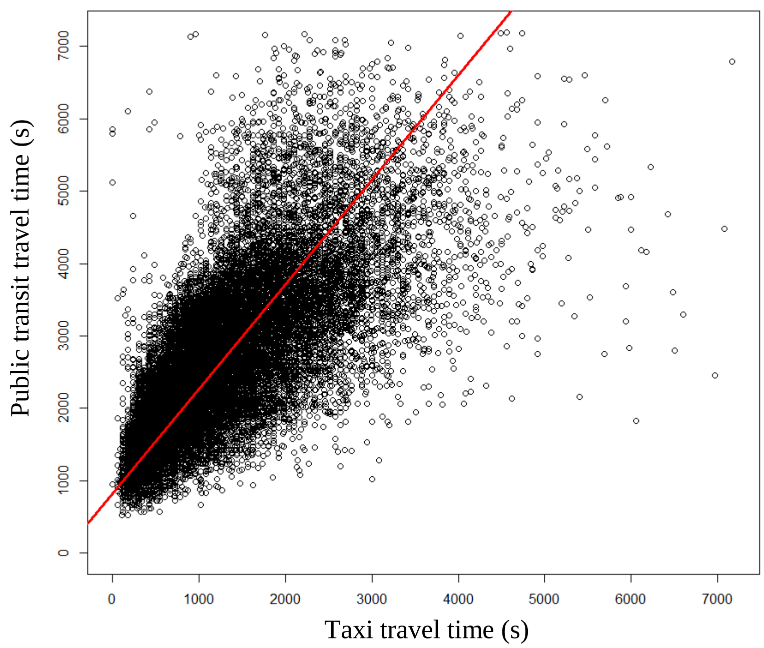


Figure 5.2 Scatter plot of O-D pairs starting at Penn Station

For each O-D pair, both public transit travel time and taxi travel time (if existing) are retrieved. Transit travel time was calculated using Dijkstra shortest path algorithm. Because all the subway stations and bus stops are connected in the public transit system network, cells in which subway stations or bus stops located, as well as cells can be reached by walking, have values for transit travel time. However, not all O-D pairs have taxi trips. For O-D pairs have more than one taxi trips, the average time for all taxi trips is used for taxi travel time of that O-D pair. When calculating RI for origins, only if one origin has no less than 10 O-D pairs to be considered as a valid location. Similarly, when calculating RI for a destination, that destination must have no less than 10 O-D pairs. In others words, to run the regression, no less than 10 points must exist on the scatter plot.

The Relative Index is considered as a property for the origin location and may be used for further applications, such as travel planning, job housing balancing, and health-related analysis. RI can also be derived for each destination. For example, one can focus on public parks in NYC as destinations to analyze the accessibility patterns to green spaces. One can also select a set of origins and compare their overall accessibility to work places in NYC.

CHAPTER 6

RESULTS AND DISCUSSION

This section provides an overview of analysis results. First are results from exploratory analysis. Maps for travel time ratio between public transit and taxi during different time periods are provided in the Section 6.1. Section 6.2 present maps of Relative Index (RI) that calculated using methodology described in section 5. For each origin, all destinations with valid trips are included and calculated towards RI for that origin (section 6.2.1). Section 6.2.2, RI of selected destinations are provided and compared for different time periods during one day. Details of these results are discussed in section 7.

6.1. Exploratory Analysis

To provide a fundamental understanding of travel time difference between public transit and taxi trips, travel time ratio is first calculated as following:

$$\boldsymbol{Travel\ time\ ratio} = \frac{\boldsymbol{time_{public\ transit}}}{\boldsymbol{time_{taxi}}} \qquad \text{Eq. 6.1}$$

Pennsylvania Station (Penn Station) was selected as the original location because it is one of the most important transit hubs connecting commuting trains from New Jersey and public transit network in NYC. All taxi trips that started within 500 meters from Penn Station and have destinations outside the 500-meter buffer zone are used to derive the ratio for each specific connection (i.e., from Penn Station to the specific destination). This method is similar to some relative accessibility measurements reviewed in section 5.3.

Figure 6.1 and Figure 6.2 show travel time ratio during two different time periods in a day. The origin (Penn Station) locates at the center of a black hole as short trips (trip distance less than 500 meters) were excluded in this analysis. In these two maps, blue colors indicate that the public transit time is shorter than taxi time, while red colors indicate that a taxi takes less time than public transit to travel from Penn Station to the destination. For some destinations, the public transit time can be more than three times longer than taxi travel time.

This exploratory analysis demonstrates the impact of subway frequency. 3 am was chosen as an example for midnight, when very few public transit services are provided. At this time, Manhattan area shows 2-3 times longer travel time using public transit than using taxi. Even though Manhattan is generally considered with the most road congestions and the most convenient public transit system, during night hours, public transit accessibility is reduced by limited public transit services.

6.2. Relative Index (RI) Results

RI, as mentioned in Section 5, is measuring accessibility as a property of a given location, assigning equal weights to all connected O-D pairs. In Section 6.2.1, RI is computed for each origin, considering trip records from this given origin to all possible destinations. RI for origin is useful considering how convenient one can go to

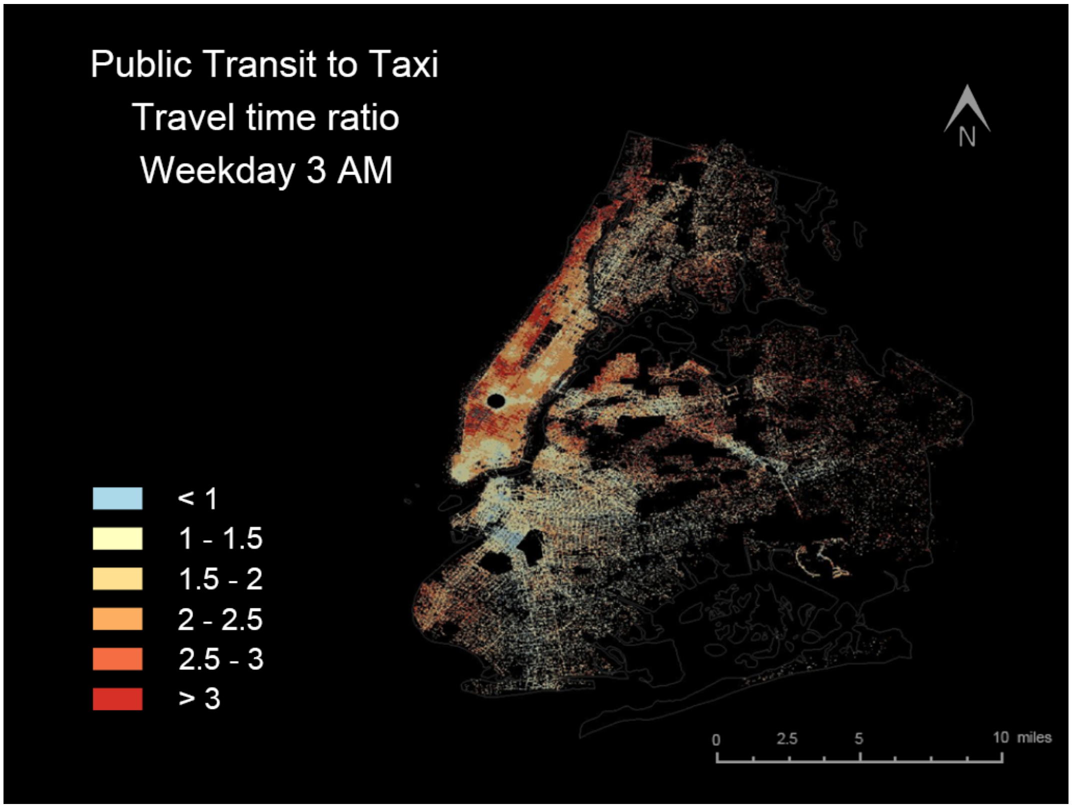


Figure 6.1: Travel time ratio for 3 am

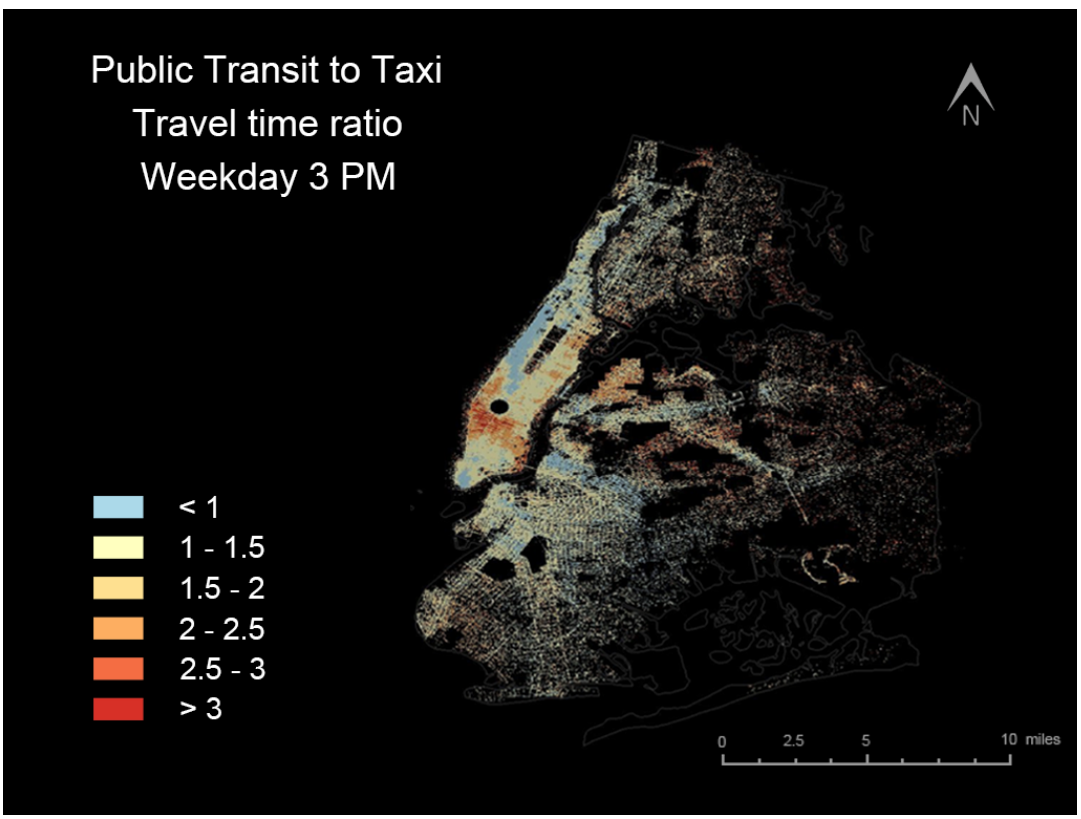


Figure 6.2 Travel time ratio for 3 pm

different places using public transit compare to using taxi, which is an improvement for opportunity-based accessibility measurement. RI for destination is calculated and presented in Section 6.2.2. In this Section, 9 hospitals were selected as destinations in this research, to indicate how convenient for people to go to hospital when using public transit compared to using taxi.

6.2.1. RI for Origins

Figure 6.3 and Figure 6.4 are two maps of RI in NYC, for two different time periods in a day. Figure 6.3 indicates RI for 3am, representing transportation conditions during night hour and Figure 6.4 shows RI for 3pm, representing that for day hours. In both figures, red color indicates steep slopes for regression lines, which means longer travel time public transit needs than taxi, while blue color indicates smaller differences between public transit and taxi. These break numbers are quantile division of all possible slopes. In other words, the array of slope values (combined 3 am and 3 pm) was divided into 9 classes and the amounts of numbers in each class are the same.

For each origin, we first plotted travel time for all the destinations onto a scatter-plot, similar to Figure . Valid locations were determined according to criteria stated in Section 5.4. With limited number of trips, many cells have no value, which are represented in black color.

In Figure 6.3 and Figure 6.4, the majority of Manhattan areas and some parts of Brooklyn have continuous values. In Queens, only areas along major subway lines and around some stations have values. Whether one cell has value or not indicates the transportation demand for people in this cell.

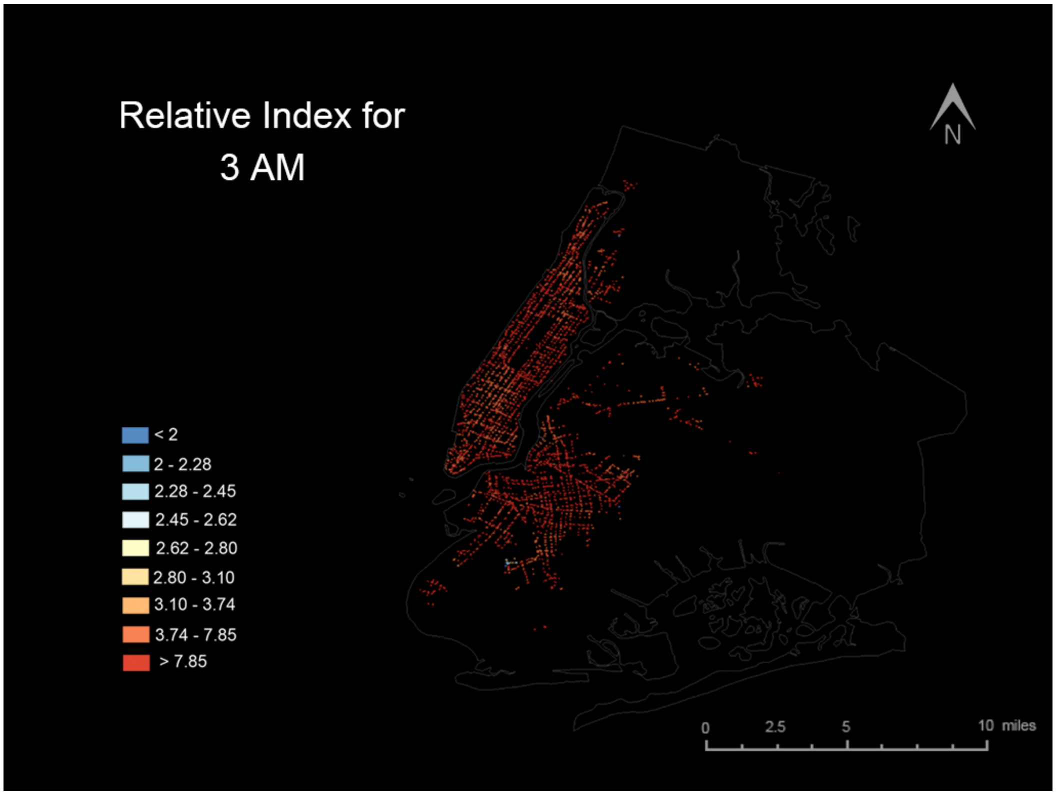


Figure 6.3 Relative Index for 3 AM

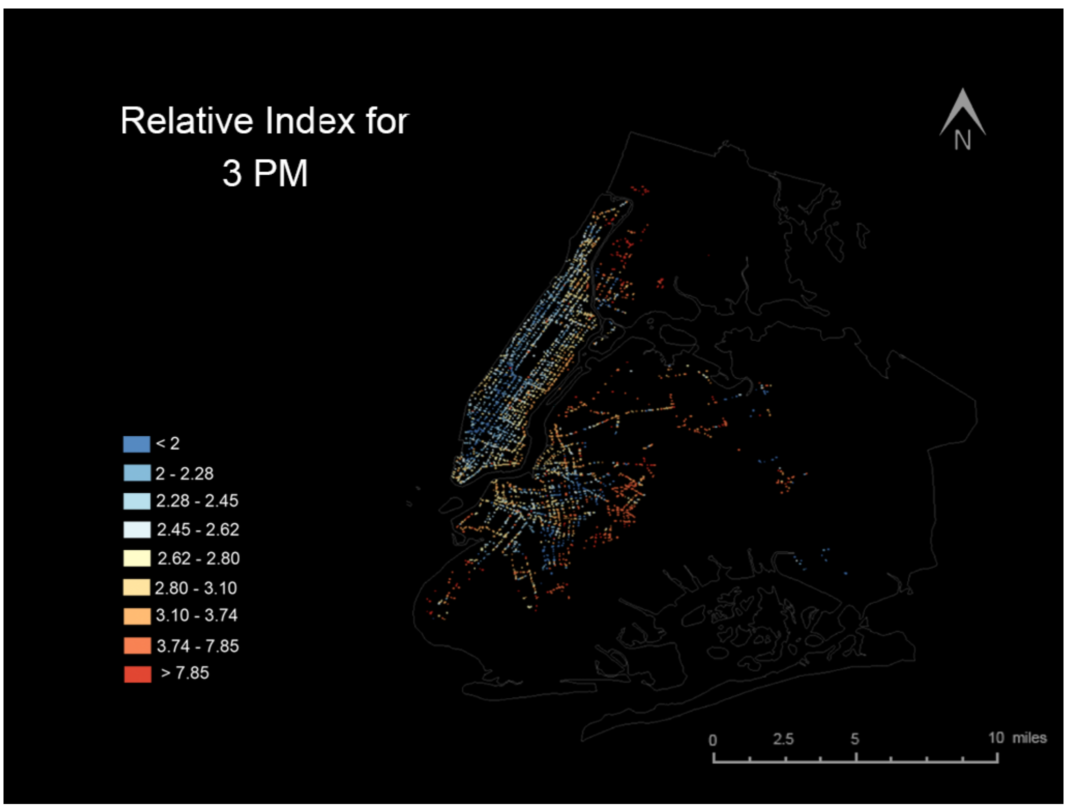


Figure 6.4 Relative Index for 3 PM

In the map for 3 am, most areas are shown in red color, which means, for every one more minute traveling in taxi, public transit riders should expect at least 4 more minutes needed when riding public transit. In most areas (shown in dark red), public transit riders should expect at least 8 more minutes for public transit. Map for 3 pm is quite different from the one for 3 am, where the majority of Manhattan is covered by blue or yellow color. This means the majority of Manhattan areas have low RI, indicating high public transit accessibility. During day hours, for every one more minute traveling in taxi, public transit riders should expect less than one or two more minutes increasing in using public transit system.

6.2.2. RI for Destinations

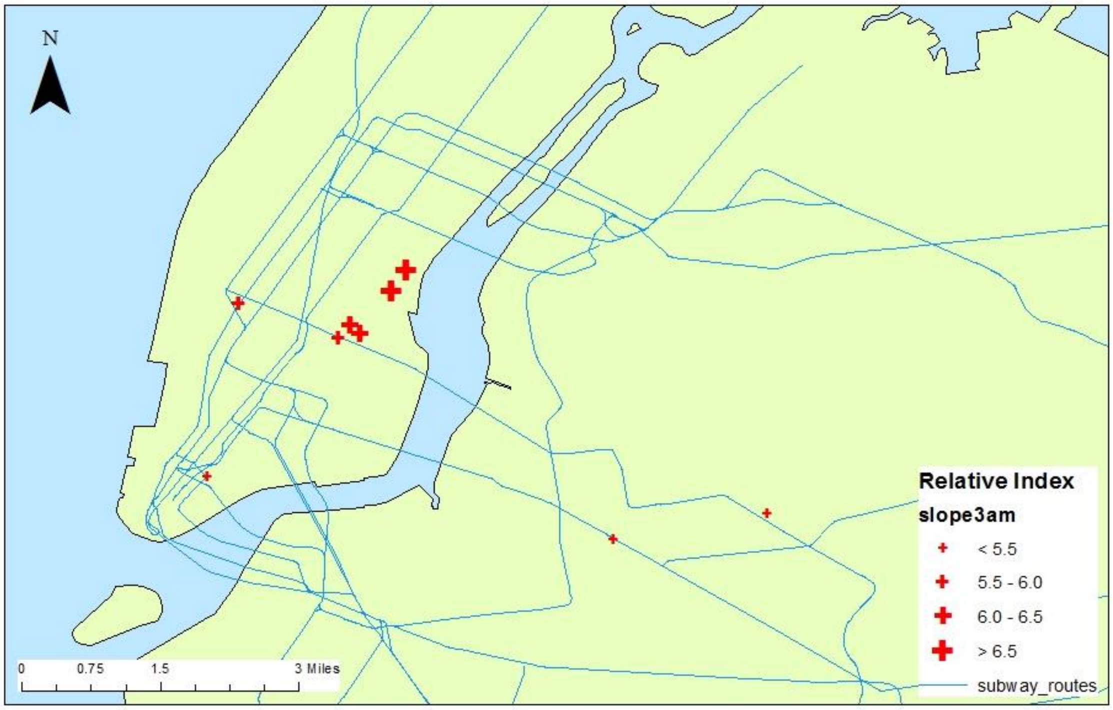
This section presents result from RI calculation for selected destinations. Nine major hospitals were selected as destinations. This result provided a practical scenario about how convenient for people to go to hospitals in 3 am and 3 pm. Similar to calculation in Section 6.2.1, for each hospital as a destination, the original cell mush have more than 10 trips to be considered as a valid origin for that O-D pair. Since all of the 9 hospitals have more than 10 O-D pairs, all of the 9 hospitals were included in this computation. Table 6.1 and Figure 6.5 showed the results of RI for these 9 hospitals as destinations during 3 am and 3 pm.

Table 6.1 RI for 9 major hospitals

Hospital ID	Hospital Name	3am	3pm
1318	Wyckoff Heights Medical Center	4.135629	2.497573
1437	New York-Presbyterian/Lower Manhattan Hospital	5.476785	2.898124
1438	Bellevue Hospital Center	7.54288	2.657518
1439	Mount Sinai Beth Israel	6.304742	2.718745
1446	NYU Hospital for Joint Diseases	6.084728	2.668831
1460	New York Eye and Ear Infirmary of Mount Sinai	5.995072	2.451585
1463	NYU Hospitals Center	7.841157	2.620224
1692	Woodhull Medical & Mental Health Center	4.317989	1.798184
9700	Lenox Health Greenwich Village	5.703344	2.613187

7 of these 9 major hospitals locate in lower Manhattan and 2 locate in Brooklyn. Similar to previous analysis, RI for 3 am is much higher than RI for 3 pm, indicating lower accessibility of public transit system during night hours. In addition, hospital Woodhull Medical & Mental Health Center has the lowest RI at 3 pm (1.798184), which is the only hospital has RI smaller than 2. This hospital also has the second lowest RI at 3 am. Compared to other hospitals, NYU Hospitals Center and Bellevue Hospital Center locate farther away from subway routes. These two hospitals have the highest RI during both time periods, which indicates low public transit accessibility to reach these two hospitals.

RI for 9 hospitals 3 am



RI for 9 hospitals 3 pm

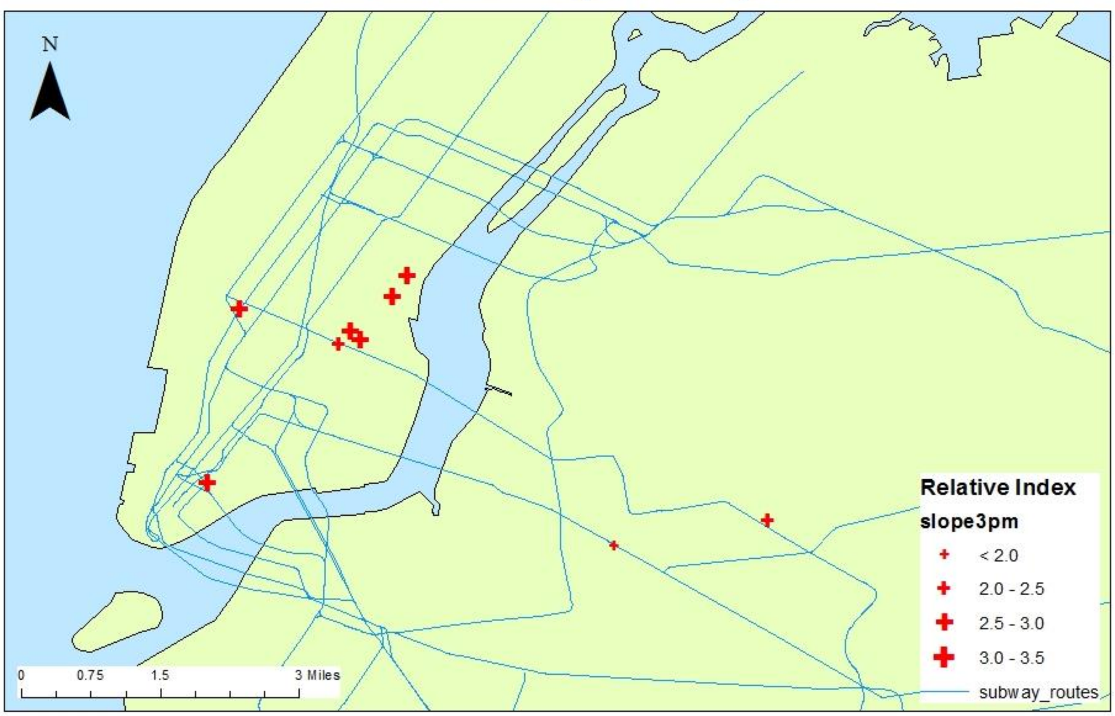


Figure 6.5 RI for 9 hospitals in NYC

CHAPTER 7

DISCUSSION

In the resulted travel time ratio maps, East part of the Central Park provides a good example indicating how subway lines are shaping travel time ratio. Subway line 1, 2, and 3 runs along the area. Assume all subways are running according to timetable and no delays happen. During rush hours, the average waiting time for line 1, 2, and 3 are 6 minutes and express subway lines only stop at several stations. However, during night hours, the average waiting time for these lines is 20 minutes. This change in travel time ratio is noticeable as the blue area, a fast corridor, exists in the east side of Central Park, which only appears during day hours.

Another fast corridor in Queens also indicates the impacts of subway line 7 and 7 express. Line 7 and 7 express share the same route but 7 express only stops at some major stations while line 7 stops at all stations. These two subway lines are the only subways connecting lower Manhattan and residential areas in Queens, where many commuters from minority races live. Areas, where line 7 and 7 express running through, show less transit travel time than taxi travel time. Areas around line 7 and 7 express still present relatively good travel time ratio.

In figure 4 and figure 5, not all locations have enough trip records to be considered as a valid location in RI measurement. Visual examination of figure 4 and 5 provided evidences about travel demands for taxis. Since public transit network almost covers the whole NYC (see Figure 4.2), whether a location is valid or not was actually determined by the number of taxi trips starting from that location. In figure 4 and 5, most areas of Manhattan have enough taxi trips to be considered as valid. Outside of Manhattan, most valid locations are along subway lines. This distribution pattern indicated taxi travel demand. From this visual examination, NYC provided a good public transit service to catch people's travel demands.

At the same time, one may notice that the pattern of subway lines are better represented by travel demand than the patterns of buses. This shows that, people preferred to ride subways than buses. Maybe riders preferred to avoid ground traffic congestion, or subway riding environment.

During 3 am, RI results for NYC was mainly in red or orange colors, even in Manhattan area, where people would expect the most convenient public transit services. In 3 pm, Manhattan area shows results as most people would expect. Blue and yellow color in Manhattan represented high accessibility. This difference between 3 am and 3 pm are resulted from the frequency of subway services during day hours and night hours. With reduced number of running subways during night hours and consequent longer waiting time, accessibility for public transit during night is much lower than accessibility during daytime.

Similar results can be found in results of RI for selected destinations as well. For all the 9 hospitals, RI during day hours for each hospital is much lower than RI during night hours. During day hours, RI for these 9 hospitals range from 1.798184 to 2.898124. During night hours, RI ranges from 4.135629 to 7.841157. The range of RI and RI differences for individual hospital indicate several factors work together to affect the general public transit accessibility. What causes this difference for each individual hospital requires further research.

CHAPTER 8

CONCLUSION AND FUTURE RESEARCH

This research developed a new measurement of accessibility that tried to bridge current methodology with the increasing availability of multimodal transportation data. Current measurements of accessibility either choose one important location as origin or destination and measure accessibility from that origin or to that destination, or researchers arbitrarily assign scores to opportunities and measure scores of different origins as accessibility. The major contribution of this research is to develop a new measurement of accessibility to integrate multiple transportation modes. This method gives equal opportunity for all possible destinations, which reduced subjective bias in opportunity weighting. To achieve these objectives, this research used historical taxi trip records and public transit timetable to compute taxi and public transit travel time. Then all the pairs of origin-destination (O-D) were plotted with taxi travel time on x-axis and public transit travel time on y-axis. One location must have no less than 10 O-D pairs to be considered as a valid location. For each valid location, total least square regression was applied and the slope from regression is defined as RI, representing the measurement of accessibility.

Mapping RI for NYC, especially during daytime, provided visualization of spatial accessibility patterns. The east side of Central Park demonstrated the fast corridor created by express subway lines. Most areas with lower RI, which means better public transit accessibility, locate along or near subway lines. Public transit, especially subway systems in NYC, provided good service to meet people's travel demands.

RI for different time periods showed the temporal changes of accessibility patterns in NYC. During night hours, limited public transit services were provided and less traffic congestion happening on the road. Therefore RI is high during night hours, indicating low accessibility level of public transit. During daytime, with more frequent subway running in the NYC and express lines, the accessibility of public transit is higher, represented as low RI on map. Comparing RI of the same location during different time of a day indicates the temporal changes of accessibility.

On the other hand, RI can measure accessibility of destination. In this research, 9 major hospitals were chosen as destinations and were compared for how convenient for people to reach hospital. This application provided practical usage to RI in urban planning and development.

However, this research shows some limitations and needs further improvement. First major limitation is about taxi data. Since taxi travel time was retrieved from historical taxi data, errors existing in taxi data would affect this measurement. For example, in the map of RI for 3 am (see **Error! Reference source not found.**), one taxi trip record with long travel time affected RI for that area. In addition, a 500-meter buffer zone was applied as taxi trip inclusion area. However, this buffer zone created larger effects of one incorrect taxi trip records to areas around that point. In future research, more efforts are needed in early-stage of data clean and filter out incorrect records in taxi trips. Second limitation of this research is about valid locations. With assumption of 500-meter walking distance, all the subway stations, bus stops, and 500-meter walking accessible areas have public transit time for accessibility measurement. But to calculate RI, each of these locations must have enough (10 was the threshold used in this research) taxi trips starting from or stopping at that location to be considered as a valid origin or destination. Many areas, especially areas other than Manhattan, were not valid in this research. In future research, either a smoothing algorithm or a scalable filter could be applied to increase the number of valid locations. Another limitation with public transit was about possible delays or other unexpected situations. If RI is applied to city development or travel planning, how to include real-time information and improve computational speed require further research. In addition, the walking distance of local people varies in different places. More details about local people's travel behaviors require further analysis.

This research also provides one applications of RI that measured accessibility for people to reach 9 major hospitals in NYC. Similarly, RI can be applied to measure accessibility for schools, public libraries, or tourism. Also, given standardized data format for taxi trip records and public transit timetable, this research can be applied to different cities.

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