Characterization and Assessment of Transportation Diversity: Impacts on Mobility and Resilience Planning in Urban Communities

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Academic Abstract

A transportation system is a critical infrastructure that is key for mobility in any community. Natural hazards can cause failure in transportation infrastructure and impede its routine performance. Ecological systems are resilient systems that are very similar to transportation systems. Diversity is a fundamental factor in ecological resilience, and it is recognized as an important property of transportation resilience. However, quantifying transportation diversity remains challenging, which makes it difficult to understand the influence of diversity on transportation performance and resilience. Consequently, three studies are undertaken to remedy this circumstance. The first study develops a novel approach – inspired by biodiversity in ecological stability theory – to characterize and measure transportation diversity by its richness (availability) and evenness (distribution). This transportation diversity approach is then applied to New York City (NYC) at the zip code level using the GIS data of transportation modes. The results demonstrate the variation of transportation diversity across the city. The characterized inherent and augmented complementarities start to uncover the dynamics of modal compensation and to demonstrate how transportation diversity contributes to this phenomenon. Moreover, the NYC zip codes with low transportation diversity are mainly in hurricane evacuation zones that are more vulnerable. Consequently, low transportation diversity in these areas could affect their post-disaster mobility.

In the second study, the influence of transportation diversity on post-disaster mobility is examined by investigating the patterns of mobility in New York City one month before and after Hurricane Sandy using Twitter data. To characterize pre- and post-Sandy mobility patterns, the locations that individuals visited frequently were identified and travel distance, the radius of gyration, and mobility entropy were measured. Individuals were grouped according to the transportation diversity of their frequently visited locations. The findings reveal that individuals that lived in or visited zip codes with higher transportation diversity mostly experienced less disturbance in their mobility patterns after Sandy and the recovery of their mobility patterns was faster. The results confirm that transportation diversity affects the resilience of individual post-disaster mobility. The approach used in this study is one of the first to examine the root causes of changes in mobility patterns after extreme events by linking transportation infrastructure diversity to post-disaster mobility.

Finally, the third study employs the transportation diversity approach to investigate modal accessibility and social exclusion. Transportation infrastructure is a sociotechnical system and transport equity is crucial for access to opportunities and services such as jobs and infrastructure. The social exclusion caused by transport inequity could be intensified after natural disasters that can cause failure in a transportation system. One approach to determine transport equity is access to transportation modes. Common catchment area approaches to assess the equity of access to transportation modes cannot differentiate between the equity of access to modes in sub-regions of an area. The transportation diversity approach overcomes this shortcoming, and it is applied to all transportation modes in NYC zip codes to measure the equity of access. Zip codes were grouped in quartiles based on their transportation diversity. Using the American Community Survey data, a set of important socioeconomic and transport usage factors were compared in the quartile groups. The results indicated the relationship between transportation diversity and income, vehicle ownership, commute time, and commute mode. This relationship highlighted that social exclusion is linked with transport inequity. The results also revealed that the inequity of the transport system in zip codes with low transportation diversity affects poor individuals more than non-poor and the zip codes with a majority of black and Hispanic populations are impacted more. Further consideration of the impacts of Hurricanes Irene and Sandy in NYC shows that people in areas with a lower transportation diversity were affected more and the transport inequity in these areas made it difficult to cope with these disasters and caused post-disaster social exclusion. Therefore, enhancing transportation diversity should support transport equity and reduce social exclusion under normal situations and during extreme events.

Together, these three studies illustrate the influence of transportation diversity on the resilience of this infrastructure. They highlight the importance of the provision and distribution of all transportation modes, their influence on mobility during normal situations and extreme events and their contribution toward mitigating social exclusion. Finally, these studies suggest that transportation diversity can contribute to more targeted and equitable transportation and community resilience planning, which should help decision-makers allocate scarce resources more effectively.

Characterization and Assessment of Transportation Diversity:
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General Audience Abstract

Transportation systems are very important in every city. Natural disasters like hurricanes and floods can destroy roads and inundate metro tunnels that can cause problems for mobility. Ecological systems like forests are very resilient because they have experienced disturbances like natural disasters for millions of years. Ecological systems and transportation systems are very similar; for example, both have different components (different species in an ecological system and different modes in a transportation system). Because of such similarities, we can learn from ecological resilience to improve transportation resilience. Having a variety of species in an ecological system makes it diverse. Diversity is the most important factor in ecological resilience, and it is also recognized as an important factor in transportation resilience. Current methods cannot effectively quantify transportation diversity – the variety of modes in a system – so determining its impact on transportation resilience remains a challenge. In this dissertation, principles of ecological diversity are adapted to characterize transportation infrastructure to develop a new approach to measure transportation diversity; metrics include the availability of transportation modes and their distribution in a community. The developed approach was applied in New York City (NYC) at the zip code level. Locations with low transportation diversity (fewer modes and/or unequal distribution) were identified, and most of these zip codes are located in hurricane evacuation zones. Consequently, these zip codes with the least diverse transportation systems are the most vulnerable, which can cause serious issues during emergency evacuations and the ability of people to access work or essential services. Therefore, in a city hit by a natural disaster, understanding the relationship between people's mobility and a transportation system's diversity is important. Twitter data was used to find the places that people in NYC visited regularly for one month before and one month after Hurricane Sandy. Subsequently, using different methods, the pre- and post-disaster mobility patterns of these individuals were characterized. The results show that after the disaster, individuals had a higher chance of maintaining their pre-disaster mobility patterns if they were living in and/or visiting areas with high transportation diversity. Based on these findings, we confirmed the influence of transportation diversity on post-disaster mobility. In addition, the transportation infrastructure should provide equitable service to all individuals, during normal operations and extreme events. One of the ways to determine this equality is equity of access to transportation modes. Hence, transportation diversity was used as an indicator for equity of access

to transportation modes to overcome the limitations of current methods like catchment area approaches. NYC zip codes were grouped based on their transportation diversity and a set of important socioeconomic and transport related factors were compared among these groups. The comparison of socioeconomic and transport related factors in zip codes showed that the zip codes with lower transportation diversity are also more socioeconomically deprived. This highlights the likely influence of transportation diversity on social exclusion. Further consideration of the impacts of Hurricanes Irene and Sandy in NYC shows that people in areas with a lower transportation diversity were affected more and the transport inequity in these areas made it difficult to cope with these disasters and caused post-disaster social exclusion. Therefore, enhancing transportation diversity should support transport equity and reduce social exclusion under normal situations and during extreme events. The investigations conducted highlight the importance of the provision and distribution of all transportation modes, their influence on mobility during normal situations and extreme events and their contribution toward mitigating social exclusion. Finally, the collective results suggest that transportation diversity can contribute to more targeted and equitable transportation and community resilience planning, which should help decision-makers allocate scarce resources more effectively.

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Chapter 1: Introduction

1.1. Transportation Resilience

The transportation system is an important lifeline that connects different parts of an urban community, enables mobility, and supports the functionality of communities. Extreme events such as natural hazards can bring about major disruptions in the transportation infrastructure and hinder routine mobility and access to jobs, food, healthcare facilities, and other infrastructure and services. The Department of Homeland Security (DHS) has identified a list of sixteen critical infrastructures where their failures would have a debilitating impact on physical facilities, economic activity, security, public health, or safety of the nation. Since transportation infrastructure is interdependent with other critical infrastructures such as energy, food, water, and emergency services, a major failure in the transportation infrastructure can cause cascading failure in the interdependent infrastructure systems.

During the past few decades, climate change has intensified the frequency and magnitude of natural hazards all over the world that has caused deaths and significant economic damage (Joshi et al., 2019). Hurricane Sandy in New York City and the New Jersey coastline in 2012, California wildfire in 2015, Hurricane Harvey in Texas in 2017, Hurricane Maria in Puerto Rico in 2017, West Virginia and Southern California floods in 2018, and Hurricane Michael in Florida in 2018 are some of the major disasters of the past decade in the U.S. The impact of such natural disasters in the U.S. prompted Presidential Policy Directive 21, Critical Infrastructure Security and Resilience, in 2013 that called for an improved and updated National Infrastructure Protection Plan (NIPP). The focus of NIPP is the call for action to enhance the resilience and security of the critical infrastructure systems.

1.2. Transportation Resilience Assessment

Since the seminal work of Holling (1973) that introduced resilience in ecology, this concept has been applied in several disciplines, from biological systems, social sciences, and economics to institutions, engineering, and infrastructure systems. In infrastructure systems, one of the very first approaches to quantify resilience was a framework developed by Bruneau et al. (2003). This framework includes four measures of robustness, rapidity, resourcefulness, and redundancy and quantifies resilience by a single metric of the quality of infrastructure that varies over time. This framework has been the foundation for several infrastructure resilience studies including transportation system resilience (e.g., Adams et al., 2012; Omer et al., 2013; Tang and Heinimann, 2018). The application of this framework provides a general understanding of the resilience of a transportation system. However, transportation infrastructure is a complex adaptive system (CAS) (Rinaldi et al., 2001). CAS is a system with a large number of components or agents that interact with each other and adapt or learn (Holland, 2006). Due to this complexity, the resilience of this infrastructure depends on several factors that collectively can enhance the ability of this infrastructure to resist extreme events and quickly recover from them. Therefore, transportation resilience cannot be described by a single measure since such a measure is not able to capture different aspects of this complex infrastructure. A comprehensive transportation resilience assessment should encompass different resilience factors. A resilient transportation system has ten dimensions: redundancy, diversity, efficiency, autonomous components, strength, adaptability, collaboration, mobility, safety, and the ability of quick recovery (Murray-Tuite, 2006). Quantifying these factors for transportation resilience assessment requires methods and metrics that can describe this infrastructure, its characteristics, and its performance. Developing metrics for the transportation resilience factors and quantifying them pave the way to investigate the influence of these factors on transportation resilience and understand the ways to improve them. One of the transportation resilience factors is *diversity*, which is defined as having multiple components that have distinct functions (Murray-Tuite, 2006). Despite being recognized as an important factor for transportation resilience, a measure to quantify transportation diversity to understand how it can enhance transportation resilience remains underdeveloped. Park et al., (2011) propose that for complex and interdependent infrastructure systems a new resilience model is required, which should be based on ecological system analogs. The concept of diversity in biological systems appears to be a suitable model to characterize diversity in transportation infrastructure, develop transportation diversity metrics, and explore its impact on transportation and community resilience.

1.3. Coupling Biological and Transportation Systems

Biological systems have survived disturbances such as natural hazards over millions of years through an iterative process of evolution and adaptation. Ecosystems are CAS (Levin, 1999; Folke et al., 2004) with a large number of components (e.g., species or groups of species) interacting at different scales. Infrastructure systems, social networks, and cities are other examples of CAS. Similar to ecosystems that go through change after a disturbance, infrastructure systems undergo change (Manyena et al., 2011) and evolve dynamically (Graham, 2010; Pescaroli and Alexander, 2016). The similarities between ecological systems and infrastructure systems are shown in Table 1.1. Both systems have distinct functional groups that are interdependent, perform at different scales (e.g., spatial, temporal, functional), and face natural hazards. The parallels between these two systems suggests that ecological resilience theory could be used to improve transportation resilience. Amoaning-Yankson and Amekudzi-Kennedy (2017) described this potential in their review of resilience in ecological, economic, and social systems suggesting that ecological concepts can be translated to infrastructures like transportation systems for resilience improvement.

Table 1.1: Similarities Between Ecological and Transportation Systems

Similarities	Ecological Systems	Transportation Systems
Complexity	Complex networks	Complex networks
Functionality	Functional groups	Individual Infrastructures
Interdependency	Between functional groups	Between infrastructures
Scale	Spatial, temporal, functional, organizational	Spatial, temporal, functional, organizational
Natural hazards	Flood, hurricane, heatwave, snow, etc.	Flood, hurricane, heatwave, snow, etc.

1.4. Research Approach

The research in this dissertation consists of three studies focusing on (a) characterizing and developing metrics for transportation diversity and quantifying it in urban communities, (b) analyzing the impact of transportation diversity on post-disaster mobility, and (c) assessing transport equity based on transportation diversity and investigating the relationship between transportation diversity and socioeconomic and transport related factors for social exclusion in normal situations and emergencies. The New York City (NYC) transportation system is analyzed in these three studies at the level of zip codes. GIS data of all transportation modes is used to measure transportation diversity in NYC zip codes. Then, using Twitter data, the mobility patterns of one month before and after Hurricane Sandy are analyzed to determine the influence of transportation diversity on post-Sandy mobility patterns. Lastly, using transportation diversity to quantify the equity of access to transportation modes, the relationship between transportation diversity and socioeconomic and transport related factors in zip codes is analyzed.

Study 1: Characterizing and Measuring Transportation Infrastructure Diversity through Linkages with Ecological Stability Theory

Transportation infrastructure plays an important role in every urban community. Disruptions caused by natural hazards can affect the routine performance of this infrastructure that can influence the quality of life and access to other critical infrastructure and services. Ecological systems are resilient systems that have survived and adapted to countless disturbances. Ecological systems, in many ways, are very similar to infrastructure systems. Diversity is a key factor in ecological resilience. Similarly, diversity is recognized as an important factor in transportation resilience; however, it lacks a quantification method. In Study 1, the concept of ecological diversity is adapted to characterize transportation diversity and to develop an approach to measure it in urban communities. Transportation diversity is characterized by two metrics of richness and evenness. The richness determines the abundance of all transportation modes in an area while the evenness quantifies the distribution of transportation modes in an area. Transportation diversity is applied in NYC at the zip code level. The developed approach allowed identifying the zip codes that have a low transportation diversity, the transportation modes in each zip code that caused it, and the transportation diversity metric that requires improvement. This study provides an approach to measure diversity in transportation systems that helps to investigate how transportation diversity contributes to the resilience of this infrastructure.

Study 2: Assessing the Impact of Transportation Diversity on Post-Disaster Intra-Urban Mobility

A transportation system connects different parts of an urban community and enables mobility across a community. A failure caused by an extreme event such as a natural hazard can affect mobility and routine activities in a city. In Study 2, the transportation diversity approach developed in Study 1 is used to investigate the influence of transportation diversity on mobility patterns in NYC after Hurricane Sandy to understand how transportation diversity can support the resilience of mobility patterns after extreme events. To do so, Twitter data is analyzed to characterize mobility patterns one month before and after Hurricane Sandy in NYC. First, the locations that individuals visited frequently are identified and then using distance, the radius of gyration, and mobility entropy their mobility patterns before and after Hurricane Sandy are characterized. Based on the transportation diversity of the locations an individual visits regularly, people are categorized into different groups and their pre- and post-Sandy mobility patterns are studied. The comparison of groups indicates that the mobility patterns of individuals that lived in or visited areas with lower transportation diversity were affected more. These individuals had a higher mean change in their mobility patterns compared to those in higher diversity quartiles. Further, the recovery time to pre-Sandy mobility patterns was longer for individuals in low transportation diversity quartiles. This study provides an approach to explore the underlying causes of changes in mobility patterns after extreme events by coupling transportation infrastructure data with post-disaster mobility data. This approach overcomes the limitations of social media data and calls data records in linking changes in mobility patterns to the transportation system. The results of this study confirm the influence of transportation diversity on post-disaster mobility patterns and demonstrate the utility of transportation diversity for mobility resilience.

Study 3: Transportation Diversity and Equity Nexus: A Socio-Economic Analysis for Resilience Planning

Equity of access to transportation modes is crucial for equal access to activities and services. All transportation modes contribute to the performance of this infrastructure; therefore, improving the provision and accessibility in all modes in the context of existing conditions and constraints should be the goal for transportation planners and designers. When an extreme event causes failure in a transportation system, the equal access to transportation modes becomes more critical since the lost service can be compensated by the intact modes. The current methods in assessing the equity of access are mainly based on the catchment area approaches and analyze transit modes. The broad classification in these methods cannot distinguish the equity of access of sub-regions of an area to identify those that need improvement. In addition, they do not take into account all transportation modes. To overcome the limitations of these methods, in Study 3, the transportation diversity approach developed in Study 1 is used to measure the equity of access to all transportation modes in NYC zip codes. Zip codes were grouped in quartiles based on their transportation diversity. Two sets of important indicators were considered for comparison between quartiles. The first set of indicators is related to transport usage and the second set are socioeconomic factors. The comparison of these factors between quartile groups indicated that there is a relationship between transportation diversity and income, vehicle ownership, commute mode, and commute time. The comparison of vehicle ownership and commute time for poverty and race groups within and between quartiles revealed the relationship between transportation diversity and social exclusion in disadvantaged groups. The investigation of the impact of Hurricanes Irene and Sandy in NYC zip codes on transport-related social exclusion indicated that areas with a low transportation diversity faced more difficulty in their mobility after these disasters. This highlights the relationship between transportation diversity and post-disaster social exclusion. The results of this study demonstrated the relationship between transportation diversity and social exclusion in normal situations and after natural disasters. This suggests that improving transportation diversity leads to a more equitable transportation system and supports mitigating social exclusion in normal situations and after natural disasters.

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Chapter 2: Characterizing and Measuring Transportation Infrastructure Diversity Through Linkages with Ecological Stability Theory[1]

Abstract

Transportation infrastructure is critical to any community. Disturbances such as natural hazards can hinder transportation infrastructure performance impacting a community's quality of life through disruptions in service and effects on interdependent infrastructure systems. Ecological systems are robust and resilient and have similarities with infrastructure systems. Diversity is a fundamental element of ecological resilience and is recognized as an important factor in transportation resilience. However, measures of transportation diversity are not well-developed. Accordingly, this paper adapts the ecological diversity concepts of richness and evenness to develop an approach to characterize transportation system diversity and distinguishes the approach from existing methods. Measures of transportation functional richness and evenness are derived and applied to New York City at the zip code level. The results facilitate the identification of zip codes in New York City with varying levels of diversity. Those zip codes with low diversity generally have limited availability (low richness) and disproportionate distribution (low evenness) of alternative transportation modes. Further, these zip codes are potentially susceptible to system disturbances as a consequence of routine disruptions or natural hazards. For instance, many low diversity zip codes are in hurricane evacuation zones. Limited complementarity in the transportation system of these zip codes will likely impact evacuations during hurricanes and recovery to pre-disturbance performance levels. Ultimately, the transportation diversity approach presented should lead to better understanding of transportation system characteristics such as inherent and augmented complementarity, which will enhance transportation system performance in urban communities.

Keywords: Infrastructure; Natural Hazard; Multimode; Transportation; Diversity; Resilience

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2.1. Introduction

The quality of life in urban areas is considerably entangled with infrastructure systems such as transportation, power, water, and communication. Natural hazards like hurricanes, floods, and earthquakes can cause failure in infrastructure systems and reduction in the level of service, which may result in significant loss of life and economic impact (Jonkman et al., 2003; French et al., 2010). Over the last few decades, climate change has also exacerbated the situation by causing more natural hazards (Mal et al., 2018; Trenberth et al., 2018). The devastating impacts of Hurricanes Harvey, Irma and Maria on Texas, Florida and Puerto Rico in 2017 as well as Hurricanes Florence and Michael on the Carolinas and Florida in 2018 are prime examples of the susceptibility of infrastructure and communities to natural hazards.

Within urban communities, transportation infrastructure provides critical connections for residents and businesses to essential services (Machado-León and Goodchild, 2017). Since a transportation system is interdependent with other infrastructure and services, its failure can trigger cascading impacts on other infrastructure and services. The performance of an urban transportation system, during normal and extreme situations, highly depends on the collective performance of all transportation modes and their complementarity. Thus, it is crucial to characterize the transportation system of an urban community by considering all modes.

A complex adaptive system (CAS) is a system with a large number of components that are continuously interacting with each other and adapting to changes (Holland, 2005). Ecosystems, infrastructure systems, and cities are CAS examples. In particular, ecosystems have experienced numerous disturbances such as natural hazards over millions of years. Ecosystems have withstood these, adapted, evolved and become more resilient to similar subsequent events. Like ecosystems that go through change after a disturbance, infrastructure systems undergo change (Manyena et al., 2011) and evolve dynamically (Graham, 2010; Pescaroli and Alexander, 2016). Amoaning-Yankson and Amekudzi-Kennedy (2017) confirmed this similarity in their review of resilience in ecological, economic and social systems suggesting that ecological concepts can be translated to transportation systems for resilience improvement.

Biodiversity is chief among the factors contributing to the stability and resilience of ecological communities (Tilman et al., 2014). Similarly, diversity is recognized as an important property of resilient transportation systems and urban communities (Murray-Tuite, 2006; Godschalk, 2003). Yet, despite the recognized importance of diversity for the resilience of transportation infrastructure and infrastructure systems in general, the use of diversity as a predictor of system resilience remains largely undeveloped. One reason for this is a lack of concrete and well-defined metrics to characterize and quantify diversity in infrastructure. Given the similarities in ecological and transportation systems, the concept of diversity in ecological systems can potentially help in deepening the concept of transportation diversity. Accordingly, this study further explores ecological diversity and its two measures of *functional richness and functional evenness* and translates them to transportation infrastructure to develop an approach for characterizing transportation diversity. Subsequently, the approach to measure transportation diversity is differentiated from comparable methods and applied to the New York City (NYC) transportation system to demonstrate its efficacy and to identify and discuss implications for transportation planning and management. A principal intent is to explain how to measure transportation diversity and to illustrate how quantifying diversity can provide a basis for assessing transportation systems, particularly in the context of disturbances like natural hazards.

2.2. Linking Ecological Diversity to Transportation Diversity

2.2.1. Ecological System

2.2.1.1. Ecological Resilience

The definition of resilience in ecological systems is *the persistence of relationships within a system and the ability to absorb change and still persist* (Holling 1973, 1996); *to retain the same functionality, structure, identity, and feedback* (Folke et al., 2004; Walker et al., 2004) *while learning from and adapting to the disturbance* (Carpenter et al, 2001). Ecological theory on the factors affecting ecosystem resilience tends to center around the concept of diversity, with the general expectation that resilience increases as diversity increases (McNaughton 1977, Tilman 1996). A similar expectation exists for the diversity of functional groups, i.e. functional diversity (McGrady-Steed and Morin 2000, Carrara et al. 2015). For the diversity-resilience relationship, there is also a rich history of investigation into the mechanistic drivers of this relationship, both from a conceptual (e.g., Ives 1995, Johnson et al. 1996, Micheli et al. 1999) and an empirical perspective (e.g, McNaughton 1977, Tilman 1996, McGrady-Steed and Morin 2000, Cottingham et al. 2001).

2.2.1.2. Biodiversity

Diversity can be generally defined as the existence of multiple forms and behaviors (Fiksel 2003). In biology, diversity is most often defined as the number of entities (e.g., species, functional groups) in a community or ecosystem and the evenness of their distribution (Hooper et al., 2005). Tilman et al. (2014) describe biodiversity as the most important factor in ecosystem dynamics and functionality, which makes communities of species more stable (Folke et al., 2004; Downing et al., 2012; Oliver et al., 2015).

Ecosystems are composed of diverse functional groups. A functional group is a multi-species group of functionally equivalent species (Naeem and Li, 1997). The resilience of biological systems is largely due to the interactions among different functional groups (Elmqvist et al., 2003, Maruyama et al., 2014) that increases (a) the range of responses to a disturbance (Bernhardt and Leslie, 2013) and (b) the capacity for recovery from a disturbance (Diaz and Cabido, 2001; Bernhardt and Leslie, 2013). Functional diversity is generally measured by its two key components: functional richness and functional evenness (see Figure 1).

- *Functional richness*: is the abundance of functional groups in a community; or volume of the functional space occupied by species (Villeger, 2008; Mason, 2005; Mouillot et al., 2013); and
- *Functional evenness*: indicates the homogeneity of the distribution of functional groups in the functional space (Mouillot et al., 2005, 2013).

In Figure 2.1, the horizontal and vertical axes represent the functional space and the abundance of species respectively. Gaussian curves show the distribution of species in the functional space and histograms show the sum of the abundance of species within the same functional category. For instance, Figure 2.1-a indicates high functional richness and high functional evenness because the functional space is almost fully occupied by species and their distribution in functional categories is even. However, while Figure 2.1-d has the same functional richness as 2.1-a, its functional evenness is lower. Figures 2.1-b and 2.1-c depict the other two combinations.

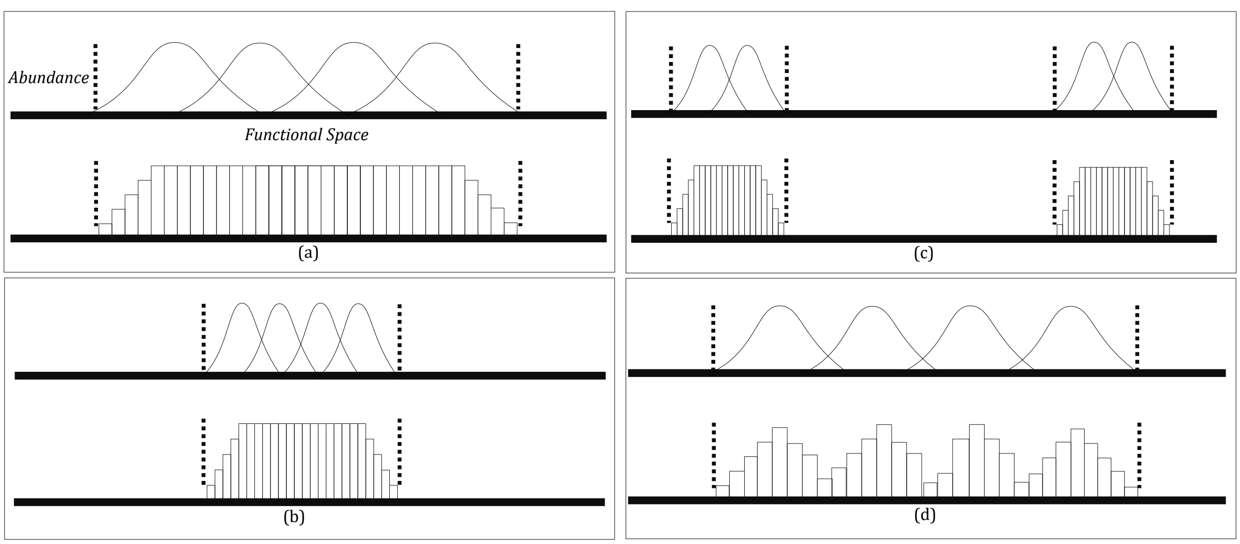

Figure 2.1: Functional Richness and Functional Evenness (adapted from Mason et al., 2005): (a) High richness, high evenness; (b) Low richness, high evenness; (c) Low richness, low evenness; (d) High richness, low evenness

2.2.1.3. Mechanistic Underpinnings of Ecological Diversity-Stability and Diversity-Resilience Relationships

All ecological systems vary through time (Micheli et al. 1999). This variability is created by endogenous factors (like the interactions between species) or exogenous variability created by environmental fluctuations (Hastings 2010). However, variability is almost never random, and the responses of communities to variation is often predictable. This variability has two dimensions: (1) *compositional variability* which indicates the change in the component species and (2) *aggregate variability* which represents changes in the properties produced by the entire community such as total biomass or productivity (Micheli et al., 1999). Mechanistic theory in community ecology is the analysis of community patterns (Schoener, 1965). Measurement of these two types of variability produces a mechanistic framework that can describe the behavior of communities and ecosystems in response to disturbances (Micheli et al. 1999). This framework presents four variability syndromes (Figure 2.2): (a) *stasis* is when a community experiences low compositional and low aggregate variability (stasis is extremely rare in nature and is included largely for completeness of the framework); (b) if species have a similar response to a disturbance, particularly a very powerful disturbance, it results in *synchrony*; (c) in a community where species have different responses to a disturbance, some degree of *asynchrony* is likely; (d) finally, *compensation* occurs when species do not respond independently to a disturbance and the loss of some species is compensated by another group of species to maintain community functionality. The important element in this framework is how these different variability patterns affect the stability and resilience of communities and ecosystems.

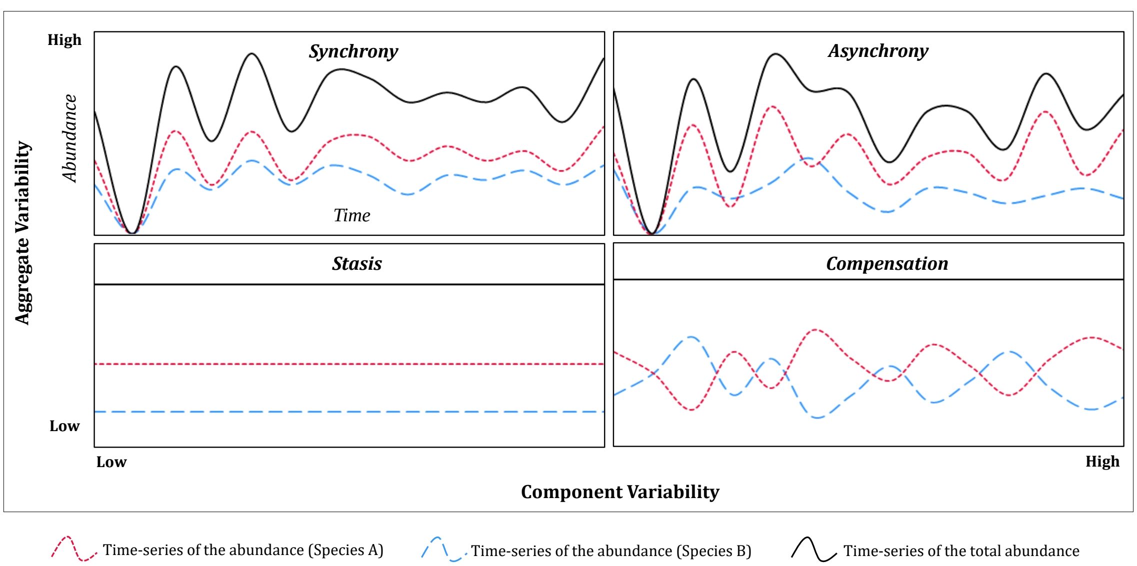

Figure 2.2: Community Variability Patterns Incorporating Both Component and Aggregate Variability (adapted from Micheli et al., 1999)

Several studies have analyzed and confirmed that high diversity increases compensatory responses in a community, which results in higher stability (Brown, 2007; Vandermeer, 2006; Gonzalez and De Foe, 2007). Three types of mechanisms form compensatory dynamics (Brown et al., 2016; Gonzalez and Loreau, 2009): (a) fluctuation-independent mechanisms, (b) fluctuation-dependent endogenous mechanisms, and (c) fluctuation-dependent exogenous mechanisms. In fluctuation-independent mechanisms, the difference in the response of species to disturbances results in compensation (Loreau and de Mazancourt, 2008; Grman et al., 2010). In fluctuation-dependent mechanisms, species are subject to fluctuation which can be endogenous like the interaction of species and resources, or exogenous such as environmental change (Brown et al., 2016; Gonzalez and Loreau, 2009).

How are these ecological concepts potentially useful to infrastructure systems? Different infrastructure sectors might have distinct responses to disturbances such as natural hazards. Characterizing the diversity of an infrastructure system to better understand how its compositional systems interact and what variability patterns emerge during various types of disturbances would be a major step towards understanding the impact of infrastructure diversity on resilience. Indeed, the first step to identify and measure variability patterns of a transportation system in an urban community is to define its transportation diversity.

2.2.2. Transportation System Diversity

2.2.2.1. Overview

Diversity is considered an important factor for infrastructure resilience (Iwamura et al., 2012; Hudson et al., 2012). It has been recognized that complex infrastructure networks should incorporate diversity and heterogeneity in order to be resilient (Pinnaka et al., 2015; Sterbenz et al., 2014). However, metrics to characterize diversity in transportation infrastructure are scarce. Literature has tended to examine transportation resilience in urban communities by focusing on a single mode such as road networks (e.g., Duan and Lu, 2014; Jenelius, 2009; Nieves-Melendez and de la Garza, 2017; Omer et al., 2013) and rail transit (e.g., De Los-Santos et al., 2012; Rodriguez-Nunez ad Garcia-Palomares, 2014). Several studies have looked at multiple modes and resilience (e.g., Leu et al., 2010; Cox et al., 2011; Jin et al., 2014; Ouyang et al., 2015) illustrating the benefits of multi-mode transportation systems to respond better to disturbances. For example, Cox et al. (2011) analyzed the resilience of the metro system in London and concluded that a multi-mode transportation system can alleviate the impact of disturbances. Jin et al. (2014) also highlighted the influence of multiple modes for improving local transportation resilience through the integration of bus and metro systems. Despite the value of this work, existing studies tend to focus on a single mode or a few modes rather than characterizing an urban community's modal diversity by considering all available modes.

2.2.2.2. Defining Transportation Diversity

Transportation diversity is generally defined as a system having multiple components with different functionalities (Murray-Tuite 2006). Converting biodiversity metrics to transportation first requires considering infrastructure system characteristics. If transportation modes are considered parallels to functional groups in ecological systems, then functional diversity in transportation can be characterized as:

(a) *Transportation functional richness*: the abundance of alternative means (modes) for functionality (connectivity and mobility) in a community; and

(b) *Transportation functional evenness*: the homogeneity of the distribution of transportation modes across a community.

Functional richness by its biological definition does not just indicate the number of functional groups, but it also reflects the amount and type of functionality that species provide (Mason et al., 2005). Therefore, based on the proposed definition of transportation functional richness, the abundance of different means indicates both the number of distinct functional groups and how they are provided. The functional evenness of biological systems demonstrates the distribution of species in the functional space (Figure 1), which indicates functional complementarity (Petchey, 2003; Mason et al., 2005). A balanced distribution of transportation modes allows people in different parts of a community to have similar access to transportation modes. This homogenous distribution of different transportation modes across a community creates the opportunity for mode complementarity in a transportation system.

Therefore, the functional richness of the transportation system is the sum of the abundance of all transportation modes in the community while the distribution of all transportation modes across the community shows the system's evenness; combined these characteristics suggest the system's potential complementarity. The abundance and distribution of individual modes are not representative of the overall transportation system since mobility and connectivity in a community are achieved through all available modes. Further, transportation diversity is distinct from redundancy, which is a different property of transportation resilience. Redundant components serve the same function (Godschalk, 2003), and redundancy is the substitutability of components that serve the same function (Bruneau et al., 2003). However, diverse components have different functionalities (Godschalk, 2003; Murray-Tuite 2006). For instance, while complementing each other, a roadway and a metro system are not substitutable since their functional traits such as flexibility of origin-destination (OD), travel cost and time, energy consumption, and schedule differ, but two roadways that serve the same function are redundant components.

2.3. Development of Transportation Diversity Metrics

To apply the translated ecological concepts to a transportation system, diversity measures of functional richness and evenness need development for transportation modes. First, metrics for richness and evenness of a community's: (a) road network, (b) bus system, (c) rail transit system, (d) bicycle routes, and (e) walkways are derived from relevant existing literature. Next, the approach to combine these metrics to represent the overall system's diversity is described. Finally, the distinction between the proposed approach to characterize transportation system diversity and other multi-modal approaches is discussed. The developed metrics are then illustrated through an application to NYC; subsequently, general and specific implications of transportation diversity in NYC are examined.

2.3.1. Measuring Richness

Each transportation mode has distinct attributes or performance measures. The richness metric determines the quantity of transportation modes provided in a given area – the amount of modal availability. The metric assumes that the intended level of service is provided by each available mode; in other words, each mode performs as expected. Thus, the richness metric needs to capture the quantity of each transportation mode in a community.

For a road network, density has been used for characterization at different spatial scales (Liu et al., 2009). Road network density quantifies the length of a road network in an area. Xie and Levinson (2009) argue that road network density in a region determines how developed a road system is. Consequently, network density is representative of richness for this mode. Density has also been used to characterize walkways and bicycle routes (e.g., Foda and Osman, 2010; Hochmair et al. 2015). Hence, it is also proposed for these modes.

For a transit system, Mishra et al. (2012) proposed the connectivity index at the node, line, transfer center, and regional levels to characterize the performance of transit systems. This metric incorporated several factors such as speed, frequency, and vehicle capacity. However, the focus of richness is on system quantification. Alternatively, Derrible and Kennedy (2010) used the number of metro lines and the number of stations, the key elements of metro systems, to measure average line length and inter-station spacing in characterizing metro systems at the community scale. Since these two factors represent the amount of rail transit provided in an area, they are proposed to characterize the richness of this mode. These factors are divided by the total number of lines and stations in the entire community. Trial calculations showed that the length of metro lines was highly correlated with the number of lines in an area; therefore, the length of metro lines is not included in the richness metric. A similar approach is adopted to characterize the richness of a bus system. Rail transit and bus system richness are scaled by the area of interest for consistency. Table 2.1 depicts the richness metrics for each mode.

2.3.2. Measuring Evenness

In addition to the abundance of transportation modes in an area, it is important to recognize whether residents across an area have comparable ability to reach or access available modes or their accessibility. A "rich" transportation system can only provide the potential for modal complementarity if it is proportionately dispersed in an area; this property is crucial during disturbances when one or multiple modes fail or experience a severe service degradation. Hence, the evenness metric must represent modal distribution in an area. Network measures have been widely used in transportation research. A transportation system in its very basic form can be represented as a set of nodes and links. The application of network measures in transportation systems typically describes the structural properties of the system. For example, network measures such as centrality (e.g., degree, betweenness, closeness), local and global efficiency, clustering coefficient, alpha, beta and gamma indices have been used in transportation literature to characterize the network structure of transportation modes or the properties of nodes and links (e.g., Duan and Lu, 2014; Jenelius, 2009; Kermanshah and Derrible 2016a; Sohn, 2006; Kermanshah and Derrible 2016b; Chopra et al., 2016; Dorbritz, 2011; Leu et al., 2010; Ouyang et al., 2015; Zhang et al., 2016). For instance, Zhang et al. (2015) illustrated how network topology influences the resilience of transportation systems and measured the resilience of a set of network structures through optimization-based frameworks based on pre- and post-disturbance throughput, OD connectivity, and compactness (average reciprocal distance).

Indeed, network metrics such as centrality and efficiency offer an avenue to capture evenness. For example, closeness centrality measures the sum of the shortest distances of a node in a network to other nodes. However, unlike network metrics, the focus of evenness is not on the structure of transportation modes or the properties of nodes and links in a network; rather, evenness measures the accessibility to modes. Therefore, network metrics have limitations for quantifying the distribution of a transportation mode in an area. The walking distance catchment area (usually 500-800m) around metro stations or bus stops is an approach that has been used extensively as a metric to analyze what portion of an area has access to transit modes or the coverage of transit modes (e.g., Derrible and Kennedy, 2009, Welch and Mishra, 2013; Quintero et al., 2013; Brezina and Knoflacher, 2014; Sharav et al., 2018). This approach can generally determine evenness as it distinguishes areas that can access a transit mode or not. However, catchment area determines the area considered within reasonable walking distance of a metro station or a bus stop; thus, it does not distinguish between the accessibility of different parts of an area to these modes. In reality, people walk, ride bicycles or drive to use these modes; therefore, the walking distance catchment area also has shortcomings when determining which parts of an area can possibly reach and use these modes. Moreover, its applicability to modes other than transit is questionable. Consequently, the evenness metric captures the distribution of modes across a region by finding the shortest distance of sub-regions to an access point for each mode. The standard deviation of the shortest distance of sub-regions to a mode indicates how well that mode is distributed in a region, which is scaled by the square root of the area of the region for consistency (Table 2.1). This method allows comparing the evenness of locations with different areas.

Table 2.1 summarizes the proposed diversity metrics for a road network, bus system, rail transit system, bicycle routes, and walkways.

Table 2.1: Metrics of Diversity in Transportation Infrastructure

Mode	Functional Richness	Functional Evenness
1. Road Network (RN)	$R_{RN} = \frac{L_{RN}}{A}$	$E_{RN} = \left(\frac{\sigma_{d_{RN}}}{\sqrt{A}}\right)$
2. Bus System (BS)	$R_{BS} = \left(\frac{n_S}{N_S^T \cdot A}\right)\left(\frac{n_l}{N_L^T}\right)$	$E_{BS} = \left(\frac{\sigma_{d_{BS}}}{\sqrt{A}}\right)$
3. Rail Transit (RT)	$R_{RT} = \left(\frac{n_S}{N_S^T \cdot A}\right)\left(\frac{n_l}{N_L^T}\right)$	$E_{RT} = \left(\frac{\sigma_{d_{RT}}}{\sqrt{A}}\right)$
4. Bicycle Routes (BR)	$R_{BR} = \frac{L_{BR}}{A}$	$E_{BR} = \left(\frac{\sigma_{d_{BR}}}{\sqrt{A}}\right)$
5. Walkways (WW)	$R_{WW} = \frac{L_{WW}}{A}$	$E_{WW} = \left(\frac{\sigma_{d_{WW}}}{\sqrt{A}}\right)$

R: richness
n_s: number of stops (stations)
N_S^T: the total number of bus (metro) stops (stations)
σ_d: SD of the shortest distance of sub-regions in a region to transportation modes
L_{BR}: Length of bicycle routes
E: evenness
n_l: number of bus (metro) lines
N_L^T: the total number of bus (metro) lines
A: area of the region
L_{RN}: Length of road network
L_{WW}: Length of walkways

2.3.3. Selecting a Scale for Area

Characterizing the diversity of the transportation system in an urban community and identifying locations with low diversity enables focusing transportation enhancement planning at varying scales. Zip codes can be used to delineate the area within a community; zip code areas are large enough to represent regions within a community but small enough to illustrate differences among the transportation modes. Further, demographic and socio-economic data are available at the zip code level. Smaller spatial units such as census blocks, block groups, and census tracts are not large enough to illustrate differentiation across all modes. However, census blocks (the US Census Bureau’s smallest geographic unit) in a zip code can be considered as sub-regions for diversity calculations. While transportation diversity can be measured in spatial units larger than zip codes, defining larger standard geographical units would be challenging; these would need to be considered on a case by case basis.

2.3.4. Calculating Richness and Evenness

Calculating richness in a zip code is relatively straightforward. However, the evenness calculation is complicated because convenient access to a particular mode for residents of a zip code may be outside of their zip code. Consequently, the evenness calculation must account for access points in adjacent zip codes. Figure 2.3 helps illustrate the approach to calculate evenness for the metro system in zip code 10312 in NYC. Figure 2.3-a shows the location of this zip code in the borough of Staten Island. In 2.3-b, squares show metro stations, and in 2.3-c points show the centers of census blocks in this zip code. In 2.3-d, metro stations and census block centers are shown together. The standard deviation of the shortest distance of each of the census block centers to a metro station determines the metro system evenness in this zip code. In 2.3-d, it is clear that some census block centers near the zip code border are closer to metro stations outside of this zip code. Since residents will likely access the metro from the closest station, the shortest distance of census block centers to a metro station is found by evaluating stations in the zip code of residence as well as adjacent zip codes in the evenness calculation. A similar approach is taken to calculate the evenness of other modes. For example, for the road network, the distance of census block centers in a zip code to the closest access points to a primary or secondary road determines evenness for this mode.

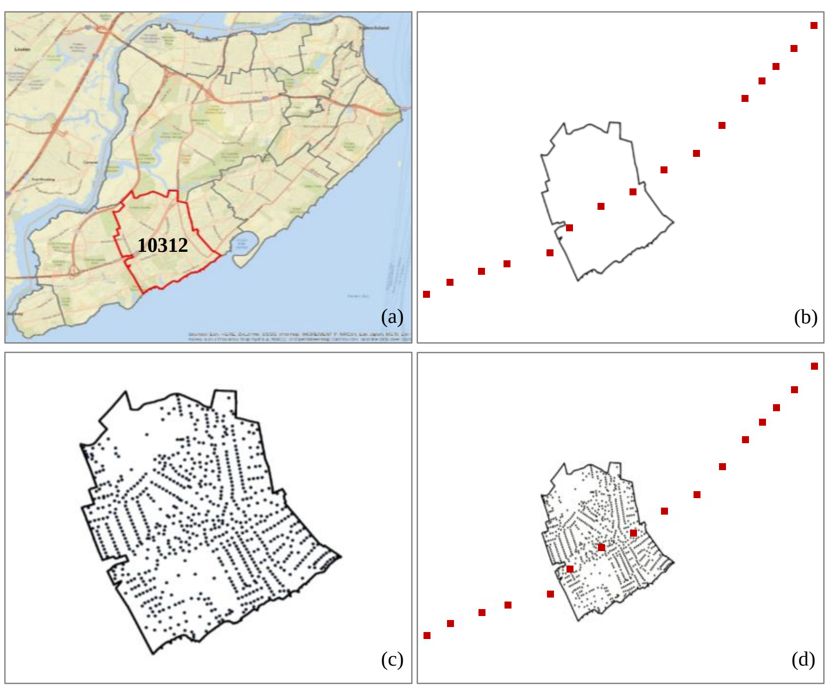

Figure 2.3: Metro System Evenness Calculation in a Zip Code

2.3.5. Integrating Richness and Evenness Values

The combination of richness and evenness of all modes in a zip code represents the transportation diversity of that zip code. Since richness and evenness metrics of different modes are not directly comparable, the combination of these ten metrics in a zip code to determine the diversity of that zip code requires a method which can take the values of all of these metrics in each zip code and assign a diversity value to it. Data Envelopment Analysis (DEA) (Charnes et al., 1978) is a widely used non-parametric multi-criteria decision-making method that can be employed to evaluate the diversity of transportation system.

DEA measures the relative efficiency of decision-making units (DMUs) based on a set of identical inputs and outputs. In the original DEA model developed by Charnes et al. (1978), the relative efficiency of each DMU is measured by maximizing the weighted ratio of all outputs over all inputs. Therefore, an increase in the output indicators and a decrease in the input indicators are desirable. If the efficiency score of a DMU is 1.0, it is considered as an efficient DMU. Otherwise, it is an inefficient DMU. The DEA model of transportation diversity has ten indicators, the five richness and evenness measures for each mode in Table 1. Higher richness and evenness equate to higher diversity, and higher diversity is desirable. Hence, all ten indicators are considered as outputs. Lovell and Pastor (1999) proposed a pure input (output) model without outputs (inputs). In this study, based on Lovell and Pastor (1999), an artificial input variable is introduced which is identical in all DMUs. For a given *n* DMUs *j = (1, 2, …, n)* using *i* inputs *xij = (1, 2, …, m)* to produce *r* outputs *yrj = (1, 2, …, s)*, the relative efficiency score of a DMU *k* can be obtained through the following output-oriented BCC (Banker, Charnes, and Cooper, 1984) model:

$$
\begin{aligned}
&\max \theta \\
&\text{s.t.} \quad x_{ik} \geq \sum_{j=1}^{n} \lambda_j x_{ij}, \qquad \forall i = 1, \ldots, m \\
&\qquad \theta y_{rk} \leq \sum_{j=1}^{n} \lambda_j y_{rj}, \qquad \forall r = 1, \ldots, s \\
&\qquad \lambda_j \geq 0, \qquad \forall j = 1, \ldots, n.
\end{aligned}
\tag{1}
$$

where θ is the efficiency of the DMU *k*, $\sum_{j=1}^{n} \lambda_j x_{ij}$ and $\sum_{j=1}^{n} \lambda_j y_{rj}$ are the set of inputs and outputs respectively, and λ_j is a non-negative scalar.

2.3.6. Transportation Diversity: Differences with Other Approaches Characterizing Multi-Mode Transportation Systems

The approach developed here is premised on the concept that higher transportation diversity in a community will promote modal complementarity, which will improve overall connectivity and mobility. Certainly, the importance of modal complementarity has been recognized in the literature. Relevant work has examined multi-mode transportation systems from various perspectives. The focus of these studies ranges from system design (e.g., Lo et al., 2004; van Nes and Bovy, 2004; Miandoabchi et al., 2012; Yao et al., 2012) and optimization (Qu and Chen, 2008; Islam and Said, 2014; Varone and Aissat, 2015) to performance assessment during normal situations (e.g., Hadas, 2013, Hong et al., 2017) and extreme events (e.g., Chang, 2003, Leu et al., 2010; Udenta et al., 2013, Kermanshah and Derrible, 2016a). Travel time/distance, throughput, capacity, accessibility, network topology, economy, a system's physical features and other measures such as socio-economic factors are among the metrics usually employed to characterize multi-mode transportation systems. Among these factors, network topology and accessibility are similar to the proposed diversity metrics.

Network topology approaches examine the structure of transportation systems and support analyzing multi-mode systems (e.g., Erath et al., 2009; Leu et al., 2010; Huang and Levinson, 2015; Dimitrov and Ceder, 2016). As discussed previously, network metrics can be used to assess system performance and vulnerability of the entire network or specific nodes to random failures or targeted attacks. Further, network metrics have been used to investigate the capacity and performance of transportation systems after disturbance scenarios (e.g., Zhang et al., 2015; Akbarzadeh et al., 2017; Aydin et al., 2018). The proposed transportation diversity metrics do not consider transportation modes as networks to find the importance of nodes within a network or the impact of the failure of specific nodes on other nodes. Instead, the purpose of the transportation diversity metrics is to determine the overall prevalence of modes and their accessibility in a given area to enable subsequent analyses and decision-making.

Accessibility has been defined as being able to access activities or locations in other areas by a transportation system (Handy and Niemier, 1997; Levine and Grab, 2002). Characterizing accessibility of a multi-mode transportation system is often based on considering the system as a set of OD nodes, which are mainly road intersections, bus stops, metro stations, or zones (e.g., Iocono et al., 2010; Sarker et al., 2014; Cheng and Chen, 2015; Ouyang et al., 2015; Xu et al., 2015; Benenson et al., 2016; Sarker et al., 2016). For example, Chang and Nojima (2001) and Chang (2003) consider the distance between ODs before and after a natural hazard for accessibility. They measured the performance of a rail and bus system after a natural hazard by coverage and accessibility loss and concluded that loss of accessibility was different across the community. Similarly, Iocono et al. (2010) analyzed the accessibility of walking and bicycling between different zones of a city based on distance and travel time. The focus of the OD approach in multi-mode accessibility studies is how accessible are other nodes in a multi-mode system, which assumes people can reach a node within the system. The difference between the proposed diversity metrics and OD accessibility approaches is that diversity characterizes regions rather than specific nodes or accessibility of other regions to a particular region. Hence, it has a more general function.

Alternatively, the catchment area accessibility approach determines the region that has access to a node (e.g., Derrible and Kennedy, 2009; Welch and Mishra, 2013), so it is comparable to the proposed diversity metrics. A comparison of the evenness and catchment area approaches for the metro system of two zip codes in NYC is illustrated in Figure 2.4 and Table 2.2 to demonstrate the advantages of the evenness metric. These two zip codes were selected because they have the same area and number of metro stations, so their coverage based on catchment area (800m≅0.5 mi) is the same. However, when considering the distance of census block centers to metro stations using the evenness metric, zip code 11209 is 3.7 times more even than zip code 11229. Further, a comparison of these approaches in the metro and bus systems of all zip codes in NYC is shown in Table 2.3 and Figure 2.5. Values of coverage and evenness for all 183 zip codes are normalized between 0 and 1 (min-max normalization) to facilitate comparison and interpretation. In both metro and bus systems, evenness represents the accessibility of these modes better than coverage. For instance, while the 90th percentile normalized value of metro system coverage is 0.140, the 90th percentile value of evenness is 0.653. Hence, coverage substantially misestimates accessibility since catchment area approaches disregard locations outside the presumed walking distance radius to a transit station or stop while evenness considers the distance of all locations in a zip code to a mode, providing a more accurate depiction of accessibility. While this might be evident by inspection in a single zip code, evenness provides an improved method for quantifying accessibility across a community and at varying scales.

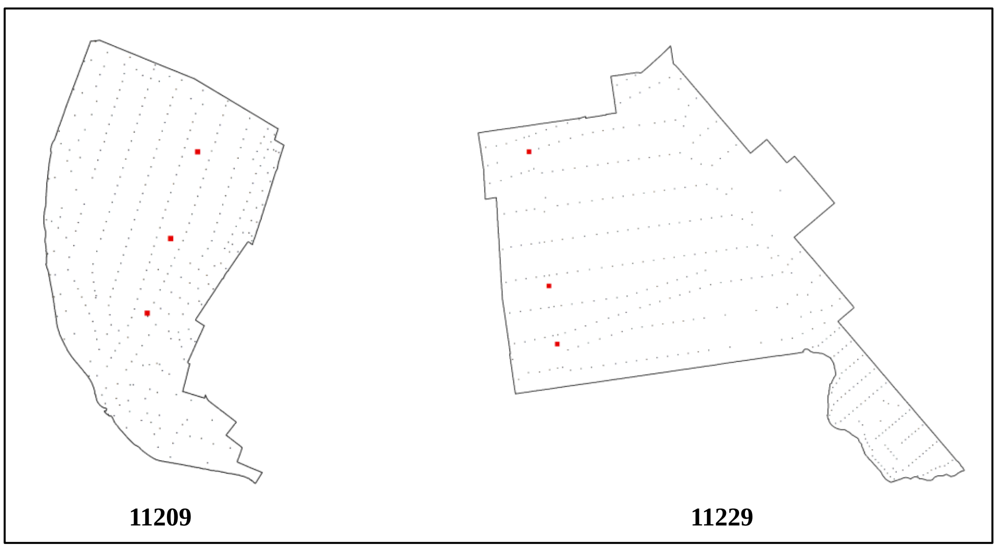

Figure 2.4: A Pair of Zip Codes with Comparable Area and Number of Metro Stations

Table 2.2: Comparison of Coverage and Evenness of the Metro System in Two Zip Codes

Zip Code	Area (mi^2)	# of Metro Stations	Coverage	Evenness
11209	2.16	3	1.09	7.66
11229	2.17	3	1.09	2.71

Coverage : $\sigma = \left(\frac{n_s \pi 0.5^2}{A}\right)$ *Evenness* : $E = \left(\frac{\sigma_d}{\sqrt{A}}\right)$

Table 2.3: Comparison of Normalized Percentile Values of Coverage and Evenness of Metro and Bus Systems in All Zip Codes

Mode	Approach	10th	25th	50th	75th	90th
Metro System	Coverage	0.000*	0.000*	0.034	0.073	0.140
	Evenness	0.000*	0.000*	0.322	0.505	0.653
Bus System	Coverage	0.083	0.135	0.200	0.268	0.363
	Evenness	0.164	0.277	0.392	0.538	0.633

**54 zip codes do not have a metro system; therefore, coverage and evenness are zero in these zip codes*

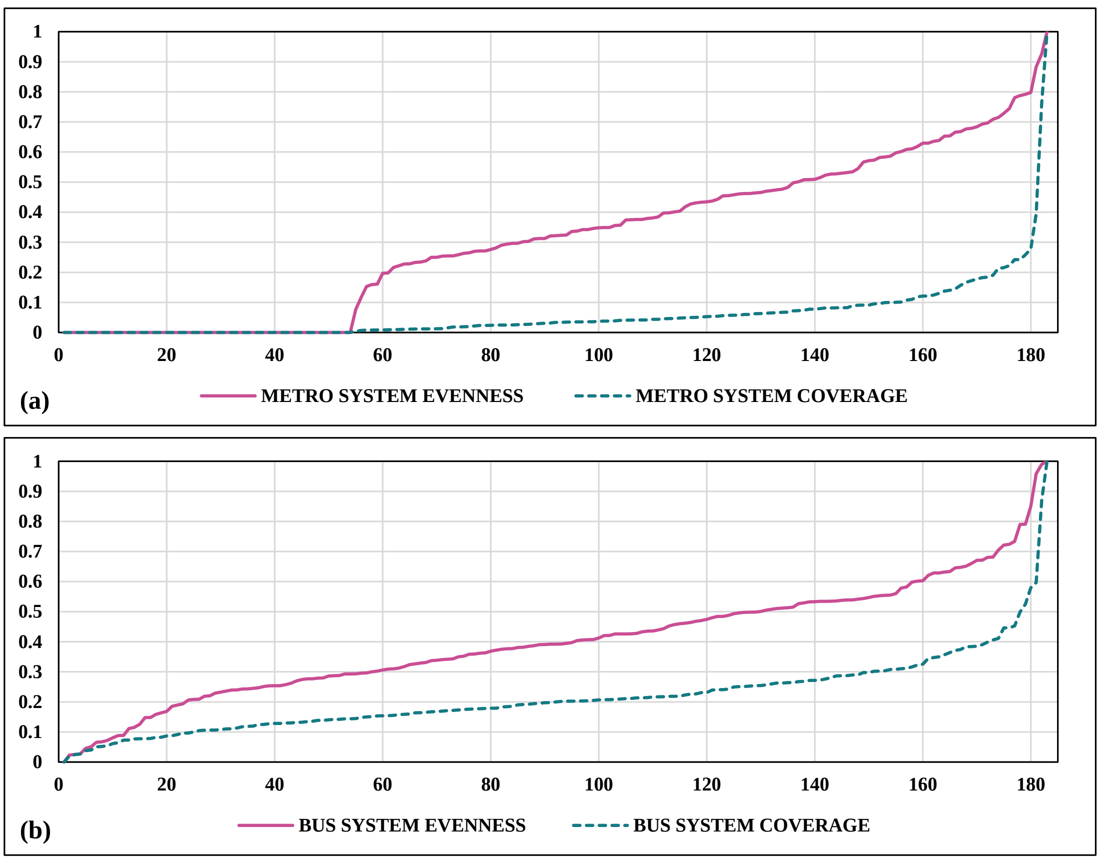

Figure 2.5: Comparison of Normalized Percentile Values of Coverage and Evenness of Metro and Bus Systems in All Zip Codes

Combining evenness with richness, transportation diversity enables identifying neighborhoods that have issues in their transportation system regarding availability and distribution. If the issue is availability, the evenness metric helps detect sub-regions in a neighborhood that are undersupplied for improvement. If distribution is the issue, the evenness metric identifies which parts of the neighborhood have less access to a mode for adjustment of service (e.g., location of bus stops) or improvement of availability. As the subsequent application to NYC will illustrate, the developed approach can do so at a large scale.

Hence, the transportation diversity approach presented is a unique method to characterize regions of an urban community based on the availability and distribution of all transportation modes. These metrics establish a baseline to analyze the complementarity of modes in each region *and* the potential to explore the relationship between transportation diversity and system performance under various conditions or other characteristics of a community.

2.4. Application

2.4.1. New York City

The approach for measuring diversity is illustrated through an application to NYC. NYC is the most populous urban area in the US with more than 8.5 million residents (US Census Bureau). The transportation system in NYC has extensive public transit with 27 metro lines and more than 300 bus lines. NYC is a coastal community that experiences hurricanes and flooding. Hurricane Isabel in 2003, the Northeast flooding in 2005, Hurricane Irene in 2011, and Hurricane Sandy in 2012 are some of the recent examples of meteorological hazards in NYC. Further, sea level rise due to climate change is expected to cause more hazards in coastal cities (TRB, 2008; Rosenzweig et al., 2014). In 2012, Hurricane Sandy crippled the New York City transportation system for weeks with an estimated impact of $7.5 billion on this infrastructure (Henry et al., 2013). Given the availability of different modes in NYC, the historical impact of natural hazards on the NYC transportation system and the likelihood of similar events in the future, NYC is an ideal community for studying transportation diversity at the zip code level. The data needed to calculate the diversity metrics for the transportation modes in NYC was collected from nyc.gov, NYC DOT, and the US Census Bureau.

2.4.2. Results

The DEA model of transportation diversity in this study with one input and ten outputs for 183 DMUs (zip codes) in NYC would be:

$$
\begin{aligned}
&\max\ \theta \\
&\text{s.t.}\quad x_{ik} \geq \sum_{j=1}^{183} \lambda_j x_{ij}, \qquad \forall i = 1 \\
&\qquad \theta y_{rk} \leq \sum_{j=1}^{183} \lambda_j y_{rj}, \qquad \forall r = 1, \ldots, 10, \\
&\qquad \sum_{j=1}^{183} \lambda_j = 1, \\
&\qquad \lambda_j \geq 0, \qquad\qquad \forall j = 1, \ldots, 183.
\end{aligned} \tag{2}
$$

The results show that zip codes might be rich in one mode, but the mode may be poorly distributed or vice versa. For instance, Figure 2.6-a depicts the richness of the metro system in the zip codes of southwest Brooklyn, which are generally low; however, the distribution of this mode is highly even in these zip codes as shown in Figure 2.6-b. This reveals that the availability of a transportation mode in a region solely cannot fully describe a transportation system's characteristics in that region; the distribution, and therefore the accessibility, of the system to users in each area is also important.

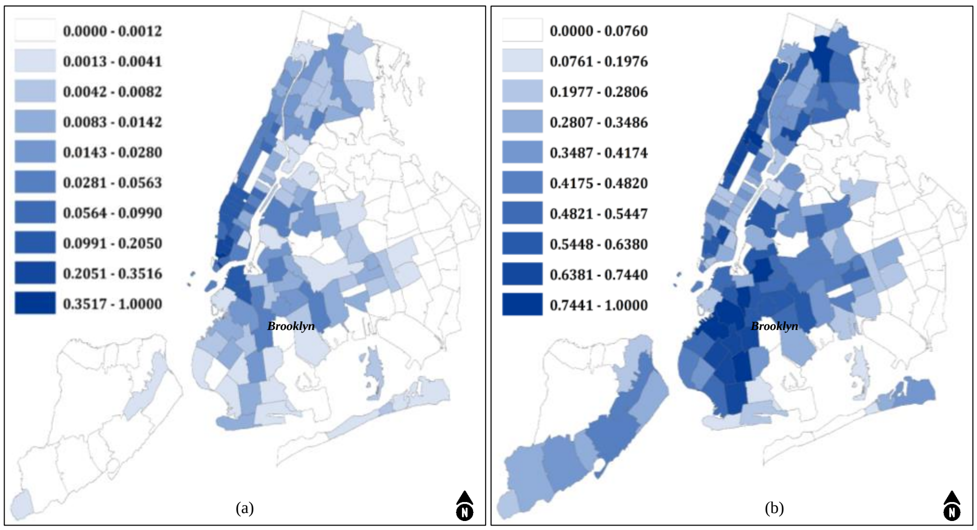

Figure 2.6: Diversity Metrics reveals of Metro System in NYC: (a) Richness (b) Evenness

The results of transportation diversity at the zip code level in NYC are illustrated in Figure 2.7. Zip codes with values closer to one have the most diverse transportation infrastructure. Low transportation diversity zip codes are mostly in Staten Island, Queens, and the Bronx while zip codes in Manhattan and Brooklyn have higher diversity. Among all zip codes, 18% have the maximum diversity score and the average diversity score is 0.81 with a standard deviation of 0.15.

2.4.3. Interpreting Diversity Metrics

2.4.3.1. Single Mode Assessment at the Zip Code Level

Determining transportation diversity across NYC supports pinpointing zip codes that lack complementarity between transportation modes. For instance, zip code 11001 has a low transportation diversity score with no rail transit and limited road network and bus system, which are not evenly distributed. Table 2.4 shows the characteristics of the bus system in 11001 and zip code 10065 which has a high transportation diversity score. Analyzing these two areas further shows that the availability of bus stops and bus lines in 11001 is significantly lower than 10065 even though both zip codes are similar in size; while 11001 has a lower population density, its density is still relatively high with over 27,000 people per square mile. In addition to the lack of bus stops and bus lines in 11001 compared to 10065, the 14 bus stops in 11001 are not evenly distributed across the zip code. Consequently, evenness in this zip code could be enhanced by considering the distance of census blocks to bus stops to optimize stop locations.

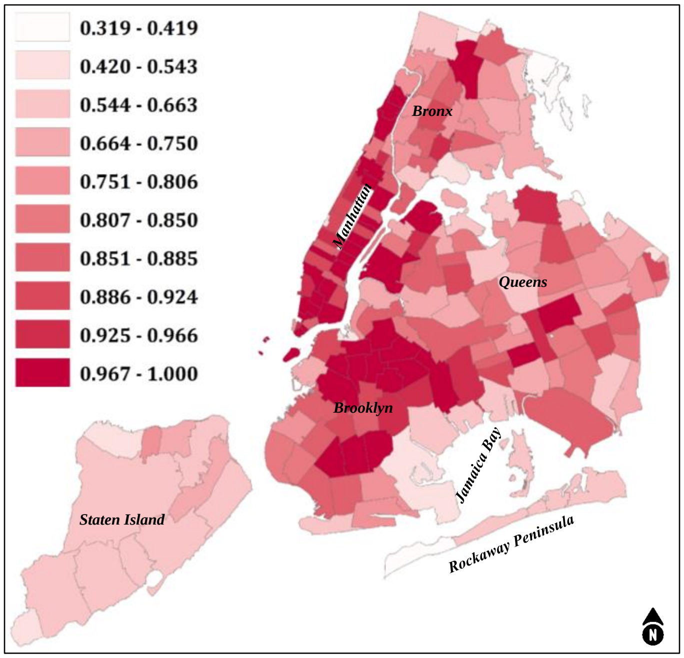

Figure 2.7: NYC Transportation Infrastructure Diversity

Table 2.4: Comparing Richness and Evenness of Bus System in Zip Codes 11001 and 10065

Zip Code	Bus Richness (Rank)	Bus Evenness (Rank)	Bus Stops	Bus Lines	Area (mi^2)	Population Density
11001	7.63E-6 (179)	6.86 (173)	14	6	0.33	27,298
10065	0.0018 (8)	36.54 (8)	50	69	0.40	40,170

2.4.3.2. Multi-Mode Assessment Across Zip Codes

Table 2.5 summarizes zip codes with the lowest diversity score and their richness and evenness values. The richness and evenness values of all five modes are below average in most of the zip codes with the lowest diversity. A closer look at the diversity scores provides additional insights. For the road network, zip code 11040 has the lowest richness (1.244) and zip code 10075 has the lowest evenness (0.935). Neither of these zip codes, however, are among the low diversity ones found in Table 5; while these zip codes are weak in one of the two diversity metrics, the availability or distribution of other modes compensates, resulting in higher overall diversity scores compared to zip codes with the lowest diversity. If the road network was the only mode analyzed, then zip codes 11040 and 10075 would likely appear more undersupplied than they actually are. This reinforces the importance of considering all transportation modes and their complementarity rather than analyzing modes independently. Moreover, the results can become the foundation for prioritizing transportation system improvements among zip codes by developing modes that are not available in a neighborhood or improving existing modes. For instance, in low diversity zip codes (Table 2.5) that do not have a metro system, developing this mode (i.e. richness) can benefit by also considering evenness to make sure accessibility is as uniform as possible.

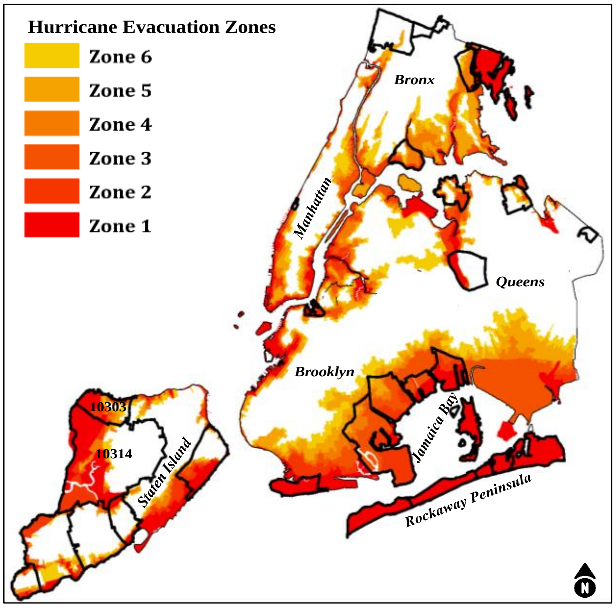

Figure 2.8: Low Transportation Diversity Zip Codes in NYC Hurricane Evacuation Zones

Table 2.5: Zip Codes with the Lowest Transportation Diversity in NYC

Zip Code	Diversity Score	Rank	Metro System		Bus System		Bicycle Routes		Walkways		Road Network	
			Richness	*Evenness*	*Richness*	*Evenness*	*Richness*	*Evenness*	*Richness*	*Evenness*	*Richness*	*Evenness*
11236	0.649	155	9E-05	5.265	2.33E-04	18.473	1.247	8.7018	40.399	21.215	22.302	6.021
11239	0.633	156	0.000	0.000	1.71E-04	15.670	8.796*	15.821*	16.988	20.123	21.431	13.845*
10309	0.632	157	3.6E-05	5.456*	7.96E-05	28.874*	3.935	9.336	14.452	87.374	17.862	7.355
10305	0.629	158	1.9E-05	5.421*	4.17E-04	27.461*	1.822	7.829	30.090	42.622	23.366	3.663
10314	0.625	159	0.000	0.000	3.43E-04	27.627*	0.678	8.126	19.507	60.506	16.859	8.473*
11360	0.625	160	0.000	0.000	8.10E-05	15.771	1.517	6.534	36.508	72.688	23.735	9.845*
10308	0.622	161	4.10E-05	5.765*	1.30E-04	12.969	1.676	5.017	35.761	87.072	26.584	3.803
11693	0.617	162	3.20E-04	2.687	5.30E-05	3.908	9.937*	4.010	33.828	4.291	24.755	1.937
10312	0.601	163	3.20E-05	6.753*	1.80E-04	25.158*	0.216	7.298	30.769	95.575	19.265	5.306
11367	0.596	164	0.000	0.000	2.50E-04	16.148	4.086	13.850*	33.148	77.843	26.016	7.862*
11691	0.593	165	1.10E-04	6.388*	1.70E-05	8.606	1.595	7.830	33.479	20.812	23.437	8.578*
10471	0.585	166	0.000	0.000	7.40E-05	13.762	1.711	7.424	19.343	79.879	21.396	11.338*
11692	0.585	167	1.60E-04	5.884*	2.70E-05	6.873	2.649	6.495	36.815	20.896	20.902	6.943
11694	0.584	168	2.40E-04	1.292	1.30E-04	6.092	5.879*	6.724	33.501	10.526	28.532	6.147
11414	0.574	169	7.10E-05	4.646	1.30E-05	13.924	2.420	11.026	34.446	21.509	25.547	4.985
11356	0.573	170	0.000	0.000	1.10E-04	15.805	0.000	0.000	35.625	36.934	20.472	5.243
11224	0.571	171	6.30E-04	2.575	2.30E-04	13.450	5.100*	12.119*	34.485	72.697	22.527	3.928
10475	0.566	172	0.000	0.000	2.10E-04	14.965	2.283	6.984	29.848	21.261	21.362	11.910*
10069	0.544	173	0.000	0.000	1.60E-05	5.811	6.548*	6.300	33.928	6.199	21.998	6.201
11251	0.512	174	0.000	0.000	4.40E-05	10.142	3.747	9.554	17.081	21.305	23.393	9.391*
10303	0.510	175	0.000	0.000	2.30E-04	24.080*	0.000	0.000	19.761	35.285	15.020	5.428
10474	0.502	176	0.000	0.000	7.90E-05	17.204	3.532	15.781*	26.685	47.927	20.108	3.533
11005	0.491	177	0.000	0.000	3.00E-05	8.122	1.116	4.563	31.980	32.096	19.399	3.088
11234	0.490	178	0.000	0.000	2.40E-04	17.024	1.130	13.676*	23.229	32.763	13.923	8.978*
10470	0.487	179	5.70E-05	3.341	4.80E-05	9.645	1.064	3.612	35.373	23.955	11.974	4.135
10307	0.465	180	8.30E-05	3.844	5.20E-05	12.462	0.083	5.140	26.293	73.268	18.474	3.217
11359	0.419	181	0.000	0.000	6.90E-06	5.131	0.238	5.471	14.440	18.875	25.450	5.030
11697	0.393	182	0.000	0.000	2.70E-07	3.837	1.997	4.647	5.290	67.784	16.710	3.843
10464	0.319	183	0.000	0.000	5.80E-06	2.743	1.995	3.128	24.271	9.915	7.987	1.704
Values among All Zip Codes												
Maximum			0.059	16.850	0.005	49.435	27.649	48.107	76.708	260.073	64.952	22.524
Minimum			0.000	0.000	2.70E-07	2.743	0.000	0.000	2.4.16	4.291	1.245	0.935
Average			0.00168	5.304	4.90E-04	21.466	4.157	11.942	42.240	97.926	29.731	7.563
Standard Deviation			0.00523	4.291	7.10E-04	8.814	4.096	8.381	10.470	56.118	10.312	3.770

*Richness and evenness values above average are marked by **

2.4.4. Diversity and Resilience

Transportation diversity metrics establish a baseline to investigate their impact on the resilience of a transportation system. Examining NYC hurricane evacuation zones and low diversity zip codes is conceptually illustrative of the potential links between diversity and resilience planning and management. NYC has six hurricane evacuation zones; these areas are prone to inundation or isolation by storm surge (nyc.gov). Figure 2.8 superimposes low transportation diversity zip codes onto a map of the NYC hurricane evacuation zones, which are shown in shades of red and orange (nyc.gov) with darker shades depicting areas with greater risk of storm surge impact. Interestingly, the majority of the low diversity zip codes are located in high-risk evacuation zones. Hence, zip codes with the least capacity for mode complementarity are among the most vulnerable.

In order to understand the response of a transportation system to a natural hazard, it is important to realize how individual modes respond (component variability) and how the whole system reacts to it (aggregate variability). For example, the zip codes located south of Jamaica Bay in the Rockaway Peninsula are surrounded by water and are in the hurricane evacuation zone (Figure 2.9). Public transit (metro and bus) in these zip codes is very sparse, so evacuating them will rely on the road network, which is also not well developed. Similarly, low diversity zip codes in the southern portion of Brooklyn and Queens (just west and north of Jamaica Bay) are also in evacuation zones. Likewise, these zip codes lack developed public transit (metro and bus), depending on the road network for evacuation. Hence, the road network will not only need to support residents from these zip codes during an evacuation, but it will also be impacted by evacuees of the zip codes in the Rockaway Peninsula. Consequently, the limited transportation system complementarity in this area could pose challenges during an evacuation or emergency response, particularly during storm surges that inundate roadways (as well as metro system tunnels) and isolate residents.

In 2012, Hurricane Sandy flooded the entire Rockaway Peninsula and severely affected all transportation modes (Kaufman et al., 2012). For instance, the overall NYC subway system was affected by the hurricane, and it took three weeks to recover most lines to full operation. However, the impact of the hurricane on the subway system in the Rockaway Peninsula was severe. It damaged train tracks in this area, which made transit by subway unavailable for seven months affecting 35,000 daily commuters (MTA, 2013). Figure 2.9-a schematically illustrates the response patterns of transportation modes in the Rockaway Peninsula to Hurricane Sandy, which shows synchrony for the transportation system.

Compensation in a transportation system occurs when a failure in one or a few modes is offset by others. Analyzing the response of the transportation system in different parts of a community which have different diversity levels can lead to understanding whether higher transportation diversity results in higher compensation. The fluctuation-independent mechanism or *inherent complementarity* in a transportation system occurs when a failure in modes caused by a disturbance is compensated by other modes. In other words, inherent complementarity exists when the availability of other modes provides the capacity to counteract the lost services of the failed mode(s). For example, the low diversity zip codes in the Rockaway Peninsula and the southern part of Queens and Brooklyn experienced a large impact since the existing modes in these areas provided little inherent complementarity.

Conversely, the fluctuation-dependent mechanism or *augmented complementarity* is a consequence of system adjustments. Such complementarities are possible in the transportation system, but they require some form of intervention such as using the spare capacity of the transit system; adjusting speeds, schedules, and routes of buses; and opening roadway hard shoulders to traffic and contraflow lane reversal. The augmented complementarity allows modifications to a transportation system to enhance its compensation capacity to better cope with a disturbance. Figure 2.9-b schematically depicts a compensatory response pattern through augmented complementarity for the Rockaway Peninsula. Understanding inherent and augmented complementarity is at the core of any transportation emergency preparedness plan as well as more general transportation planning and management. Hence, determining the response patterns and identifying levels and types of complementarity in a transportation system can improve understanding of the root causes of these patterns and the underlying dynamics of compensation. This can result in better resilience planning and management of this critical infrastructure system.

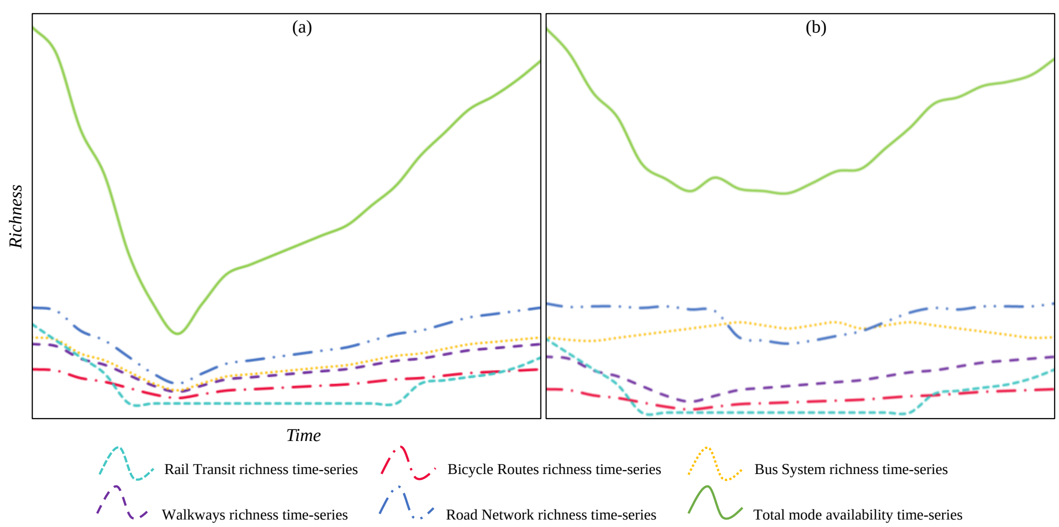

Figure 2.9: Variability Patterns of Transportation Modes:
(a) Synchronous response to a hurricane, (b) Compensatory response to a hurricane via augmented complementarity in road network and bus system

2.5. Discussion

Faturechi and Miller-Hooks (2014) suggest that transportation resilience should focus on system level performance rather than component level performance or the performance of individual modes separately. The transportation diversity approach facilitates analyzing a multi-mode transportation system in an urban community to find low diversity regions and to examine them for general improvements and to identify specific strategies for them during disturbances like natural hazards that will likely affect the entire urban area. Further, the potential of developing system and component response patterns was examined in the context of an extreme event and inherent and augmented complementarity was introduced. Future research can explore these concepts further through empirical studies. For instance, the types of natural hazards that an urban community experiences and the intensity and/or the frequency of these disturbances are important in characterizing the variability patterns of a transportation system since transportation modes might respond differently in various situations. Future work on variability patterns of a transportation system can increase understanding of the response of a transportation system to various disturbances.

The proposed transportation diversity method provides a system level perspective of the entire transportation system as well as analysis at the component level of modes. One major challenge of infrastructure resilience models is their translation into practical methodologies or their applicability (Gay and Sinha, 2013) since there are no detailed guidelines for their implementation (Labaka et al., 2016). Hence, the concepts of diversity and modal variability offer a new approach to characterize transportation infrastructure in urban communities to counter such challenges.

The application to the NYC transportation system demonstrated the method in a very large urban transportation system by identifying zip codes with low diversity and whether richness, evenness or both were the cause. This can facilitate future work to compare such regions with highly diverse ones to suggest improvement strategies. If the richness of a transportation mode needs improvement in a zip code, the calculated distance of each census block to that mode in the evenness metric demonstrates which parts of the neighborhood have accessibility issues. The approach can be modified to examine larger scale regions. For more routine disturbances like congestion, it is likely better to analyze diversity at a larger spatial unit than zip codes. This flexibility of spatial scale in the developed diversity metrics also allows, for example, comparison of urban communities at the city scale to determine similarities/differences between transportation systems in different cities. This enables comparison of communities, which can help overcome the lack of methods and metrics to contrast communities, community resilience improvements and regional resilience (Bruneau et al., 2003; Cimellaro et al., 2013; Sun et al., 2018).

Additionally, transportation diversity analyzes the supply side of the transportation infrastructure. Socio-economic factors describe the characteristics of the users of the provided service. Focusing solely on the physical aspects of a transportation system cannot capture the dynamic nature of human-infrastructure interaction per se. Amoaning-Yankson and Amekudzi-Kennedy (2017) state that transportation resilience studies have predominantly focused on the physical aspect of this infrastructure and suggest that socioeconomic factors should be included. Hence, transportation diversity can be analyzed with socio-economic factors such as population, number of households, average income, age, number of elderly residents and vehicle ownership. Such analyses can provide an understanding of the likely connection between transportation infrastructure and socio-economic factors to better plan and enhance this infrastructure for improved mobility and connectivity. In addition, it can pinpoint neighborhoods that might require more attention during evacuation periods based on socio-economic and transportation system characteristics. For example, the unsuccessful evacuation of New Orleans during Hurricane Katrina in 2005 was largely due to the lack of adequate consideration of transit-dependent residents who did not have personal vehicles for evacuation (Naghawi and Wolshon, 2012).

Certainly, the approach presented and its application has some limitations. The proposed metrics of richness and evenness consider the transportation system in unperturbed situations where all modes are intact and complete. In an unperturbed-state, physical systems are not always in a state of good repair; thus, the estimates of diversity are somewhat inflated, albeit the metrics are internally consistent. Indeed, Levenberg et al. (2017) highlighted the importance of considering component condition and deterioration in resilience analysis and evaluated the resilience of a pavement network under a set of damage scenarios. Their results show the impact of component conditions on infrastructure resilience. During an extreme event or perturbation in transportation modes, richness and evenness values will decrease. A system that can track the availability and distribution of modes could continuously adjust these metrics to account for degradation. Finally, the evenness calculation finds the shortest distance based on a straight-line distance ("as the crow flies"), which approximates the actual distance of walking, biking or driving. While the accuracy of the calculated distances could be improved by using Google Distance API or Bing Map Distance API, the associated cost is very high and it is computationally intensive.

2.6. Conclusions

The impact of transportation infrastructure on the functionality of a community and its influence on the performance of its interdependent infrastructure has made transportation resilience a critical challenge. While recognized as an important property of transportation resilience, diversity generally remains undeveloped. The proposed method to measure transportation diversity provides a new approach to characterize a transportation system at a disaggregate scale to find areas that lack diversity and the source of this issue, which supports prioritizing enhancements in modal availability and distribution. Moreover, the transportation diversity approach supports establishing a baseline to study the impact of diversity on mobility and the variability patterns of this infrastructure during disturbances.

Characterizing the diversity of a transportation system in a community can also support analyzing the impact of transportation diversity on mobility patterns during and after extreme events through empirical studies using call data records or geo-tagged social media data. Patterns of mobility can be characterized by identifying the locations individuals frequently visit which can be analyzed along with the transportation diversity of these locations' zip codes. A comparison of pre- and post-disturbance mobility patterns could reveal the influence of transportation diversity on maintaining pre-disturbance mobility patterns and recovery of these patterns after an extreme event.

Empirical derivation of response patterns of transportation modes to natural hazards would also improve emergency and resilience planning. Identifying zones with higher vulnerability can help to better prioritize zones and modes for enhancement programs. This, in turn, will enhance community resilience and security by decreasing the impact of natural hazards on economic activity and residential safety. In addition, the time scale could be potentially extended from days and weeks to years and decades to study the evolution of an urban transportation system. Indeed, the proposed method for characterizing transportation diversity provides a unique and flexible basis for exploring its influence on transportation system performance in urban communities.

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Chapter 3: Assessing the Impact of Transportation Diversity on Post-Disaster Intra-Urban Mobility[2]

Abstract

Transportation infrastructure enables mobility in urban communities and impacts the functionality of other infrastructure and services. Natural hazards can cause failures in a transportation system, which can affect mobility and other economic activities in a community. Diversity is recognized as an important factor of resilience in transportation infrastructure, but empirical work linking the two is limited. In this study, the impact of transportation diversity on mobility in New York City after Hurricane Sandy is explored. Transportation diversity, defined as the availability and distribution of modes in a community, is measured by employing a recently developed approach at the zip code level using transportation system GIS data. The geo-tagged Twitter data of one month before and after Hurricane Sandy in New York City are used to understand mobility patterns before and after this extreme event. The primary locations of individuals and mobility patterns are subsequently determined by measuring travel distance, the radius of gyration, and mobility entropy; individuals are grouped in quartiles based on the transportation diversity of their primary locations, which is determined by two different methods that overcome the lack of transportation system information in call detail records and social media data. The results indicate that after Sandy the distance, radius, and entropy of all individuals were significantly decreased. The comparison of the significance of change in mobility metrics by diversity quartiles revealed that one-week distance and radius metrics in low transportation diversity quartiles were considerably changed and statistically significant. Thus, individuals with primary locations in zip codes with higher transportation diversity generally had higher maintained distance and radius one week after Hurricane Sandy. The comparison of diversity quartiles in the one-month analysis showed that the radius of low transportation diversity quartiles was impacted more than high transportation diversity quartiles and was statistically significant. Further, the comparison of results of one week and one month after the hurricane indicated that distance, the radius of gyration, and entropy improved after a month as the transportation system was recovering. The findings establish an empirical link between transportation diversity and intra-urban mobility in the wake of natural disasters such as Hurricane Sandy and confirm that transportation diversity influences individual post-disaster mobility. In addition, the results contribute to mobility resilience by deepening our understanding of the underlying drivers of changes in human mobility following extreme events. Further, the approach

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adopted supports pinpointing areas with low transportation diversity, which can enable more targeted infrastructure and urban resilience management.

Keywords: Infrastructure; Natural Hazard; Hurricane Sandy; Multimode; Twitter; Geosocial Networking; Urban Computing; Transportation; Diversity; Resilience; Mobility.

3.1. Introduction

Critical infrastructure systems such as energy, water, and transportation support and shape urban communities and collectively influence the functionality of society. Since infrastructure systems and socio-economic activities in a community are interconnected, the impact caused by a failure in infrastructure systems is not limited to the physical aspect of these lifelines (Ha et al., 2017); it can affect safety, security, public health and economic activity (DHS, 2018). Among these systems, the transportation system is the physical foundation that affects the movement of people and goods in an urban area and supports the performance of its interdependent infrastructure systems like food and agriculture, energy, communication, and emergency services. Identifying the patterns of travel behavior and human mobility is important for urban transportation planning. Aside from normal situations, understanding how mobility patterns are affected by extreme events such as a natural hazard is critical for pre- and post-disaster planning and response. An extreme event affects infrastructure systems by both reducing serviceability and increasing demand (Choi et al., 2019). A disruption in the transportation system caused by a natural hazard can significantly impact mobility, community activities, and consequently the function and performance of other infrastructure systems.

A natural hazard can affect intra-urban mobility on multiple levels. Some of the most important factors influencing intra-urban mobility are: (a) purpose or need, (b) urban morphology and land use, (c) transportation system, (d) transportation mode choice, and (e) socio-economic characteristics (Crane, 2000; Kwan, 2000; Snellen, et al., 2002; Dieleman, 2002; Kang et al., 2012; Wang et al., 2018a). These factors are often interdependent and a disaster can cause cascading effects on multiple levels. For example, failures in a transportation system after a disturbance will likely cause changes in an individual’s mobility patterns and mode preferences. Depending on the intensity of the disturbance, the level of pre-disturbance mobility patterns that is maintained and the duration of recovery to these patterns might vary. In this case, the root cause of variation in post-disturbance mobility patterns is likely associated with disruptions or failures in a transportation system.

Prior to the development of information and communication technologies (ICT), mobility was generally studied through travel surveys, which were costly and not quite accurate (Vij and Shankari, 2015; Zhao et al., 2015; Wang et al., 2018a). Moreover, identifying locations and trajectories from travel surveys were imprecise (Wang and Taylor, 2015). ICT data sources, however, such as loop detectors, taxicab GPS, transit smartcards, mobile phone data such as call detail records (CDR), social media and check-ins have provided larger, more reliable and accurate mobility data. ICT data has been used in several studies analyzing general mobility and travel patterns (e.g., Wang et al., 2015; Zhong et al., 2016; Fang et al., 2017; Gong et al., 2017; Xu et al., 2017; Gariazzo and Pelliccioni, 2018; Vazifeh et al., 2018, Wang et al., 2018b). ICT data was also employed to study mobility during extreme events such as emergency preparedness planning (Krisp, 2010), evacuation (Song et al., 2013), mobility patterns identification (Wang and Taylor, 2014) and situational awareness (de Albuquerque et al., 2015). After an extreme event, a community is in the recovery phase and individuals attempt to restore their pre-disaster mobility patterns. Studies on post-disaster mobility indicate the impact of disturbances on mobility patterns such as changes in mode choice (Zhu et al., 2010) and travel time (Donovan and Work, 2017), (e.g., Zhu et al., 2010; Carrion and Levinson, 2012; He and Liu, 2012; Donovan and Work, 2017; Kontou et al., 2017; Ilbeigi, 2019). These studies confirm modifications in post-disturbance mobility patterns due to failures in a transportation system caused by natural hazards. However, it is not clear how a transportation system influences post-disturbance mobility. In other words, the significance of a transportation system in maintaining pre-disturbance mobility patterns and recovery to these patterns is largely unexplored.

A resilient system has the ability to withstand a disturbance, quickly recover from it, and adapt to future incidents by learning from the disturbance. The resilience of mobility patterns is intertwined with the resilience of transportation infrastructure. Further, the performance of a transportation system during normal and extreme events builds on the collective performance of all transportation modes.

Transportation diversity is a property of resilient transportation systems, which is defined as having multiple components (i.e., transportation modes) with different functionalities (Murray-Tuite, 2006). Rahimi-Golkhandan et al. (2019a) developed an approach to characterize and measure transportation system diversity by richness (abundance) and evenness (distribution) of transportation modes in a community. The approach has been applied to characterize and analyze the influence of transportation systems diversity on routine disturbances (e.g., Rahimi-Golkhandan et al., 2019b, Khaghani et al., 2019) and extreme events (Wang et al., 2019). Wang et al. (2019) indicated that transportation diversity influenced the ability of people to visit different parts of Houston after Hurricane Harvey.

At a neighborhood scale like zip codes, transportation diversity determines how all transportation modes are provided in a zip code and how the available modes are accessible across the zip code. If an extreme event causes failure in one or some modes, other modes in a diverse transportation system can compensate for the lost service. The mode complementarity that diversity provides can potentially mitigate the impact of failure in a transportation system on mobility. Consequently, analyzing transportation diversity along with post-disaster human mobility can reveal the influence of mode complementarity on maintaining pre-disturbance mobility patterns (i.e., their robustness) and recovery of these patterns.

In this study, the impact of transportation diversity on the post-disturbance mobility patterns in NYC in the aftermath of Hurricane Sandy in 2012 is explored. The approach to measure transportation diversity in NYC zip codes identifies ranges of modal complementary in NYC, and it is capable of identifying the areas where transportation modes are undersupplied and/or unevenly distributed. In order to characterize mobility patterns, geotagged Twitter data is used. Analyzing data of one month before Hurricane Sandy, undisturbed mobility patterns of individuals are found by the number of locations each individual visits, the frequency of visits to each location, and their travel distance. A similar characterization of mobility patterns after Hurricane Sandy shows the deviation from pre-disaster patterns. This is coupled with measures of transportation diversity at the zip code level to determine how transportation diversity impacts individual mobility patterns pre- and post-Sandy; in particular, a key objective is to ascertain whether transportation diversity facilitates maintaining pre-disturbance mobility patterns and promotes recovery to these patterns.

The remainder of this paper is organized as follows: Section 3.2 discusses the background of transportation diversity and the application of social media data in mobility. In Section 3.3, the methods used to measure transportation diversity and characterize mobility patterns are described. The results and analysis are presented in Section 3.4. Discussion of the results and limitations are detailed in Sections 3.5 and 3.6 respectively. Conclusions are drawn in Section 3.7.

3.2. Background

3.2.1. Transportation Diversity

An urban transportation system consists of various modes, which perform jointly and complement each other. The capacity of transportation modes for complementarity is critical when modes are affected by major disturbances such as natural hazards. Thus, transportation resilience assessments should encompass all transportation modes. However, transportation resilience analysis has focused predominantly on individual modes, such as road networks (e.g., Omer et al., 2013; Jenelius and Mattsson, 2015; Ganin et al., 2017) or transit systems (e.g., Han and Liu, 2009; Derrible and Kennedy, 2010; Rodríguez-Núñez and García-Palomares, 2014; Cats and Jenelius, 2015); these works have not directly examined the contribution of all modes and their complementarity to the performance and resilience of a transportation system in a community. Therefore, analyzing the resilience of individual transportation modes does not comprehensively describe how the entire system responds to perturbations such as natural hazards. Literature has explored various facets of multi-modal transportation systems such as system design (e.g., van Nes and Bovy, 2004; Yao et al., 2012), optimization (Ismail and Said, 2014; Varone and Aissat, 2015), performance assessment (Hadas, 2013; Udenta et al., 2013; Hong et al., 2017), accessibility (Iacono et al., 2010; Benenson et al. 2016), and network characterization (Huang and Levinson, 2015; Dimitrov and Ceder, 2016). However, far fewer studies have examined multi-mode transportation resilience (e.g., Leu et al., 2010; Cox et al., 2011; Jin et al., 2014; Ouyang et al., 2015). For example, the study of Cox et al. (2011) on the resilience of the London subway system highlighted the significance of a multi-mode transportation system and how the complementarity it provides can decrease the impact of disturbances. Likewise, Jin et al. (2014) studied how integrating bus and metro systems can enhance local transportation resilience.

The developed transportation diversity approach estimates the richness, or availability of transportation modes, and the evenness, or the distribution of modes in a community. Combined, these metrics indicate the level of diversity in a given area, indicating mode complementarity. See Rahimi-Golkhandan et al. (2019a) for details of the approach.

3.2.2. Application of Location-based Social Media in Mobility

Different types of ICT data can be used to investigate and characterize mobility patterns. Each type of data has advantages and disadvantages (Table 3.1). For example, taxicab GPS data can report pick-up and drop-off locations, travel time and travel route and transit smartcards can collect data of origin and destination stations, trip duration and frequency of trips. This data can help analyze the performance of road networks or transit systems for transportation planning and optimization. However, since it cannot capture the actual activity locations of individuals, the data is not suitable for the analysis of individuals' patterns of mobility. In addition, data sources such as taxicab GPS (e.g., Donovan and Work, 2017; Ilbeigi, 2019) or loop detectors (Zhu et al., 2010; He and Liu, 2012; Carrion and Levinson, 2012) that have been used to analyze post-disturbance mobility patterns can only capture road-based mobility and not the entire transportation system. In order to fully analyze variations in mobility patterns before and after a disturbance, all modes need consideration.

Datasets such as CDR or social media geotagged data, like Twitter, are not limited to a single transportation mode. While CDR and social media data cannot describe a specific transportation mode such as transit smartcards, loop detectors, or GPS data, it can be used individually or in combination with other mode-based data sources to describe general mobility. CDR can be used to study the mobility patterns of individuals. High penetration of cell phones, which provides a large amount of call dates and text messages along with relatively high spatial coverage, has made CDR the most popular type of cell phone data used in mobility studies (Wang et al., 2018a). CDR has been used in several studies to illustrate different characteristics of mobility patterns such as traffic conditions (Iqbal et al., 2014; Çolak et al., 2016; Olmos et al., 2018), finding range of travel (e.g., Yuan et al., 2012; Jiang et al., 2016), social activities (e.g., Calabrese et al., 2011; Yang et al., 2016) and regularly visited locations (Xu et al., 2015; Yuan and Rabul, 2016).

Table 3.1: Location-Based ICT Data in Mobility Analysis

ICT Data	Description	Advantages	Disadvantages	References
Loop Detectors	Loop detectors are installed in the pavement and can record information related to traffic.	• Report information about vehicle such as count, timestamp, and speed	• Require a large number of detectors for traffic analysis • Usually is limited to highways • Can only capture road-based mobility	Zhu et al. (2010); He and Liu (2012); Carrion and Levinson (2012)
Taxicab GPS	The GPS of taxicabs captures the trajectory of operations.	• Can provide information about pick-up and drop-off locations, timestamps, distance covered, travel time, speed, etc. • Can be useful for traffic demand and roadway congestion analysis	• Cannot detect the locations of activity • Can only capture road-based mobility • Unable to provide information about individuals' mobility	Tang et al. (2015); Qian and Ukkusuri (2015); Donovan and Work (2017); Ilbeigi (2019)
CDR	CDR collects the information of voice calls and short messages of individuals.	• Report information about timestamp of the call and the geolocation of users • Provides a large amount of data • The spatial coverage of CDR data is large • Not limited to any transportation mode	• Not easily accessible • The cell tower density can influence the accuracy of reported locations • Can detect the locations in which users make a call/send a message	Yuan et al. (2012); Calabrese et al. (2011); Schneider et al., (2013); Yang et al. (2016); Xu et al. (2015); Yuan and Rabul (2016); Jiang et al., (2016)
Twitter	Collects the information of users' activities on Twitter.	• Provides the geolocation, timestamp and the content of tweets. • Provides large amount of data • Not limited to any transportation mode • Reports high resolution geolocations	• The coverage might not be as large as CDR • Can detect the locations in which users send a tweet	Steiger et al. (2015); Wang and Taylor (2014, 2015, 2016); Martin et al. (2017); Lloyd and Cheshire (2017); Cvetojevic and Hochmair (2018); Kumar and Ukkusuri (2018); Wang et al. (2018b)

An alternative approach is using geotagged data of Twitter, which can report high-resolution locations of an activity using the built-in GPS of mobile devices. This makes it easier to identify where individuals visit and their actual locations. The application of Twitter data in mobility studies is substantial. For example, Steiger et al. (2015) used Twitter data to identify individuals' activities with respect to space and time and demonstrated the reliability of Twitter data by correlating their analysis of workplace with census data. They concluded that Twitter could be an indicator for analysis of workplace activities. Recently, Wang et al. (2018b) explored urban mobility and neighborhood isolation in the top 50 large cities in the US using Twitter data. Their findings showed that neighborhoods with mainly Hispanic and African-American residents travel more, but less to middle-class white or non-poor neighborhoods and highlighted the isolation of poor white neighborhoods from non-poor white areas.

Twitter data has also been used to analyze mobility patterns during extreme events. Wang and Taylor (2014, 2015) studied human mobility perturbation in NYC during and after Hurricane Sandy and expanded their examination to a variety of natural disasters across multiple urban areas around the world (Wang and Taylor 2016). They found that while human mobility is governed by the power law during disasters, extreme weather can break the resilience of human activities.

In addition, the dynamic of evacuation during Hurricane Matthew was explored by Martin et al. (2017). They discovered that 50% of the users evacuated from coastal areas, indicating the capability of Twitter data for assessing compliance with evacuation orders. Similarly, Kumar and Ukkusuri (2018) studied evacuation of NYC during Hurricane Sandy by analyzing whether people were inside or outside of evacuation zones and if they evacuated or not. They concluded that decision-making on evacuation highly depends on people's social bonds.

Although these studies uncovered or assessed patterns of mobility during extreme events, they did not fully consider the underlying dynamics of these patterns. This is mainly because CDR and social media data lack information about transportation systems to determine their influence on mobility patterns after extreme events. To overcome this limitation, this study examines the pivotal role of a transportation system on mobility by coupling human mobility and transportation system data. In particular, it takes a critical step further by developing a quantitative approach to evaluate the impact of transportation diversity on individual mobility in NYC zip codes. We link transportation diversity metrics with pre- and post-Sandy mobility patterns developed from Twitter data. The linkage allows us to explore the reciprocal influences between transportation diversity and mobility.

3.3. Methodology

To examine linkages between transportation diversity and mobility patterns, first GPS data of transportation modes was used to measure richness and evenness of each mode in NYC zip codes; these measures were then combined to determine the transportation diversity of each zip code. Subsequently, Twitter data was used to identify primary locations of individuals. The identified primary locations were employed to characterize pre- and post-Sandy mobility patterns by measuring radius of gyration, traveled distance, and mobility entropy.

3.3.1. Measuring Transportation Diversity

Transportation diversity is measured following the approach outlined in Rahimi-Golkhandan et al. (2019a). This approach to determine transportation diversity in a community examines five modes: (1) road network, (2) bus system, (3) rail transit system, (4) bicycle routes and (5) walkways. Richness, the availability of a mode in a given area, and evenness, the distribution of a mode in a given area, are calculated to determine the diversity of each mode. Diversity is characterized at the level of zip codes because they can represent neighborhoods and allow comparisons of transportation system characteristics in different parts of a community at a disaggregate level. The GIS data of transportation modes are derived from NYC DOT and the data of geographical units are gathered from the US Census Bureau. For road network, bicycle routes and walkways, the density of these modes in a zip code determines their richness. The richness of the bus system and rail transit system is calculated by considering the number of bus (metro) stops (stations) and the number of bus (metro) lines, which are scaled by the total number of lines and stations and the area of zip codes for consistency (Rahimi-Golkhandan et al., 2019a). Several other factors can potentially be considered in the richness of these modes (e.g., frequency in transits systems which can decrease due to failure in transit modes or increase to compensate for the failure in other modes after an extreme event). However, the focus of the approach is on the physical structure of transportation modes. Evenness is determined using census blocks, which represent different parts of a zip code. This enables quantifying the level of access that different parts of a zip code have to each transportation mode. The standard deviation of the shortest distance of census blocks of a zip code to a mode determines the evenness of that mode in that zip code, which is scaled by the square root of the area of the zip code for consistency (Rahimi-Golkhandan et al., 2019a). Data Envelopment Analysis (DEA) (Charnes, et al., 1978), a widely adopted non-parametric multi-criteria decision-making method, is used to measure the overall transportation diversity based on the richness and evenness values of all modes. Measuring the transportation diversity of each zip code enables identifying the diversity of a transportation system in different locations that each individual visits. This allows examining relationships between transportation diversity and the patterns of mobility before and after an extreme event like Hurricane Sandy. For more details of the characterization and quantification of transportation diversity, please refer to Rahimi-Golkhandan et al. (2019a).

Several approaches have been used in the literature to characterize transportation systems. Network metrics are widely used approaches to characterize the properties of the network of transportation modes (e.g., Erath et al., 2009; Dimitrov and Ceder, 2016). The purpose of network metrics is representing the transportation system based on a set of nodes and links to identify vulnerable nodes, their accessibility to other nodes, or the vulnerability of the entire system (Akbarzadeh et al., 2017; Aydin et al., 2018). By contrast, transportation diversity approach employed here characterizes areas of an urban community based on the provision of transportation modes and their distribution. Accessibility metrics usually consider the network as a set of origin-destination (OD) to analyze how the accessibility between OD pairs changes after a disturbance, which is based on the assumption that the transportation modes in each node are accessible. Conversely, the transportation diversity approach employed scrutinizes the accessibility to modes and determines how the modes in each area are reachable from different parts of that area. Therefore, it is different from existing network and accessibility approaches. In addition, accessibility approaches such as catchment area methods (e.g., Welch and Mishra, 2013) have some limitations. Since they quantify accessibility based on the walking distance to transit stations, they do not distinguish the difference between accessibility in different parts of an area. Additionally, in reality, people can walk, ride bikes, or drive to transit stations, and these distinctions are not captured in either the network or the catchment area approaches. Therefore, transportation diversity provides an alternative method to characterize different areas in an urban community based on the provision of all transportation modes and differentiates the accessibility to all these modes in a specific area. A detailed comparison of transportation diversity and other metrics characterizing transportation systems can be found in Rahimi-Golkhandan et al. (2019a).

3.3.2. Mobility Metrics

Different methods were used to characterize mobility patterns. For each individual, the locations that they visit frequently were identified. The identification supports measuring distance, radius of gyration and mobility entropy. Since distance and radius of gyration can capture the movement of individuals, the length of their movements, and the relative location of their primary locations from their home regardless of transportation modes, they were selected to characterize mobility patterns; moreover, these measures are common metrics used in many studies to depict mobility patterns (Gonzalez et al., 2008; Lu et al., 2012; Yuan et al., 212; Wang et al., 2018a). Further, entropy is a factor that can measure predictability of mobility patterns in time-series analysis and describe perturbations in mobility patterns (Song et al., 2010; Qin et al., 2012). Thus, these metrics are used to establish baseline mobility patterns and to identify changes in these patterns in NYC after Hurricane Sandy impacted the transportation system. Distance determines the total distance individuals travel between their frequently visited locations; radius of gyration quantifies how far individuals travel to and from their center of mass (e.g., their home location); and entropy shows the complexity and predictability of mobility patterns. The comparison of pre- and post-Sandy distance, radius of gyration for individuals can help identify how they maintained their mobility patterns after the hurricane and the change in the post-Sandy entropy can suggest how the predictability and complexity of their mobility patterns changed.

3.3.2.1. Primary Locations

Pinpointing where people live, which places they visit and the distance they travel is necessary to identify variations in mobility patterns after Sandy. An individual usually visits a small number of locations frequently (Csaji et al., 2013; Steenbruggen et al., 2015). Identifying these primary locations is important for transportation and community planning (Huang et al., 2010). Home location is the most important primary location of an individual. Generally, activities that are in the same location during the night indicate a home location (Wang et al., 2018a). Here, tweets that were sent between 8:00pm and 12:00am are employed to identify home locations. Density-based spatial clustering of applications with noise (DBSCAN) (Ester et al., 1996) was used to recognize primary locations. DBSCAN calculates the distance between the geolocation of tweets and forms clusters (i.e., primary locations). In this study, DBSCAN parameters of ε (distance between points) and n (minimum number of points) are ~ 50 meters and 5 respectively, which aligns with Wang et al. (2018b); 50 meters is an estimate of the size of a house while a minimum of 5 tweets to form a cluster makes sure that the cluster is a place that is visited regularly and it is not a randomly visited location. Those tweets that are not assigned to a cluster are considered noise. Pinpointing primary locations enables measuring radius of gyration, distance, and mobility entropy.

3.3.2.2. Radius of Gyration

Radius of gyration calculates the root mean square distance of all primary locations of an individual from their center of mass (here, home location). The radius of gyration determines how far the primary locations of individuals are or how far they travel. Radius of gyration can be formulated as:

$$R_G = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[2r \times arcsin\left(\sqrt{sin^2\left(\frac{\varphi_i-\varphi_h}{2}\right) + cos\phi_i\phi_h sin^2\left(\frac{\phi_i-\phi_h}{2}\right)}\right)\right]^2} \tag{1}$$

In Equation (1), *n* is the number of primary locations of an individual, *r* is the radius of the earth, *Φ* and *φ* indicate latitude and longitude respectively, *h* denotes the home location and *i* shows primary locations.

3.3.2.3. Distance

Individuals might drive, use a transit system, bike, walk or choose a combination of these modes to travel from one primary location to another. Since CDR and Twitter do not differentiate among transportation mode(s) used to travel between primary locations, it is difficult to determine the exact travelled distance. Alternatively, haversine distance provides an approximation of the travelled distance, and it has been widely used in mobility studies (e.g., Lu et al., 2012; Chen et al., 2014; Wang and Taylor, 2014, 2016). Therefore, the distance that an individual traveled is calculated by haversine distance in (2):

$$d = 2r \times arcsin\left(\sqrt{sin^2\left(\frac{\varphi_i - \varphi_j}{2}\right) + cos\phi_i\phi_j sin^2\left(\frac{\phi_i - \phi_j}{2}\right)}\right) \tag{2}$$

where d indicates how the distance between two consecutive primary locations i and j can be measured. Here, r is the radius of the earth, Φ is the latitude and φ is the longitude.

3.3.2.4. Mobility Entropy

Entropy can be used to measure the predictability of mobility patterns impacted by a disturbance. A lower entropy indicates higher predictability in an individual's mobility. In this study, since the ability to visit the pre-disaster primary locations is important, random entropy, which takes into account the number of primary locations, is calculated for each individual in (3):

$$S_{rand} = \log_2 n \tag{3}$$

where n is the number of primary locations. Song et al. (2010) employed entropy to predict mobility patterns; using mobile phone data they concluded that despite differences in the traveled distance of individuals, human mobility has high predictability. Other studies have also used entropy to predict mobility patterns (e.g., Qin et al., 2012; Lin et al., 2012; Sinatra and Szell, 2014). For instance, Gallotti et al. (2013) used entropy to predict patterns of mobility using GPS data. Using different datasets, Paul et al. (2018) employed entropy to predict mobility patterns of taxicabs, undergraduates, drifters, and the browsing habits of Canadian moose and found similarities and differences between these groups. Table 3.2 summarizes the mobility metrics used in this study as well as the prior work that has used them to characterize and predict mobility patterns.

3.3.2.5. Characterizing Pre- and Post-Sandy Mobility in NYC

Hurricane Sandy made landfall in NYC on October 29, 2012. To characterize mobility patterns in NYC before and after the hurricane, nearly one million geotagged tweets, which were sent between September 30th and December 15th in NYC, were collected. While the data of Twitter does not include demographic information of users, Wang and Taylor (2015) analyzed the demographic information of Twitter users in the US and confirmed that Twitter users are distributed in various demographic classes and are largely representative of the general public. Geolocation and timestamp data were extracted, and potential bot tweets were excluded based on the frequency of activities and their geolocation.

Table 3.2: Summary of Mobility Metrics

Measure	Description	Measurement	References
Radius of Gyration	Determines how far an individual travels from their home location.	The root mean square distance of primary locations of an individual from their home location.	Yuan et al. (2012); Wang and Taylor (2014, 2016); Blondel et al. (2015); Wang et al. (2018b)
Distance	Determines the total distance that an individual travels.	The haversine distance between all primary locations of an individual.	Lu et al. (2012) Chen et al. (2014); Wang and Taylor (2014, 2016)
Entropy	Determines the predictability and complexity of mobility patterns by considering the number of visited primary locations.	The logarithm of the total number of primary locations of an individual to the base of 2.	Qin et al. (2012); Lu et al. (2013); Sinatra and Szell (2014); Jurdak et al. (2015); Osgood et al. (2016)

The post hurricane timeframe was extended to December 15th (as opposed to November 28th) to capture one month's worth of data; several days after Hurricane Sandy did not have sufficient data to support the analysis. In this study, we analyzed the mobility patterns of 1,435 individuals. To minimize the likelihood that these Twitter users are not bots, we checked 15 databases of Twitter bots (https://botometer.iuni.iu.edu/bot-repository/). The aggregate of these data sets includes nearly 117,000 detected bots. We compared this data set with the Twitter users in our study and confirmed that no bots listed in the data set were present among the Twitter users in this study. Then, the primary locations of these individuals were found and their radius of gyration, distance, and entropy were measured for one week and one month before and after Hurricane Sandy.

The transportation system in NYC was severely impacted by Hurricane Sandy and the recovery of this infrastructure took at least a few weeks (Kaufman et al., 2012). For example, it took three weeks to restore the functionality of most metro lines while in some areas like Rockaway Peninsula it took months to recover. While transit system and roadways were recovering, people were exploring alternative routes and increasingly using alternative transportation modes such as walking and biking (Kaufman et al., 2012). Therefore, comparing mobility a week and a month after the hurricane can help in distinguishing the impact of transportation system recovery on the return of mobility to pre-disturbance levels. In addition, analyzing one month before and after Sandy provides a larger and richer set of data for a longer period of time to characterize mobility patterns before and after the hurricane more accurately. A transportation diversity score is assigned to each primary location, which was the transportation diversity score of each location's associated zip code. Individuals were then grouped in four quartiles based on the transportation diversity score of their primary locations.

We adopted two methods to calculate the transportation diversity score, an unweighted and a weighted one. In the unweighted method, individuals were grouped by the average transportation diversity score of primary locations. Here, the score assigned to each individual reflects the average transportation diversity score of the places they visited (3). This approach shows the general relationship between the diversity of the transportation system and primary locations.

$$\overline{\mathrm{d_a}} = \frac{\sum_{i=1}^{n} \mathrm{dp_i}}{n} \tag{3}$$

In Equation 3, $\overline{d_a}$ denotes the average transportation diversity assigned to individual *a*, dp_i is the transportation diversity of primary location *i*, and *n* is the total number of primary locations of this individual.

For an individual, the frequency of visits to a primary location can be viewed as the importance of that primary location for that individual; the higher the number of visits to a primary location, the more important that location is (i.e., the individual visited that location with a higher frequency or spent more time there). After an extreme event, people may prioritize visiting the primary locations they "need" rather than the ones they "want". In the weighted approach (4), the frequency of visits to each primary location (i.e., the total number of tweets in each primary location) was included to account for the importance of primary locations, and thus these frequencies were used as the weight to adjust the transportation diversity score. We multiplied the transportation diversity score of each primary location by its total number of visits before averaging.

$$\overline{\mathrm{d_{\omega_a}}} = \frac{\sum_{i=1}^{n} \mathrm{dp_i} \times \omega_i}{\sum_{i=1}^{n} \omega_i} \tag{4}$$

In (4), $\overline{\mathrm{d_{\omega_a}}}$ indicates the weighted average transportation diversity of individual *a*, dp_i is the transportation diversity of primary location *i*, ω_i denotes the number of tweets in primary location *i*, and *n* shows the total number of primary locations of this individual.

The weighted approach, therefore, gives higher values to locations that are visited more frequently and captures the ability of people to visit the places that are most important to them. Subsequently, individuals were grouped based on the weighted average transportation diversity score.

3.3.2.6. Statistical Analysis

We did a paired t-test of all individuals to compare the distance, radius of gyration, and entropy in one-week and one-month before and after Hurricane Sandy and confirm that the hurricane impacted mobility patterns. Individuals were then grouped in quartiles based on the diversity of their primary locations. To demonstrate that the impact of Hurricane Sandy on mobility patterns is statistically significant in all quartiles, paired t-tests on distance, the radius of gyration, and entropy were done for one-week and one-month after the event for both unweighted and weighted approaches. A significant change in mobility metrics for the individuals studied here can indicate that mobility was impacted by the hurricane. This would be the baseline to investigate how this impact was different in groups of individuals with primary locations of varying transportation diversity. Subsequently, the one-way analysis of variance (ANOVA) tests were conducted to examine whether the changes in mobility patterns (in terms of distance, radius of gyration, and entropy) are different among four quartiles under weighted and unweighted approaches. Tukey post hoc tests were then performed to determine the significance of the change in mobility patterns among quartiles.

3.4. Results and Analysis

3.4.1. NYC Transportation Diversity

Richness and evenness of all transportation modes are measured and combined to characterize transportation diversity of each zip code. The richness and evenness values of the bus system in NYC are shown in Figure 3.1. The figure shows that zip codes with high richness do not necessarily have high evenness. This indicates that the availability of a transportation mode in an area per se cannot demonstrate its efficacy since that mode might not be readily accessible from different parts of that area. Figure 3.2 illustrates overall transportation diversity in NYC in which zip codes with darker shades (values closer to 1) have higher diversity. Diversity varies among zip codes, which indicates that the availability (richness) and distribution (evenness) of transportation modes differ between zip codes. Specifically, zip codes in Manhattan and Brooklyn generally have higher diversity than the other boroughs of Bronx, Queens and Staten Island.

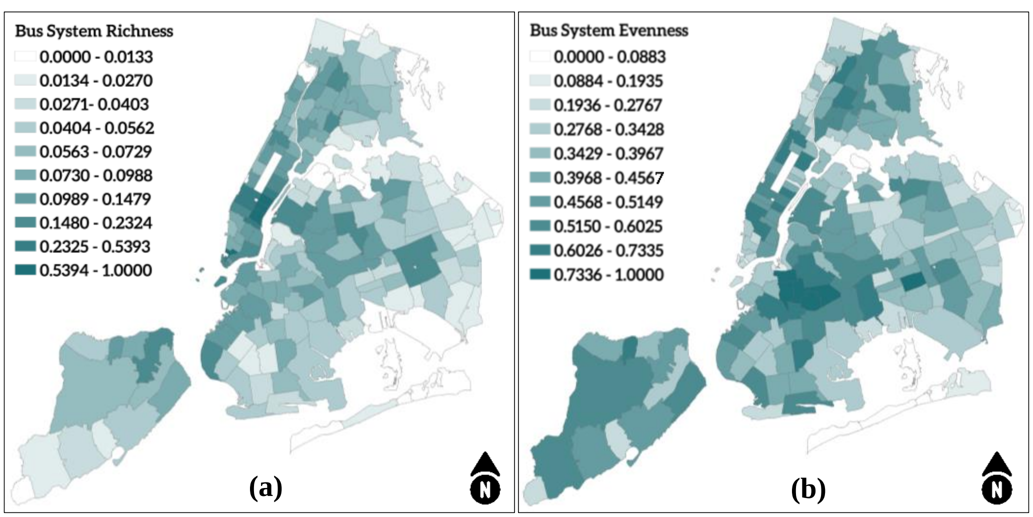

Figure 3.1: Bus System in NYC: (a) Richness; (b) Evenness

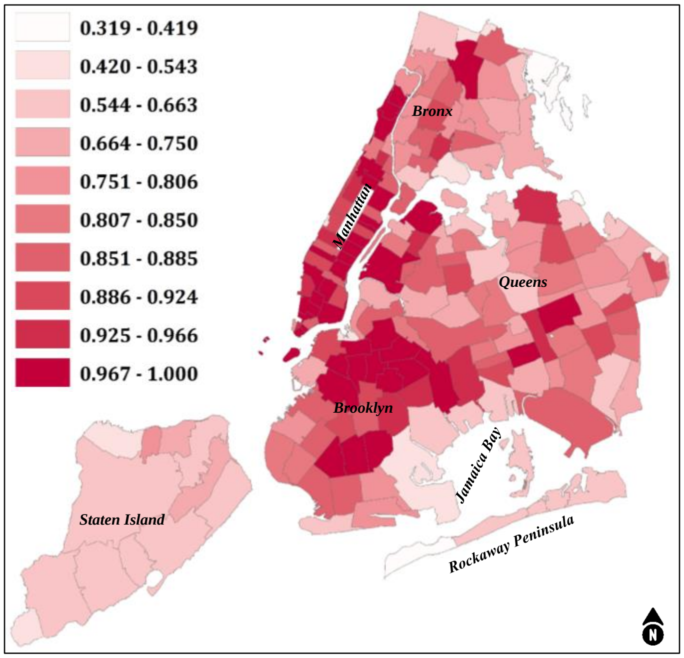

Figure 3.2: NYC Transportation Infrastructure Diversity

3.4.2. Pre- and Post-Sandy Mobility Patterns

Home locations and the primary locations before and after Hurricane Sandy were identified for each individual. Then, their radius of gyration, total traveled distance and entropy were measured. We conducted a paired t-test on the individual mobility metrics pre and post hurricane on both the individual level and the aggregated level by transportation diversity quartile. The results of the paired t-tests for all individuals, shown in Table 3.3, demonstrate that the post-Sandy distance, radius of gyration, and entropy were lower and statistically significant ($p<0.001$) than pre-Sandy values in both one-week and one-month analysis. The results suggest that, regardless of transportation diversity, Hurricane Sandy impacted mobility patterns and while the patterns of mobility were recovering, the impact on individuals remained until at least a month after the hurricane. The results of paired t-tests in quartiles (Table 3.3), show that the values of the post-Sandy mobility metrics (except one-week and weighted one-month distance in Q4, and unweighted one-month distance in Q3 which is moderately significant $p<0.1$) were lower and statistically significant than the pre-Sandy values suggesting that the mobility patterns of all quartiles were impacted by the hurricane.

The results of ANOVA tests between quartile groups showed no significant difference for entropy (both one-week and one-month), and distance (one-month), so they were excluded from the between quartile group analysis. Entropy is directly associated with the number of places individuals visit. After Hurricane

Sandy, the entropy of all quartiles drops which means that their mobility patterns became less complex after Sandy (Table 3.3). Residents in all quartiles likely traveled to their high priority primary locations or the ones they needed to travel to rather than those they wanted to travel to; consequently, the post-Sandy mobility patterns of all individuals became more predictable. Therefore, the insignificant difference in the entropy among quartiles is likely because all individuals limited their mobility to their key primary locations. This result also confirms the limitations of entropy for prediction of mobility patterns when other factors such as weather are not considered (Ikanovic and Mollgaard, 2017; Cuttone et al., 2018; Teixeira et al., 2019).

Statistically significant differences were found between quartiles for one-week distance by one-way ANOVA tests (unweighted: $F(3,1432) = 3.65$, $p = 0.012$; weighted: $F(3,1432) = 4.34$, $p = 0.005$). In the unweighted approach, a Tukey post hoc test revealed that after Hurricane Sandy, the changes in distance were lower and statistically significant in Q4 (0.45 ± 10.92) compared to Q1 (4.66 ± 19.47, $p = 0.02$) and Q2 (4.88 ± 17.69, $p = 0.006$). Similarly, in the weighted approach the post hoc analysis indicated that the post-Sandy changes in distance were lower and statistically significant in Q4 (0.40 ± 11.85) compared to Q1 (4.58 ± 16.33, $p = 0.008$) and Q2 (5.45 ± 20.61, $p = 0.007$).

Furthermore, the results indicated statistically significant differences between quartiles for one-week radius (unweighted: $F(3,1432) = 3.63$, $p = 0.013$; weighted: $F(3,1432) = 4.95$, $p = 0.002$). The post hoc results in the weighted approach showed that after Hurricane Sandy, the mean changes in radius were lower and statistically significant in Q4 (1.47 ± 5.76) compared to Q1 (3.46 ± 8.75, $p = 0.034$) and Q2 (3.83 ± 8.49, $p = 0.006$). In addition, in the weighted approach the post hoc test revealed that the changes in radius were lower and statistically significant in Q4 ($0.1.20 \pm 5.62$) compared to Q1 (3.73 ± 9.30, $p = 0.005$) and Q2 (3.83 ± 8.55, $p = 0.002$). These results suggest that the mobility patterns of individuals in Q4 were impacted far less than individuals who had primary locations in areas with a lower transportation diversity (Q1 and Q2). The higher transportation diversity in the primary locations of individuals in Q4 provided them with more options for mobility and supported them to maintain their pre-Sandy mobility patterns better.

For one-month radius, differences among quartiles were statistically significant as determined by one-way ANOVA tests (unweighted: $F(3,1432) = 5.67$, $p = 0.001$; weighted: $F(3,1432) = 7.38$, $p = 0.000$). A Tukey post hoc test revealed that in the unweighted approach, the mean change in the radius was lower and statistically significant in Q4 (0.76 ± 3.42) compared to Q1 (1.83 ± 6.21, $p = 0.022$), Q2 (2.16 ± 5.09, $p = 0.000$), and Q3 (1.47 ± 3.93, $p = 0.05$). Likewise, in the weighted approach, the results indicated lower and statistically significant changes in radius in Q4 (0.86 ± 3.74) compared to Q1 (2.40 ± 6.57, $p = 0.001$) and Q2 (1.79 ± 4.79, $p = 0.021$). In addition, radius differences in Q3 (1.16 ± 3.35) were lower and statistically significant than Q1 (2.40 ± 6.57, $p = 0.008$).

The between quartile comparison results for both unweighted and weighted approaches confirmed the impact of transportation diversity on maintaining mobility patterns. The mobility patterns of individuals in high transportation diversity quartiles were significantly less perturbed than those in low diversity quartiles. Figure 3 depicts the comparison of mean change of radius, distance and entropy among quartiles in one-week and one-month, which illustrates the statistically significant (solid lines) and insignificant (dashed lines) changes in the mobility metrics. The one-week and one-month results indicate that as the transportation system was recovering between a week and a month after Hurricane Sandy the individuals' mobility patterns were rebounding, albeit they still had not fully recovered from the event.

For the first approach to calculate transportation diversity (the average diversity score: $Q1_{Div}$=0.71, $Q2_{Div}$=0.87, $Q3_{Div}$=0.93, $Q4_{Div}$=0.98), in general, the changes in mobility patterns in Q1 and Q2 are less than the changes in mobility patterns in Q3 and Q4 one week before and after Sandy. This indicates that individuals who were traveling to primary locations with higher transportation diversity were able to better maintain their mobility patterns. The second approach (the weighted diversity score) shows similar results. Although the maintained radius in Q2 is greater than Q1, in general an increase in the weighted average diversity score by quartiles shows increases in the maintained radius.

The results of both approaches reveal that transportation diversity influences mobility patterns and the ability of people to maintain their patterns of mobility after a natural hazard. Specifically, this implies that the availability of transportation modes and the balanced distribution of these modes across a community provides the capacity for mode complementarity. The mode complementarity in the primary locations of individuals in Q3 and Q4 clearly helped them better maintain visiting these places while low mode complementarity in Q1 and Q2 hindered them from retaining their mobility patterns.

The results of radius for a month before and after Hurricane Sandy overall follow the same pattern; an increase in the transportation diversity score by quartiles in both approaches results in higher ability to retain mobility patterns (Figure 3.3). Notably, almost all the values of change in the radius in all four quartiles one-month after Hurricane Sandy are higher than these values a week following its aftermath. This improvement in the maintained radius suggests that as the transportation system (and overall community) was recovering during the month after Sandy, individuals were able to regain their mobility patterns; further, individuals with primary locations in high transportation diversity zip codes managed to restore their mobility patterns to pre-hurricane levels more easily.

Table 3.3: Paired t-Tests Results of Distance, Radius of Gyration, and Entropy Before and After Hurricane Sandy

Quartiles	Distance				Radius				Entropy			
	Mean (SD)		***t***	**95% CI of Difference**	**Mean (SD)**		***t***	**95% CI of Difference**	**Mean (SD)**		***t***	**95% CI of Difference**
	Before	**After**			**Before**	**After**			**Before**	**After**		
One-Week (All Individuals)	10.55 (15.12)	7.24 (13.41)	6.15***	[2.25, 4.36]	7.15 (8.03)	4.32 (6.72)	10.15***	[2.28, 3.38]	1.65 (0.70)	1.30 (1.00)	11.74***	[0.29, 0.41]
One-Month (All Individuals)	9.01 (14.07)	7.35 (13.00)	4.91***	[0.99, 2.32]	5.22 (5.21)	3.67 (4.26)	12.21***	[1.30, 1.80]	1.84 (0.81)	1.58 (1.05)	10.69***	[0.22, 0.31]
One-Week (Unweighted)												
Q1	11.59 (16.72)	6.93 (12.47)	3.68***	[2.16, 7.16]	8.08 (9.29)	4.33 (6.72)	5.86***	[2.49, 5.01]	1.63 (0.68)	1.29 (0.99)	5.74***	[0.22, 0.46]
Q2	13.25 (18.29)	8.37 (16.16)	4.25***	[2.61, 7.14]	8.14 (8.96)	4.37 (7.21)	6.12***	[2.55, 4.98]	1.73 (0.78)	1.34 (1.08)	6.38***	[0.27, 0.51]
Q3	10.88 (14.01)	7.60 (14.24)	3.02***	[1.14, 5.42]	7.01 (7.60)	4.75 (7.33)	4.50***	[1.27, 3.25]	1.66 (0.70)	1.27 (1.00)	6.70***	[0.28, 0.51]
Q4	6.66 (9.12)	6.09 (9.99)	0.63	[-0.94, 1.84]	5.35 (5.45)	3.82 (5.46)	3.54***	[0.68, 2.38]	1.57 (0.64)	1.30 (0.94)	4.66***	[0.16, 0.39]
One-Week (Weighted)												
Q1	11.66 (12.64)	7.09 (12.72)	4.32***	[2.49, 6.67]	8.01 (8.53)	4.28 (6.24)	5.74***	[2.45, 5.01]	1.64 (0.68)	1.29 (1.02)	5.83***	[0.23, 0.47]
Q2	13.03 (20.04)	7.59 (14.37)	4.06***	[2.81, 8.09]	8.60 (9.65)	4.77 (7.53)	6.41***	[2.65, 5.01]	1.69 (0.77)	1.29 (1.00)	7.05***	[0.29, 0.51]
Q3	10.66 (15.09)	7.84 (15.32)	2.73**	[0.78, 4.85]	6.67 (7.43)	4.12 (7.29)	4.73***	[1.39, 3.62]	1.69 (0.72)	1.32 (1.08)	5.91***	[0.25, 0.49]
Q4	6.87 (9.67)	6.45 (10.84)	0.52	[-1.19, 1.91]	5.30 (5.57)	4.10 (5.67)	3.06**	[0.43, 1.98]	1.58 (0.64)	1.30 (0.91)	4.74***	[0.16, 0.39]
One-Month (Unweighted)												
Q1	10.33 (13.93)	7.90 (13.92)	2.80***	[0.72, 4.14]	5.76 (6.32)	3.93 (4.96)	5.57***	[1.18, 2.47]	1.80 (0.81)	1.51 (1.09)	5.75***	[0.19, 0.39]
Q2	10.75 (18.95)	8.71 (16.12)	2.11*	[0.13, 3.93]	6.02 (5.57)	3.86 (4.43)	8.03***	[1.63, 2.69]	1.89 (0.82)	1.61 (1.08)	5.27***	[0.18, 0.38]
Q3	7.51 (10.54)	6.54 (12.37)	1.64	[-0.20, 2.15]	5.24 (4.56)	3.77 (3.97)	7.05***	[1.06, 1.87]	1.90 (0.86)	1.64 (1.03)	5.38***	[0.16, 0.35]
Q4	8.60 (14.01)	6.97 (11.11)	3.30***	[0.66, 2.58]	3.87 (3.78)	3.11 (3.53)	4.18***	[0.40, 1.11]	1.79 (0.74)	1.56 (1.01)	4.98***	[0.14, 0.33]
One-Month (Weighted)												
Q1	9.00 (12.95)	6.88 (11.69)	2.91**	[0.69, 3.54]	6.15 (6.50)	3.75 (4.79)	6.92***	[1.72, 3.08]	1.77 (0.80)	1.50 (1.08)	5.39***	[0.18, 0.38]
Q2	10.31 (14.30)	8.41 (15.38)	2.65**	[0.49, 3.30]	5.87 (5.32)	4.08 (4.68)	7.06***	[1.29, 2.29]	1.89 (0.81)	1.59 (1.07)	5.93***	[0.20, 0.40]
Q3	10.26 (17.98)	7.99 (13.89)	3.28***	[0.91, 3.63]	4.80 (4.35)	3.64 (3.70)	6.54***	[0.81, 1.51]	1.95 (0.87)	1.64 (1.06)	6.25***	[0.21, 0.41]
Q4	6.48 (9.55)	6.02 (10.26)	0.84	[-0.61, 1.52]	4.07 (4.03)	3.21 (3.73)	4.35***	[0.47, 1.25]	1.77 (0.74)	1.59 (1.01)	3.74***	[0.08, 0.27]

$^{*}p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

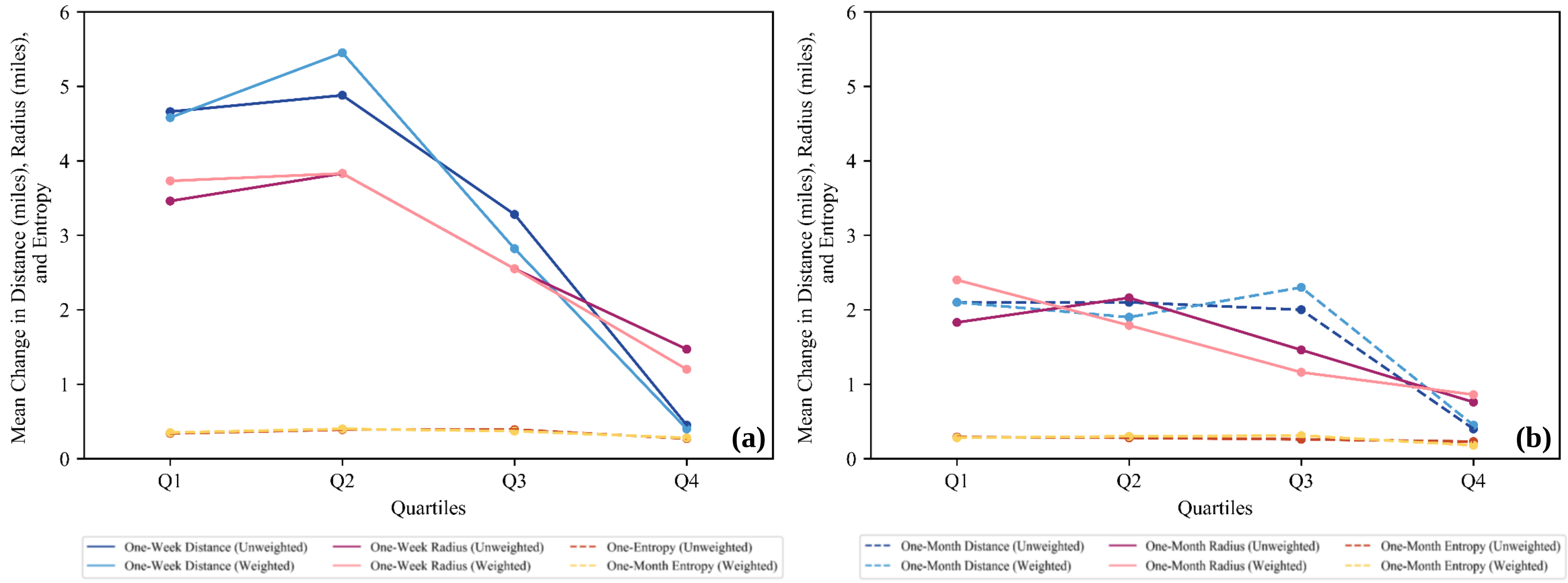

Figure 3.3: Changes in Mobility Metrics: (a) One-Week Analysis; (b) One-Month Analysis

3.5. Discussion

Managing infrastructure systems is critical for the resiliency of lifelines and urban communities. Such management includes preparation for extreme events like natural hazards, immediate and effective emergency response during such events, and quick recovery to the pre-disaster performance levels. Restoring pre-disaster functional levels is not a sustainable strategy as it does not reduce the impact of future disasters (Eid and El-adaway, 2017). Thus, beyond restoration infrastructure management for urban resilience must also include learning from past events. Careful adaptation can reduce the impact of future events (Ha et al., 2017) by improving preparedness, response, and recovery plans. In general, communities that are more resilient experience less impact from a disturbance (robustness) and more rapid recovery (Yoon et al., 2016). One of the first steps in analyzing infrastructure resilience and developing strategies to enhance their resilience is to measure the impact of disasters on infrastructure systems (Ilbeigi and Dilkina, 2018). Human mobility studies mostly investigate the routine travel behavior and mobility patterns; far fewer studies have been done on the changes in mobility patterns after natural disasters (e.g., Wang and Taylor, 2015; Kumar and Ukkusuri, 2018; Ahmouda et al., 2019). Understanding the impact of a transportation system in maintaining mobility patterns and recovery of these patterns is lacking in post-disaster mobility studies making it difficult to determine the root causes of mobility change after extreme events. The results of this study demonstrated the influence of a transportation system on mobility patterns after a natural disaster. The analysis of the pre-and post-disaster mobility patterns in the quartile groups confirms our premise that improving transportation diversity will likely lead to enhanced resilience of post-disaster mobility, such as an event like Hurricane Sandy and advances our understanding of the dynamics of changes in post-disaster mobility. People in high transportation diversity quartiles (Q3 and Q4) managed to maintain their pre-disaster mobility patterns better (higher robustness) and their rate of recovery was generally higher (faster recovery) than low transportation diversity quartiles (Q1 and Q2). Hence, transportation diversity played a role in maintaining mobility patterns after Hurricane Sandy; this recognition can aid transportation infrastructure management and resilience planning since it identifies areas with low transportation diversity for further assessment and possible subsequent improvement. The transportation system of the low diversity zip codes can be analyzed in future research to find the root causes of their low scores; whether low richness, low evenness or both resulted in low diversity. Such an analysis can help identify whether the low availability of one or more modes and/or whether an unbalanced distribution of modes was the cause of low diversity. Therefore, it helps shift efforts for enhancing transportation resilience from the general city scale to targeted areas and communities. The approach enables a potentially more effective and efficient approach where decision-makers can invest in the transportation modes most in need of improvements.

Hurricane Sandy obviously disturbed the multi-mode transportation system, and consequently the mobility in NYC. Despite the disturbance, this multi-mode system helped alleviate the impact of Sandy on mobility. For instance, the amount of walking and biking increased after Sandy (Kaufman et al., 2012) when the transit system and road network experienced failure at different levels. However, most cities in the US do not have a multi-mode transportation system as developed as the one in NYC; residents in these cities rely on cars and buses for their travel (Kaufman et al., 2012), and such cities may not have either the structure or infrastructure to realistically support walking and biking. Natural hazards of similar magnitudes in these cities will likely have a more significant impact on their transportation system and their economy. Indeed, future research can explore cities with alternative characteristics to assess the impact of transportation diversity on human mobility in the wake of natural hazards or routine events.

The average traveled distances in a week and a month before and after the hurricane clearly increase from Q1 to Q2, but drop from Q2 to Q4 (Table 3.3). While it might be expected that higher diversity in Q3 and Q4 provides people with the ability to travel longer distances than low-diversity quartiles, this anomaly is likely related to the location of high diversity zip codes in NYC. Zip codes with higher diversity are mainly located in Manhattan and Brooklyn (Figure 3.4). These boroughs have a more compact built environment with more infrastructure and resources than the Bronx, Queens and Staten Island. Kang et al. (2012) studied mobility patterns in a group of cities with various morphological characteristics in China. They concluded that residents in less compact areas travel more to access services and infrastructure than those in areas with more compact urban morphology, where such are likely better provided. The richness values of transportation modes in NYC boroughs reinforces the findings of Kang et al. (2012) since transportation modes are generally better provided in Manhattan and Brooklyn. Compared to other boroughs, residents in Manhattan and Brooklyn are more likely to travel shorter distances for their needs and activities. Therefore, the results also confirm the impact of urban structure and morphology on mobility patterns.

In 2012, NYC had more Twitter users than any other city in the world with more than 2.6 million users, and users were tweeting from all over the city (Kaufman, 2012). The high granularity and representativeness of Twitter makes it a distinctive option to study mobility patterns in high resolution. This study only considered Twitter data of one month before and after Hurricane Sandy (last quarter of 2012), a period of time that could well demonstrate the impact of Sandy on mobility. This short period, however, limited the number of individuals analyzed in this study. While this number is relatively low compared to the population of NYC, the distribution of home and primary locations in the five boroughs of NYC aligns with the population density per square mile in these boroughs (Figure 3.5). This indicates that the distribution of the users is representative of the population within the boroughs and consequently the mobility patterns in NYC, despite the low number of individuals studied.

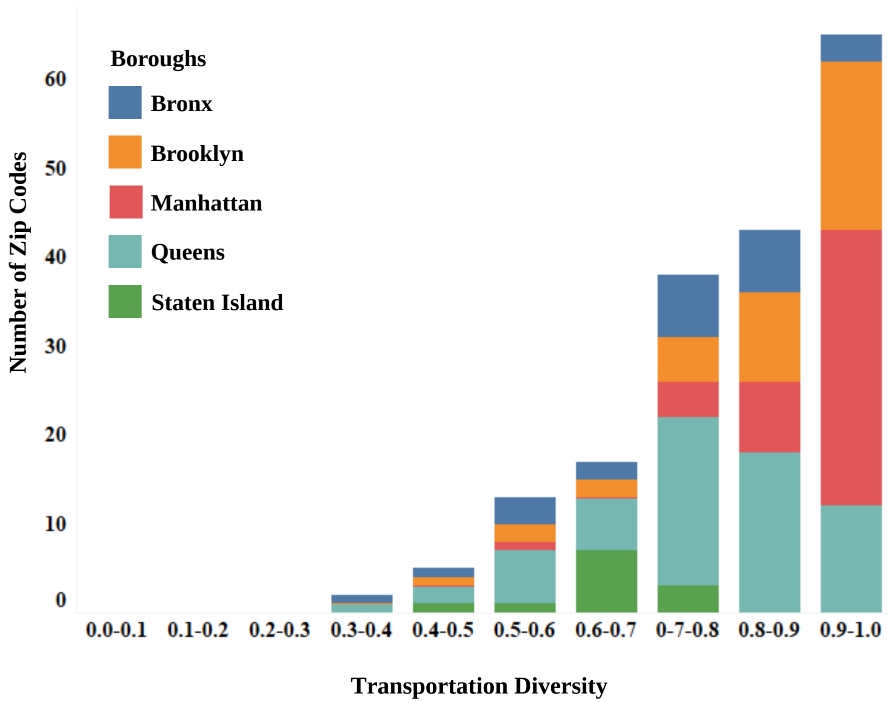

Figure 3.4: Transportation Diversity by Boroughs

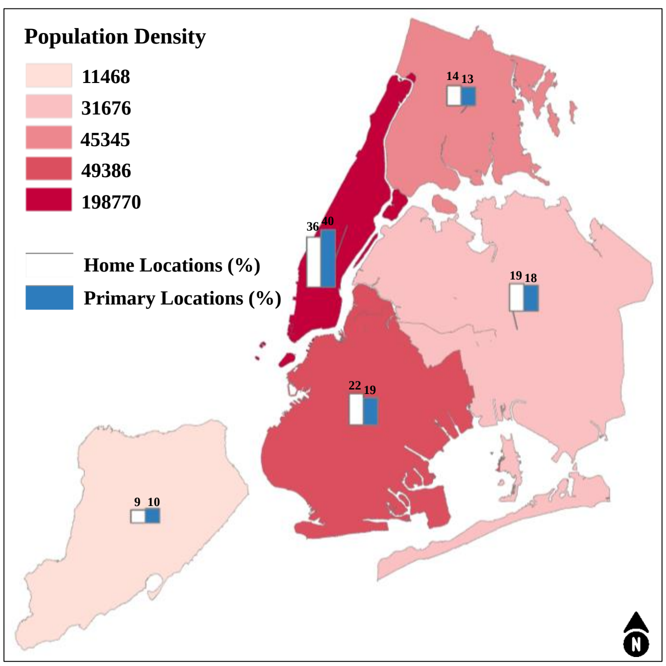

Figure 3.5: Home Locations, Primary Locations and Population Density (population/mi^2) in NYC

3.6. Limitations

We recognize that this study has limitations. The relationship between transportation diversity and post-disaster mobility is analyzed in one city and for one natural hazard. Future studies could be done in other communities and for other natural hazards to further understand how transportation diversity impacts mobility in other urban areas or during different natural hazards. In addition, due to the absence of data indicating transportation modes used to travel between primary locations, the distance calculation is based on the haversine distance that approximates the actual distance. If we assume that individuals travel by driving on existing roadways, then the driving distance of a month before and after Sandy was measured for all individuals in this study using Bing Maps API. The results confirmed that the haversine distance is less than the roadway distance for all individuals. Hence, the results of the haversine distance calculations were consistent, albeit as expected with less accuracy (80% of driving distance). In reality individuals might use any of the transportation modes to travel, so driving distance does not represent all transportation modes. Further, the modes considered in this study do not represent all the available modes in NYC; however, 98.5% of the population of NYC use the modes examined, so the individuals in the study likely used one of the five modes assessed (US Census Bureau). While Twitter data is generally representative of the U.S. population, demographic information on Twitter users from NYC is not available; hence, we cannot confirm with certainty to what extent the individuals studied are representative of the NYC population. Yet, the individuals are dispersed throughout NYC's five boroughs, so they provide reasonable coverage of NYC's geography and population. As discussed previously, the approach used in this study to measure transportation diversity is focused on the physical characteristics of this infrastructure; future research can incorporate other factors such as the frequency of transit systems. Further, we used zip codes as the spatial scale of analysis; a comparison of mobility patterns at different spatial scales could provide insights on the influence of other factors such as urban structure and demographics on mobility patterns. This limitation, unfortunately, is shared by all data sets in mobility studies, including call detail records, Twitter, and data sets from other social media. Lastly, this study considered the data from September 30, 2012 to December 15, 2012 (one month's worth of data before and after); this limited the number of individuals studied, and it included the Thanksgiving holiday season. Analyzing longer time periods and combining other data sources such as CDR would increase the number of individuals and the accuracy of their primary locations as well as mitigate any seasonal impacts; consequently, this would further our understanding of the long-term link between transportation diversity and individual mobility patterns.

3.7. Conclusions

Existing mobility studies during and after natural hazards have provided a clearer picture of the mobility patterns in these situations. However, the underlying drivers of these patterns and the root causes of deviation from the normal patterns after extreme events have been largely unexplored. This study examines the influence of NYC's transportation system on the resilience of mobility patterns after Hurricane Sandy by characterizing transportation diversity and pre- and post-disaster mobility patterns.

The contributions of the study are threefold. First, it contributes to the quantification of the impact of transportation diversity on post-disaster mobility by developing two methods. The first method focuses on the places that individuals visited by taking the average transportation diversity score of their primary locations into account. The second method incorporates the frequency of visits to each primary location to account for the importance of primary locations. The incorporation of frequency allows us to understand how the weights of primary locations can change the quantification of impacts. The proposed method can be applied in future mobility studies when the *weights* of visits or "stay points" need to be considered. These developed methods overcome the lack of transportation system information in CDR and social media data and allow analyzing the influence of a transportation system on post-disaster mobility.

Second, the findings of the studies directly contribute to understanding the linkage between transportation diversity and human mobility. Our work provides a quantitative and data-driven confirmation that transportation diversity can significantly impact post-disaster mobility, which to our knowledge is one of the first studies to do so. We demonstrate that individuals with primary locations in zip codes of high transportation diversity were less affected than those with primary locations in low diversity zip codes; these outcomes were consistent across the two approaches, indicating diversity impacts where individuals both want and need to travel. Moreover, transportation diversity is a factor in the post-disaster recovery of mobility patterns since high transportation diversity quartiles recovered faster than low diversity ones. The impact of transportation diversity on robustness and recovery of mobility patterns demonstrates the importance of a multi-mode transportation system that is both available and accessible throughout a community. The mode complementarity in a diverse transportation system helps individuals maintain their mobility patterns even when an extreme event causes failure or loss of service in some modes.

Third, we innovatively applied established measures of human mobility to study its perturbations caused by Hurricane Sandy, contributing to the field of mobility resilience. Human mobility research has long been focused on the discovery of systematic behaviors in a certain range of the stable state. The study takes a first transformative step of scientific advance by examining urban dwellers' mobility change during a major disaster as well as the possible underlying causes behind these changes. For example, we demonstrated that people traveling in zip codes with lower transportation diversity travel longer distances. The findings align with and complement previous research that examines how neighborhood attributes can influence mobility. People living in compact areas of a city tend to travel far less than those living in less compact neighborhoods (Kang et al., 2012). Also, socio-economic factors are important in mobility patterns

(Dieleman 2000; Kang et al., 2012; Wang et al., 2018a). For instance, literature has shown that disadvantaged groups usually travel longer distances (Wang et al., 2018b). In particular, future research could explore if residents with primary locations in low diversity zip codes are from socially isolated neighborhoods or whether other socio-economic factors are influential.

The case of NYC after Hurricane Sandy demonstrated the relation between transportation diversity and mobility. Natural hazards threaten other urban areas in the US. Hence, assessing transportation diversity in other cities like Houston and Miami, which have experienced major hurricanes in recent years, could potentially help identify zip codes with low transportation diversity. This approach can thus allow city planners to connect citywide transportation improvement plans with neighborhood level (e.g. zip code) transportation diversity and resilience strategies. Additionally, characterizing the mobility patterns of these communities after a natural hazard would advance our understanding of the similarities/differences between these patterns in various communities with differing transportation diversity. Our study offers an alternative approach to quantify mobility perturbation and transportation diversity, making the comparison of disturbances caused by different extreme events, such as flood, hurricane, snowstorm, and earthquakes, with different intensities possible. Ultimately, such analyses on mobility patterns during and after disturbances will support building robust transportation systems and achieving urban mobility resilience.

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Chapter 4: Transportation Diversity and Equity Nexus: A Socio-Economic Analysis for Resilience Planning[3]

Abstract

Equity of access to transportation modes is crucial for routine activities and opportunities. If inequality of access to a transportation system hinders reaching activities and services, social exclusion may result. Certainly, all transportation modes contribute to accessibility. Yet, equity of access studies have focused primarily on transit systems where catchment area approaches were employed; this approach has several limitations such as failing to distinguish the equity of access to transportation modes in regions within an area and potentially inflating/deflating the measurement of accessibility. Transportation diversity measures the provision and distribution of all transportation modes in an area and addresses the shortcomings of other approaches. Here, an approach to measure transportation diversity is used to quantify the equity of access to all transportation modes in New York City at the zip code level. The application revealed that transportation diversity varies across the city. The comparison of socioeconomic and transport related factors showed the relationship between transportation diversity and income, vehicle ownership, commute time, and commute mode and highlighted the social exclusion associated with transport inequity. The results also illustrated that the inequity of the transport system in zip codes with low transportation diversity affects poor individuals more than non-poor. In addition, zip codes with majority black or Hispanic populations in areas with low transportation diversity face more challenges as result of transport inequality. The transport equity is also critical during extreme events. Considering the impacts of Hurricanes Irene and Sandy in New York City indicated that transport inequity in areas with lower transportation diversity led to greater post-disaster socioeconomic issues and social exclusion. This analysis suggests that improving transportation diversity will enhance transport equity and mitigate social exclusion in normal situations and after natural disasters.

Keywords: Infrastructure; Multimode; Accessibility; Transportation; Sustainable Development; Diversity; Resilience; Equity.

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4.1. Introduction

The transportation network of an urban community connects different parts of the community, enables mobility, and supports activities of the residents, which are crucial for the development of society. Ideally, all residents in every part of a city should have equal opportunities to access transportation modes; however, often an imbalance exists in the supplied transportation infrastructure in different parts of a city leaving some areas underserved. This inequality in the transportation system can bring about mobility issues that can cause social exclusion.

Social exclusions triggered by transport inequity can be classified as *physical*, *geographical*, *economic*, *space*, *fear-based*, *time-based*, and *exclusion from infrastructure and facilities* (Church et al., 2000). Inequality in the provision of a transportation system usually causes more mobility issues for deprived groups in their basic needs and activities (Ledoux and Vojnovic, 2013). Improving transport equity supports decreasing social exclusion by reducing the opportunity gap for essential needs, services, and activities such as employment, grocery shopping, and schools (Brodie and Amekudzi-Kennedy, 2017).

Several studies have explored equity of transportation systems from various perspectives such as access to opportunities (Foth et al., 2014; El-Geneidy et al., 2016a), access to transportation modes (Boarnet et al., 2017; Tiznado-Aitken et al., 2018), mode choice (Jou and Chen, 2014), travel time (C. Zhao et al., 2018), and travel cost (Eliasson and Mattsson, 2006; Hensher and Chen, 2010) or a combination of these. Transport equity studies usually divide people in a set of groups to explore how impacts are distributed among different groups (TRB, 2011; Markovich, 2013). Grouping can be based on geographical location, economic, demographic, generation, and usage of the transportation modes (TRB, 2011), although it can be based on more than one factor. For example, Delbosc and Currie (2011) analyzed access to the transit system in different groups of age, income, and vehicle ownership in various areas in Melbourne, Australia and found that 70% of the people have access to only 19% of the supplied service in this city. In another study, Brodie and Amekudzi-Kennedy (2017) evaluated the equality of transit and auto accessibility for disadvantaged groups of African-American, Hispanic, and low-income groups by analyzing the accessibility to opportunities in different areas by car and transit, and found that these groups have unequal accessibility.

Disadvantaged groups such as low-income households, transit-dependent individuals, elderlies, children, and ethnic groups of Hispanics and African-Americans are usually more vulnerable to natural disasters. For instance, Hurricane Katrina in 2005 in New Orleans impacted low-income and African-American households and individuals the most (Gabe et al., 2005). The unsuccessful evacuation of New Orleans during Hurricane Katrina, which failed to consider transit-dependent residents, prompted the US Department of Transportation and the Department of Homeland Security to find solutions for the evacuation of residents who do not have cars or are unable to drive (Naghawi and Wolshon, 2012). Disturbances in a transportation system after extreme events can be more severe for disadvantaged groups causing greater social exclusion. Therefore, considering vulnerable groups is critical for equitable transportation resilience planning. Inclusion of socioeconomic factors in transportation resilience assessments, which have focused significantly on technical issues, will likely enhance transportation and urban community resilience (Amoaning-Yankson and Amekudzi-Kennedy, 2017).

All transportation modes are important to connect different areas of a city and support mobility. Ease of access to all modes becomes more critical during and after extreme events when failures in one or more modes can force people to change their routine mobility plans. These changes might be in the form of travel mode, departure time, destination, travel schedule, and demand (Khan and Habib, 2018) or may cause trip cancelation due to the unavailability of alternative transportation systems. Currently, common approaches analyzing access to transportation modes for equity are mainly focused on transit systems quantifying what portion of an area is covered by a transit system. Ideally, an equitable transportation system has an equal supply of all modes and provides uniform access to these modes in every part of an urban community; however, this is not realistic due to various constraints that will influence equal provision and distribution of transportation modes. Thus, a more pragmatic goal for a transportation system is to enhance provision and accessibility given the constraints and specific conditions of each area such as the built environment characteristics, geographic and topographic conditions and population distribution as well as consideration of capital and operating costs associated with any improvements. Therefore, to analyze the equity of access to transportation modes, transportation diversity (Rahimi-Golkhandan et al., 2019) is proposed as an alternative approach. Transportation diversity, which is inspired by biodiversity, measures the availability of *all* modes in an area and the homogeneity of the distribution of these modes. The goal is to analyze the equity of access to all transportation modes, identify areas with a less equitable transportation system and transport related social exclusion, and determine how inequality of access to transportation modes could jeopardize transportation resilience, which could intensify post-disaster social exclusion. To explore the relationship between transportation diversity and equity, we first characterize the transportation diversity of all zip codes in New York City. Then, based on transportation diversity, we compare factors pertaining to transportation mode usage and socioeconomic status among zip codes. This approach permits the analysis of the relationship between the equity of the transportation system and social exclusion. The implications of the analysis for equitable transportation resilience planning to improve robustness to natural hazards and recovery from such events are also discussed in detail.

4.2. Background

4.2.1. Transportation Equity

Transportation equity can be explored from various perspectives since different impacts can be considered, several groups of individuals can be formed for comparisons, and various approaches can be taken to study the impacts on these groups (TRB, 2011). Litman (1999) describes equity of transportation infrastructure as a *fair distribution of benefits and costs* and categorizes equity types as horizontal or vertical, with vertical related to social justice or mobility needs. Horizontal equity determines an equal allocation of resources to equal groups without favoring any certain group. Vertical equity from a social justice perspective takes into account income and social class in the distribution of resources, benefits, and costs in order to support deprived groups. Vertical equity that concerns mobility needs considers the distribution of benefits and costs with respect to people that have special needs for their mobility through inclusive design. Church et al. (2000) classified transportation equity studies into *category* and *spatial* approaches. Category approaches attempt to tackle this problem from the perspective of transport demand of disadvantaged groups while spatial approaches look into social exclusion from the service supply perspective.

4.2.1.1. Category Approaches

Lotero et al. (2016) studied the spatiotemporal mobility patterns of groups with different socioeconomic characteristics. The results show that socioeconomic classes have different mobility patterns. In particular, people with higher socioeconomic status have less morning activities and short-ranged mobility patterns compared to those in lower socioeconomic classes. Zhao and Li (2016) examined commute time in Beijing, China, and found that because of transport inequality low-income workers have longer commute time than middle- and high-income commuters. They suggested that incorporating mixed land use and housing and employment development with transportation planning could improve equality. Lee et al. (2018) examined inequality of the transportation system in Detroit, Michigan with respect to urban form, gender, and car/non-car travel and confirmed the findings of previous research that women in Detroit travel less and shorter distances when compared to men. They also reported that women living in socioeconomically disadvantaged and racially segregated areas are affected more. In addition, Wang et al. (2018) analyzed mobility patterns in the fifty largest cities in the US and concluded that while people who live in disadvantaged areas travel longer and wider, they are socially segregated.

4.2.1.2. Spatial Approaches

Access to Opportunities

Accessibility is a spatial approach that has been used as a proxy for transport equity (Markovich, 2013). Accessibility can generally be described as the ability of people in one area to reach opportunities in other areas. Several accessibility measures have been developed. Bhat et al. (2000) classified these measures as (1) graph theory and spatial separation models which are based on the distance between two zones, (2) cumulative opportunities models determine potential accessible opportunities within a specific time/distance threshold, (3) gravity models that account for accessible opportunities and also have an impedance factor to give less value to opportunities as distance/time increases, (4) utility models are based on the utility that a traveler would gains in a set of travel options, (5) time-space models account for the time constraint for accessibility, and (6) empirical comparisons that employ different accessibility measures.

Accessibility measures – commonly cumulative opportunities, gravity-based models, and utility models – have been used in many studies for transportation equity assessment (Casas et al., 2009; Nahmias-Biran et al., 2014; El-Geneidy et al., 2016a; Legrain et al., 2016; Serulle and Cirillo, 2016; Deboosere and El-Geneidy, 2018; Lee and Miller, 2019; Chen et al., 2019). The focus of these studies is usually on analyzing the accessibility of car and transit (Iacono et al., 2010). For instance, Foth et al. (2014) studied accessibility to job opportunities in Ontario, Canada, and concluded that transit development increased accessibility, especially for socially disadvantaged groups. El-Geneidy et al. (2016a) analyzed equity of access to jobs by transit based on commute time in Toronto and Hamilton, Canada, and found that socially disadvantaged groups have equal or better access to jobs compared to other groups. A similar study was done by (El-Geneidy Levinson et al., 2016b) to analyze equity of access to jobs in Montreal, Canada, with commute time and transit fare. The results show that if commute time is considered as the only indicator, it inflates the number of accessible jobs compared to when travel cost is also factored in. The socioeconomic factors of low-income groups and their access to job opportunities by car and transit in the Washington metropolitan area were analyzed by Serulle and Cirillo (2016). They concluded that investment in the transit system better supports these individuals compared to strategies to decrease the operation cost of vehicles. Accessibility to jobs might not be consistent over time. Therefore, (Hu and Downs (2019) included temporal changes in job opportunities and workers to account for the job supply and worker demand dynamics over space and time. They analyzed job accessibility in Tampa Bay, Florida, using a modified gravity model and found that job accessibility varies significantly over time and space.

Access to Transportation Modes

The equity of a transit system can be also due to the supply of the transportation system or access to these modes (Preston and Rajé, 2007). Approaches such as transit coverage and transit supply index attempt to determine transport equity by analyzing the reachability of people to transit access points within a region based on the catchment area of transit stops/stations. The catchment area-based methods determine the equity of the provided service within an area. However, the accessibility approaches quantify the equity of access to opportunities by means of the provided transportation system with an assumption that the provided service is equitable. For example, Mamun and Lownes (2011) combined three accessibility measures of the local index of transit accessibility that includes frequency, route coverage, and capacity, transit coverage which is based on the catchment area of bus stops; and temporal coverage of the transit system and analyzed the equity of access of several vulnerable groups. Welch and Mishra (2013) proposed a method for transit equity by calculating the zonal connectivity index (Mishra et al., 2012) with catchment areas around housing units and considering the Gini index, applied it to the transit system in Washington-Baltimore region and identified areas with a less equitable transit system. Ricciardi et al. (2015) analyzed the equity of public transit systems in three different disadvantaged groups: households without a vehicle, low-income households, and elderlies in Perth, Australia, using transit supply index and Lorenz Curve. They found that transit equity in these groups is less than the general population. Specifically, 70% of the population only have 33% of the supplied transit system. The social exclusion caused by the transportation system in areas of Perth and Sydney, Australia, was investigated by Xia et al. (2016) using the Lorenz curve and Gini index. They calculated the transit supply index, normalized it by the population of each area to account for demand, and compared socioeconomic factors. The general finding was that while Perth has less provision, its transit system is more equitable than Sydney's transit. The equity of access to transit stops by a 1000m catchment area and quality of walking paths in Santiago, Chile, was explored by Tiznado-Aitken et al., 2018 (2018). Their findings indicate that 35% of municipalities in this city suffer from at least one of the two factors considered.

4.2.2. Transportation Diversity

Transportation infrastructure is a complex system and its resilience to manmade and anthropogenic disruptions should be viewed from the lens of several factors. Diversity is one of these influential factors, which requires a system to have a set of components that are functionally distinct (Murray-Tuite, 2006). Rahimi-Golkhandan et al. (2019) introduced two measures of *richness* and *evenness* to characterize transportation diversity. The richness of a transportation mode quantifies the provision of that mode in an area and evenness of a mode evaluates how it is distributed throughout an area. A transportation mode might have high richness in an area; however, this solely cannot ensure that people from across that area have equal access to it. This notion can be extended across modes. Holistically, when considering the equity of access to a transportation system, all modes should be provided and distributed equally – to the extent possible. Aggregating the richness and evenness of all modes determines the diversity of the transportation infrastructure in an area.

The richness of transit modes in an area takes into account the number of stops/stations and the number of lines in that area, which are normalized by the total number of lines and stops/stations. For roadways, bicycle routes, and walkways, the extent of these modes in an area determines their richness. Since evenness intends to capture the homogeneous distribution of each mode in an area, the standard deviation of the shortest distance of sub-areas in an area to each mode is used for this metric. Scaling richness and evenness values by area adds consistency and allows comparison of different parts of a community. A detailed description of transportation diversity, its characterization and quantification are provided in Rahimi-Golkhandan et al. (2019).

Since the spatial unit of analysis in this study is a zip code, the richness and evenness of road network, rail transit, bus system, bicycle routes, and walkways are measured for each zip code in NYC. Census blocks in each zip code are considered as a representation of sub-areas and the shortest distance of census block centroids to transportation modes is calculated. Spatial boundaries such as a zip code are hypothetical boundaries; so, people in one zip code can use the transportation system in adjacent zip codes, especially if the distance is shorter. This distance is more important specifically for those that are closer to the boundaries of a zip code; which is considered in the evenness calculation. Subsequently, these measures are aggregated by a Data Envelopment Analysis model (Charnes et al., 1978) to determine the transportation diversity of each zip code.

4.2.3. Equity of Access to Transportation Modes: Comparing Transportation Diversity with Other Methods

Research on access to transportation modes tends to focus on transit systems and analyzes access to rail transit stations and bus stops. Travel surveys that collect travel behavior data and socioeconomic information have been used in a few studies (Prasertsubpakij and Nitivattananon, 2012; Hess, 2012) to determine access to transit stops/stations or understand the perception of accessibility to these modes. The main limitation of such analyses is that the subjective nature of the collected data undermines the accuracy of the data and the absence of the transportation modes' data makes it difficult to use surveys for a reliable transportation equity assessment.

As described previously, catchment area methods such as transit coverage and transit supply index are the principal methods for assessing access to modes. Table 4.1 summarizes these methods and lists their advantages and disadvantages. Transit coverage determines what parts of an area are covered in the catchment area of a transit mode that is usually 0.25 mi for bus stops and 0.5 mi for metro stations. The transit supply index uses the same approach and includes the frequency of the transit service in each stop/station to account for the supplied service in each area. These methods are useful as they are computationally very efficient and the obtained results are easily interpretable. Moreover, these methods are suitable for larger spatial scales and for applications where the density of the transit system is low. However, these methods have limitations. The main drawback is that the catchment area approaches cannot distinguish between the accessibility of sub-areas in an area to a transit stop/station. The places that are outside of a catchment area are treated the same (having no access), and those locations that are in the catchment area are considered equal (having access). In other words, an area is classified as either with access or without access, but a detailed examination of the difference in access among locations is not well-understood. For example, Figure 4.1a illustrates how the catchment area/supply index approaches treat points in a region as having either access or no access; only point *A* has access to the mode whereas points *B-F* do not. However, it is clear that the accessibility of these points varies. Since transportation diversity quantifies the accessibility of all subareas in an area to transportation modes, it distinguishes between the access of all points based on the shortest distance of each point to that transportation mode.

Additionally, some parts of an area might be covered by the transit stop/stations outside of that area (Figure 4.1b) or conversely parts of a catchment area of a stop/station might be outside of the area of analysis (Figure 4.1c). Since catchment area methods depend on the number of transit stops/stations within an area, these issues can inflate/deflate the covered area; depending on the spatial unit of analysis, the magnitude of error can vary. For instance, in Figure 4.1b, based on the catchment area, only point *A* has access; however, points *C*, *F*, and *G* have access to stations outside of the area of analysis. The accessibility of other points in Figure 4.1b differ and these points are closer to stations outside of the area of analysis.

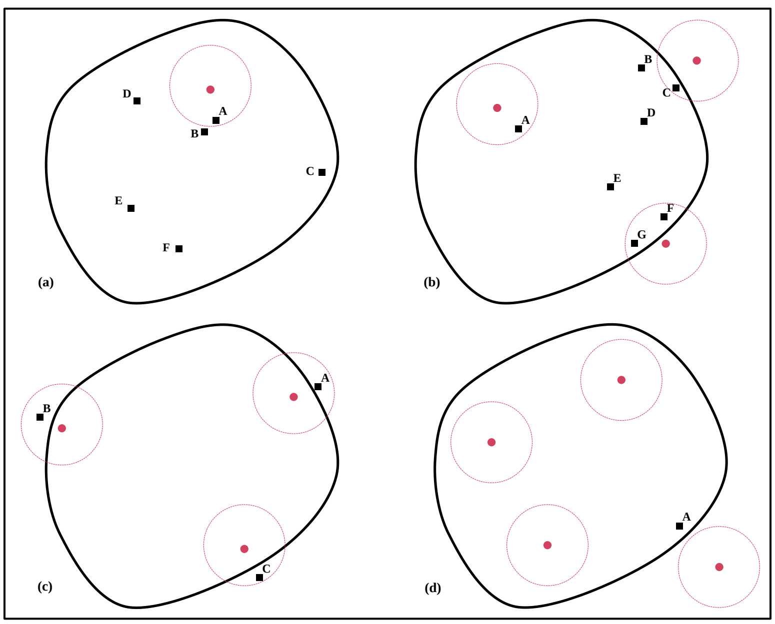

Figure 4.1: Limitations of the Catchment Area Approaches

Since evenness in transportation diversity is based on the shortest distance of a point to a transportation mode regardless of the area boundaries to better reflect reality, the transportation diversity approach considers the access of points *B* to *D* in Figure 4.1b to the stations outside of the area that these points are located in. Conversely, in Figure 4.1c, the coverage of stations within that area is deflated while they cover points (*A* to *C*) outside of that area. As mentioned earlier, the residents living near the boundaries of an area

Table 4.1: Comparison of Methods for Equity of Access to Transportation Modes

Method	Description	Advantages	Disadvantages
Travel Survey	Conducting a survey to collect travel behavior and socioeconomic data. The analyses on transportation equity are in the form of descriptive statistics (Hess, 2012; Prasertsubpakij and Nitivattananon, 2012) or using regression methods.	• Little computational labor • General assessment of transportation service from users' perspectives, and their feedback on strengths and weaknesses of the service	• No/limited transportation modes' data • Difficult to use the results for transportation planning/development • Responses are subjective that can affect the quality of the collected data • Sample size influences the responses. • Collecting sufficient number of responses can be challenging.
Transit Coverage $\sigma = \frac{n_s \pi r^2}{A}$	Walking distance catchment area of transit stops/stations (Mamun and Lownes, 2011; Zakowska and Pulawska, 2014; Welch and Mishra, 2013).	• Computationally efficient • Results are easily interpretable • Suitable for comparison of large spatial units • Suitable for areas with low density of transit stops/stations • Determines the walking distance area covered by transit systems	• Cannot distinguish the difference in the access to transit stops/stations • Relies on the number of stops/stations inside an area. • Parts of a catchment area of a stop/station might be outside of the boundaries of the spatial unit of analysis or some parts of the spatial unit of analysis might be covered by stops/stations outside of it. The magnitude of error in the coverage can vary depending on the scale of the spatial unit of analysis. • Does not account for access to stops/stations outside of an area, which might be more realistic options for residents closer to the boundaries of an area. • Catchment areas of stops/stations might overlap which can inflate the covered area. • Catchment area generally only considers walking distance; transit users might use other modes to reach a stop/station. • Limited to transit systems
Supply Index $SI = \sum_{i=1}^{n_s} \sigma_i f_i$	Considers transit stops/stations as the points of interest in an area and determines transit supply based on: (a) the frequency of transit service in all stops/stations, (b) the walking distance catchment area of all stops/stations. Combined with socioeconomic data, supply index determines transit equity (Ricciardi et al., 2015; Xia et al., 2016; Chen et al., 2019).	• Improved Catchment Area to include the frequency of service	• Similar to Catchment Area
Transportation Diversity	Considers the availability of all transportation modes and their distribution in an area	• Distinguishes between the accessibility of sub-regions in an area • Accounts for accessibility to modes outside of an area • Not limited to transit systems, applicable to all modes. • Considers both the availability and distribution of modes for equity assessment.	• Computationally intensive compared to other approaches • Only considers the physical infrastructure of transportation modes • Evenness calculation is based on Euclidian distance

$\boldsymbol{\sigma}$: transit coverage $\boldsymbol{n_s}$: number of transit stops/stations $\boldsymbol{r}$: radius of a stops/stations catchment area $\boldsymbol{A}$: area $\boldsymbol{SI}$: supply index $\boldsymbol{f_i}$: frequency of transit service at stop/station i

likely use the transportation modes in adjacent areas if the distance is shorter which is a condition that cannot be captured with catchment area approaches, but transportation diversity overcomes it by considering the shortest distance (access of point *A* to a station outside of the area in Figure 4.1d). Further, since access to transit systems can be by walking, biking, or driving, the common walking distance catchments, which is the basis for the calculation of the transit coverage, neglects access by modes other than walking. Another major limitation of these methods is that they are only able to analyze the equity of access to transit systems that can hardly be generalized for equity assessment of other modes.

Catchment area approaches are useful to determine the equity of access to transit modes in a broad perspective, especially in larger spatial units. Transportation diversity offers an alternative approach that can distinguish the equity of access to modes at a more fine-grained scale that allows identifying sub-areas that require improvement (Table 4.1). In addition, transportation diversity is not limited to transit systems. Since both the provision of all transportation systems and their distribution are important for equity of access to transportation modes, transportation diversity considers both factors. In addition, the evenness metric in transportation diversity determines the shortest distance of all sub-areas in an area to a transportation mode, making it easy to compare different sub-areas and distinguish those that have a longer distance to transit modes for improvement. Further, the evenness calculation is not bounding access of sub-areas to modes that are within an area, so it is a more realistic approach to determine the equity of access to transportation modes. Hence, the transportation diversity approach provides an alternative way to investigate the equity of access to transportation modes more comprehensively. Here, transportation diversity is characterized in New York City zip codes that allows comparing them based on transport equity and the relationship between transport equity and transport usage and socioeconomic factors.

4.3. Methodology

4.3.1. Socioeconomic Investigation

The transportation diversity approach delineates equity of access to transportation modes from a spatial viewpoint by comparing different areas. To explore the relationship between transportation diversity and other factors and analyze if areas with similar transportation diversity have comparable socioeconomic and transport usage characteristics, zip codes will be grouped in quartiles based on transportation diversity. To investigate the equity of access for specific groups for a categorical equity analysis (Church et al., 2000), two sets of important indicators commonly used in transportation equity assessments are examined. The first set of indicators are transport related factors of *commute mode* and *commute time* that help to analyze the relationship between transport equity and transportation system usage. Commute mode and commute time will be compared in quartile groups by descriptive statistics to understand the distribution modes in each quartile and the difference in the commute time between quartiles. The second set of indicators are socioeconomic factors of *average household income*, *vehicle ownership (at least one car), poverty*, and *ethnicity*. These factors describe the socioeconomic status of people and allow investigating the relationship between transport equity and socioeconomic status. Similarly, these factors are compared among quartile groups to determine the relationship between socioeconomic factors and transportation diversity by descriptive statistics.

We considered transport usage factors along with socioeconomic factors to explore the likely social exclusion caused by transport inequity. Therefore, we analyzed the relationship between income, vehicle ownership, and drive/carpool commute mode to determine if transportation diversity and transport equity influence these factors. Studies on equity of the transportation system among disadvantaged groups often contrast the equity of these groups with the rest of the population in an urban area. However, people that are socioeconomically deprived might have more/less-equitable access to a transportation system depending on their home location, as shown in some studies such as El-Geneidy et al. (2016a). Hence, an alternative approach is to group individuals based on the level of transport equity and compare the socioeconomic factors within and between groups for a more detailed analysis. Therefore, for poverty, we classified zip codes as poor and non-poor and compared their vehicle ownership and commute time within their quartile group and between quartile groups. These comparisons help identify the differences between poor and non-poor groups that have a similar transport equity and allows differentiating between poor and non-poor groups that have different transport equity. Similarly, for ethnicity, vehicle ownership, transportation mode usage and commute time are contrasted among transportation diversity quartiles and ethnic groups to understand the differences among ethnic groups within and between quartiles.

4.3.2. Transportation Diversity and Mode Split

Limited access to transportation modes leaves residents with fewer options for mobility. This limited access could perhaps lead to longer travel time for those living in areas with less access to transportation modes. For workers, this limited access could cause a longer commute time. Additionally, drive/carpool is an unsustainable commute mode (Kim and Ulfarsson, 2008; Ibraeva et al., 2020) that can have several social, economic, and environmental impacts, especially if it is imposed on residents due to inadequate development of other transportation modes. To explore the relationship between modal share and transportation diversity and how this relationship can influence factors such as commute time and vehicle ownership, we use the k-means clustering method. Regardless of transportation diversity, zip codes are clustered based on commute modes. If zip codes with a similar distribution of commute modes also have a comparable transportation diversity, perhaps it is an indirect influence of the equity of access to transportation modes on mode choice, commute time, and vehicle ownership. Subsequently, the inequitable access to transportation modes can be explored from social exclusion and sustainable development perspectives.

k-means is an unsupervised clustering method that groups *n* data points of *X* (x_i, $i=1, 2, 3, \ldots, n$) into *k* discrete clusters of *C*. Each C_j cluster in the cluster set has n_j data points and every cluster is described by μ_j, $j= 1, \ldots, k$, which is the centroid of data points in C_j. The k-means algorithm takes a random centroid and minimizes the distance between data points within a cluster and the cluster centroid by:

$$Min\,J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i - \mu_j \right\|^2 \qquad (1)$$

To determine the optimum number of clusters, *Min J* is quantified for a range of k values that shape to an elbow curve. The rate of dispersion between k values on the elbow curve determines the optimal number of clusters.

In addition to clustering zip codes, the data of home-work distance of zip codes is also analyzed to investigate the relationship between the identified clusters and the distance to the workplace as a representation of access to opportunities.

4.3.3. Study Area: New York City

The approach of transportation diversity for assessing the equity of access to transit modes is applied to NYC. With 8.6 million residents, NYC has the highest population among cities in the US. The transportation system of NYC has multiple modes that make this city a practical case for the analysis of transportation equity by considering different modes. Further, NYC is a coastal city that has gone through natural disasters such as Hurricane Irene and Hurricane Sandy in recent years. The historical data and the empirical evidence of the impact of these disasters on the transportation system and mobility in NYC provide a means to investigate the influence of equity/inequity of access to transportation modes on the mobility and connectivity of people after an extreme event. The linkage between transportation diversity, socioeconomic and transport related factors, as well as the impact of natural disasters on mobility, could potentially provide implications for adaptation of the transportation infrastructure to natural disasters while incorporating equity of access to transportation modes in resilience planning. The data of transportation infrastructure is obtained from the NYC Department of Transportation. We collected the socioeconomic factors from the American Community Survey and derived the data of home-work distance from the Longitudinal Employer-Household Dynamics of the US Census Bureau.

4.4. Results

4.4.1. Transportation Diversity in NYC

The richness and evenness of transportation modes are measured in all zip codes following the approach (Rahimi-Golkhandan et al., 2019). Figures 4.2a and b demonstrate these values for the bus system. It is clear that the bus system is not equally provided throughout the city and people do not have equal access to this mode in different zip codes. The richness and evenness of all modes are aggregated and transportation diversity is characterized (Figure 4.2c), which indicates that the transportation system is not equitable across the community. While zip codes in Manhattan and Brooklyn have higher transportation diversity, the zip codes in Staten Island, Queens, and Bronx experience a lower transportation diversity. Identifying zip codes with lower transportation diversity assists in analyzing how the transportation system is spatially equitable. The richness and evenness values of each mode in each zip code show which modes require enhancement. In zip codes with a low transportation diversity, the underdeveloped modes that caused a low transportation diversity can be further analyzed to identify whether the richness, the evenness, or both should be enhanced to improve the equity of access to that mode.

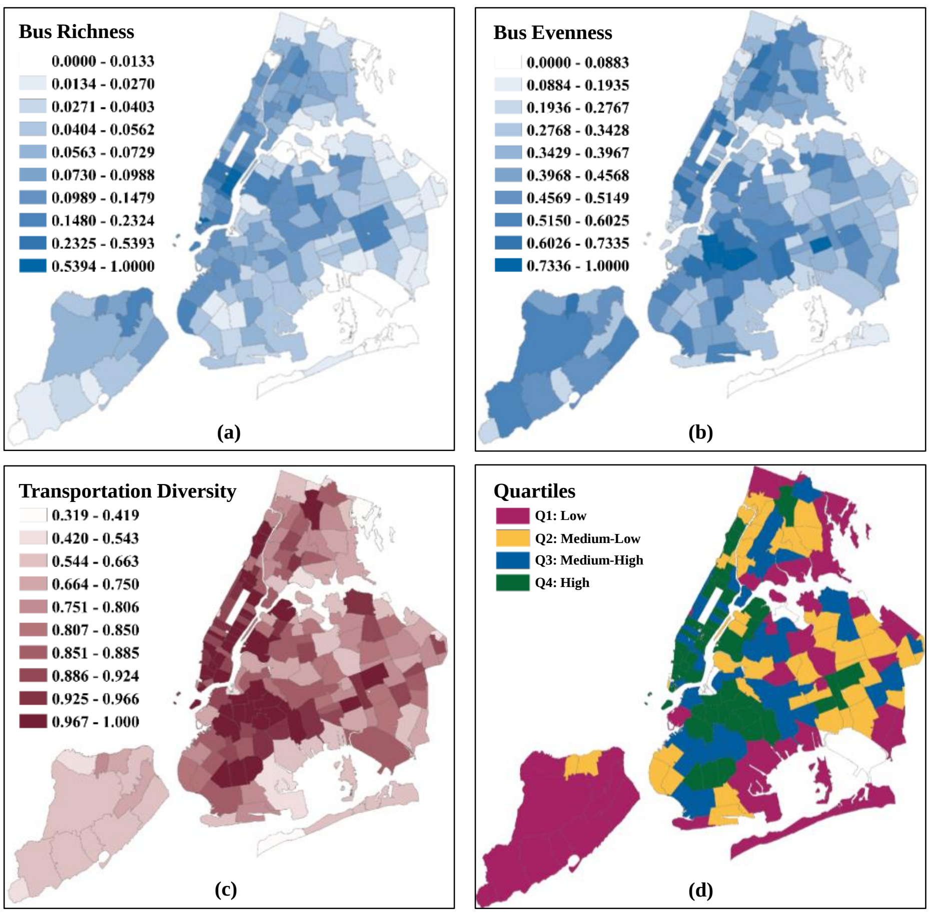

Figure 4.2: (a) Bus System Richness, (b) Bus System Evenness, (c) Transportation Diversity, (d) Zip Code Quartiles

4.4.2. Socioeconomic Analysis

4.4.2.1. Income and Vehicle Ownership

Based on transportation diversity, we grouped zip codes into four quartiles of L (*low)*, ML (*medium-low)*, MH (*medium-high)*, and H (*high)* (Figure 4.2d). Comparing quartiles based on their average household income (Figure 4.3a) indicates that quartiles with lower transportation diversity (L and ML) generally have lower income. Commonly, income is expected to increase vehicle ownership (Paulley et al., 2006). However, there is a weak correlation (*r*= 0.15, *p*<0.05) between income and vehicle ownership in zip codes (Table 4.2). When vehicle ownership is compared between quartiles, there is a negative correlation between transportation diversity and vehicle ownership (*r*= -0.56, *p*<0.05) (Table 4.2). As transportation diversity increases from L to H, vehicle ownership decreases (Figures 4.3b-c). This decreasing trend suggests that although people in low transportation diversity quartiles have a lower income, they need to have personal vehicles for their mobility needs to compensate for the limited transportation options. Currie and Delbosc (2009) studied vehicle ownership in low-income groups and argued that while not having a car causes mobility issues, vehicle ownership in low-income groups might be imposed on them.

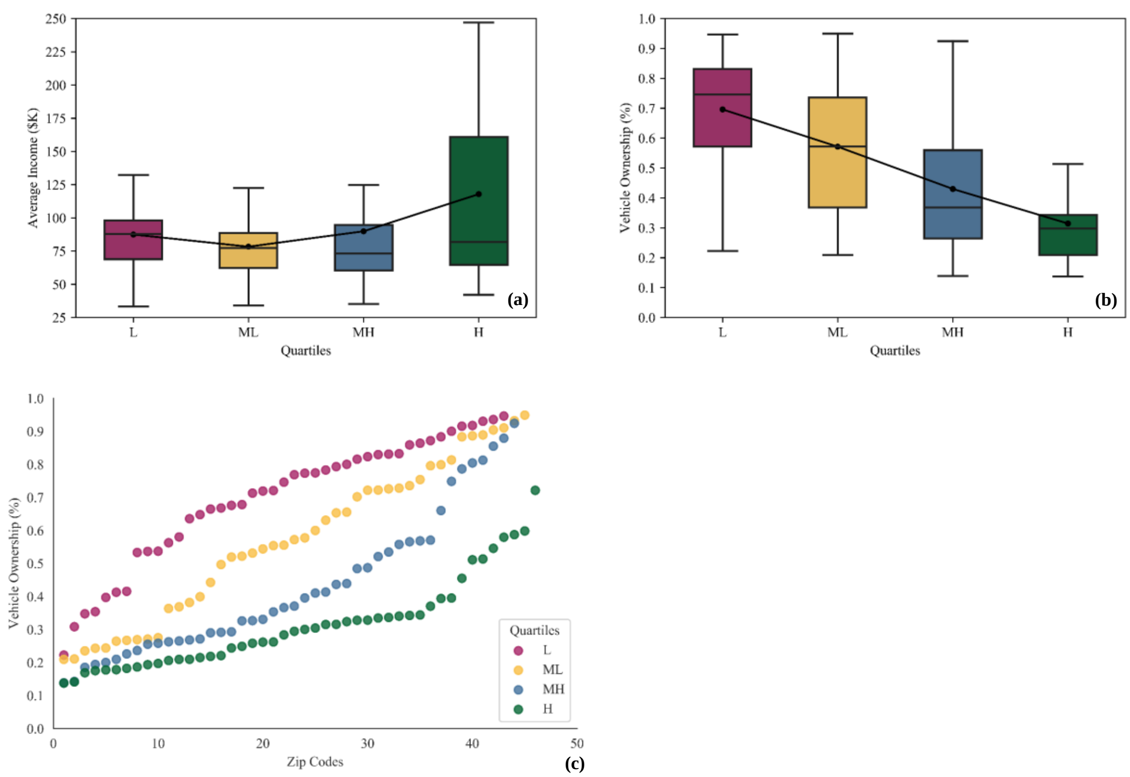

Figure 4.3: (a) Income in Zip Code Quartiles, (b) Vehicle Ownership in Zip Code Quartiles, (c) Vehicle Ownership in Zip Codes

Thus, the higher vehicle ownership in L and ML can be viewed as an imposed ownership. On the other hand, since transportation diversity is higher in MH and H, it reduces the necessity to own a car for mobility; therefore, vehicle ownership in these groups is likely for convenience.

Table 4.2: Pearson Correlation between Factors

Factor a and Factor b	***r***	***p*-value**
Income and Vehicle Ownership	0.15	0.00*
Vehicle Ownership and Drive/Carpool	0.96	0.00*
Transportation Diversity and Vehicle Ownership	-0.56	0.00*
Transportation Diversity and Average Commute Time	-0.45	0.00*

**p<0.05.*

4.4.2.2. Commute Mode

Transportation diversity indicates the provision and distribution of transportation modes. In each mode, these factors determine the equitability of that mode is in an area and might influence its usage. The distribution of commute modes in zip codes of all quartiles (Figure 4.4a-e) reveals that drive/carpool is the dominant mode of commute among zip codes of L and ML, while for MH and H metro is the main commute mode. As transportation diversity increases from L to H, drive/carpool and bus usage decrease while usage of the metro, biking, and walking increases. The high level of drive/carpool in L and ML along with higher vehicle ownership in these quartiles suggests that this vehicle ownership is needed for routine activities such as commuting. The strong correlation (r= 0.96, p<0.05) between vehicle ownership and drive/carpool supports that vehicle ownership in quartiles with low transportation diversity is likely imposed on them (Table 4.2). The lower volume of drive/carpool and higher use of the metro, walking, and biking in MH and H demonstrate that access to these modes decreases the need for vehicle ownership for daily basis activities. The radar chart of Figure 4.4f demonstrates the distribution of all commute modes in each quartile group except bicycle that has a lower usage in all quartiles. It indicates that drive/carpool and metro are the dominant modes of commute and as transportation diversity increases from L to H, the main commute mode shifts from drive/carpool to metro. In addition, while bus and walk are not the main modes of commute in any of the quartile groups, as transportation diversity increases, the usage of bus decreases from L to H while walk increases.

4.4.2.3. Commute Time

Commute time is a factor that can be directly influenced by the transportation system. Although the transportation system is not the only factor that can impact commute time, a negative correlation (r= -0.45, p<0.05) between transportation diversity and commute time (Table 4.2) reveals the effect of an equitable multimodal transportation system on commute time. Figure 4.5a-b demonstrates commute time in quartiles.

This comparison shows that L has the highest commute time and as transportation diversity increases in quartiles, commute time declines. The relationship between transportation diversity, vehicle ownership, drive/carpool as a commute mode, and commute time is illustrated in Figure 4.5c. It can be seen than zip codes with higher vehicle ownership and drive/carpool are mainly in L and ML with longer commute time than zip codes in MH and H. The distribution of jobs across the city and consequently, the home-work distance could be an important factor in commute time. However, vehicle ownership for commuting in households with lower income in zip codes that have low transportation diversity highlights the consequences of an inequitable transportation system.

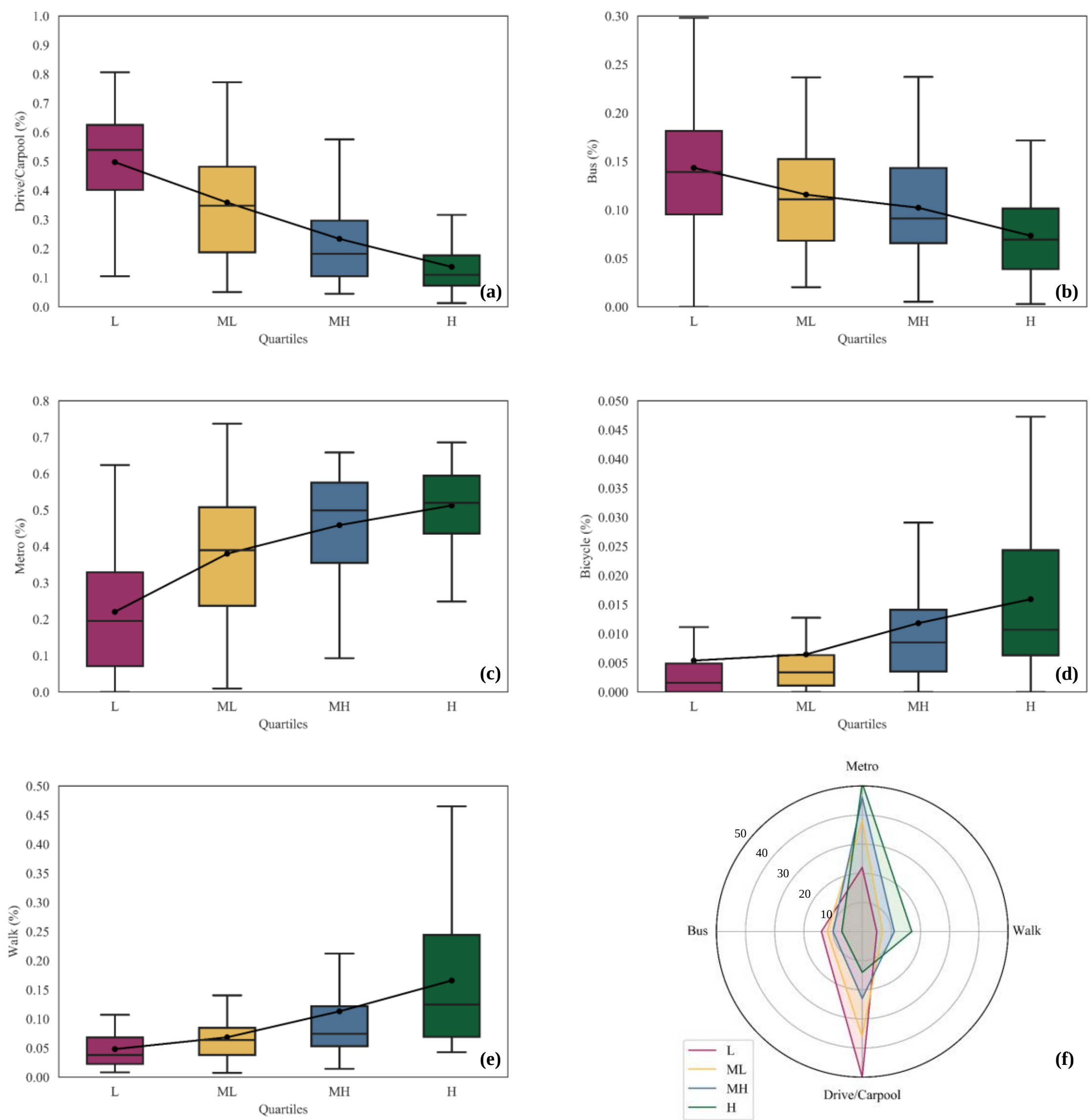

Figure 4.4: Commute Mode in Quartiles

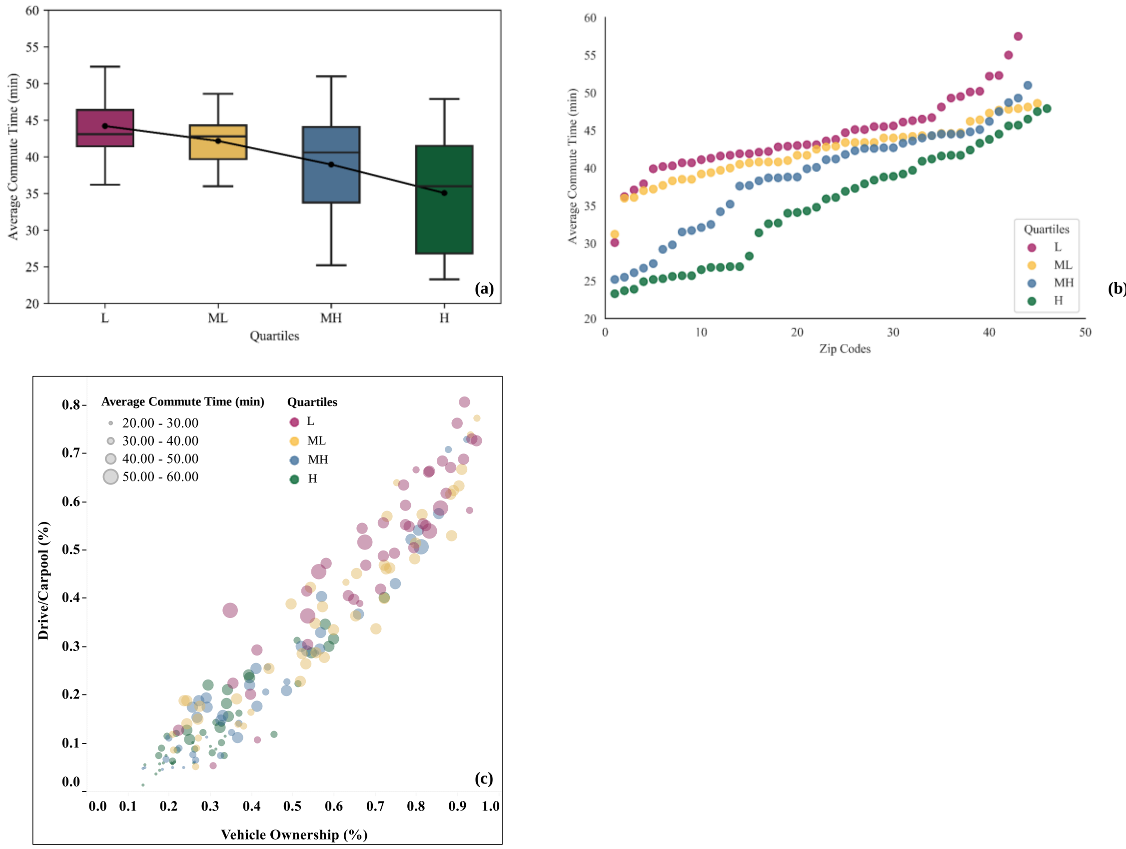

Figure 4.5: (a) Commute Time in Zip Code Quartiles, (b) Commute Time in Zip Codes, (c) Commute Time According to Vehicle Ownership and Drive/Carpool

4.4.2.4. Poor and Non-Poor

Preston and Rajé (2007) differentiate between social exclusion and income-based deprivation. They highlight that the transportation system influences the redistribution of income since a high-income person can be socially excluded due to limited access to opportunities, infrastructure, and activities. Therefore, comparing people based on the equity of the transportation system can better identify the ones that experience transport inequality and the social exclusion associated with the transportation system. In each quartile, zip codes are classified as poor and non-poor based on the ratio of the residents under poverty. Similar to previous research (Wang et al., 2018), if at least 30% of the population of a zip code is under the poverty line, it is considered as a poor zip code. A comparison of vehicle ownership in poor and non-poor groups in quartiles (Figure 4.6a) shows that as transportation diversity increases, vehicle ownership decreases among non-poor groups. However, there is not a significant difference between vehicle ownership in poor groups in all quartiles. Moreover, the difference in the vehicle ownership of poor and non-poor groups in L and ML is significant with non-poor being higher; this difference becomes smaller in MH and H, but still, non-poor groups have higher vehicle ownership in these quartiles. Despite lower transportation diversity in L and ML, the non-poor group afford to own a vehicle to fulfill their mobility needs. However, poor groups in these quartiles likely suffer more than non-poor groups from an inequitable transportation system and a lower rate of having a personal vehicle. Although poor groups across all quartiles probably have difficulty with the expenses of owning a vehicle, the ones that are in MH and MH likely have fewer problems in their mobility compared to the poor groups in L and ML.

The comparison of commute time in poor and non-poor groups (Figure 4.6b) demonstrates that except in ML that the average commute time is very close for both poor and non-poor groups, in other quartiles poor groups have a higher commute time than non-poor groups. In addition, commute time for both poor and non-poor groups declines as transportation diversity improves. Demonstrating that in low diversity quartiles non-poor groups have longer commute time than similar groups in other quartiles and likely imposed vehicle ownership, confirm that social exclusion and income-based deprivation differ. However, the comparison of poor and non-poor groups within and between quartiles underlines the greater impact of lower transportation diversity on poor groups.

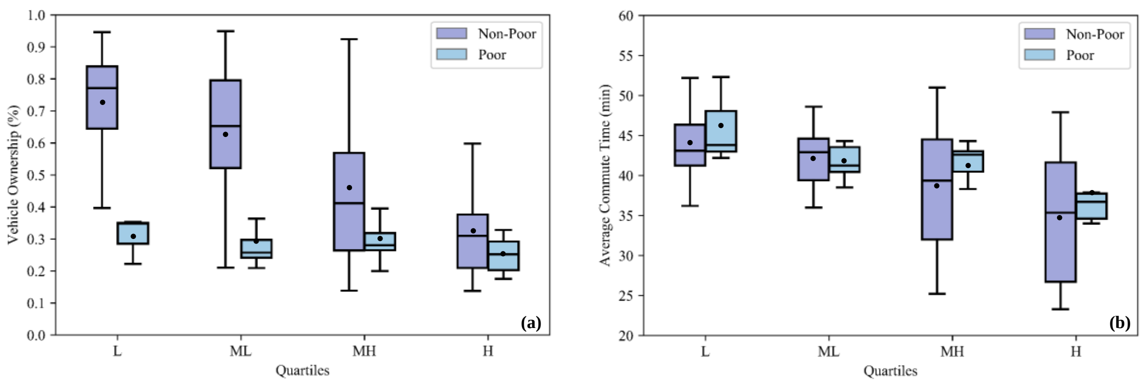

Figure 4.6: Vehicle Ownership in Poor and Non-Poor Groups, (b) Commute Time in Poor and Non-Poor Groups

4.4.2.5. Comparison of Race and Hispanic Origins

Similarly, zip codes are classified by the majority of their population (at least 50%) in three groups of non-Hispanic black, non-Hispanic white, and Hispanic origins; only zip codes with the majority of one of these groups are analyzed and other zip codes are excluded. In addition, very few zip codes had a majority of the Asian population; therefore, these zip codes are also excluded. The relationship between vehicle ownership and commute time in the three groups and their corresponding transportation diversity quartiles are illustrated in Figures 4.7a and b. In general, zip codes with low vehicle ownership and high average commute time are mainly the ones with a majority Hispanic and black population that are distributed among all transportation diversity quartiles. However, zip codes that have both high vehicle ownership and commute time mostly have a majority back or white population, which are predominantly from L and ML. Among these zip codes, the ones with higher commute time and vehicle ownership are the zip codes with the mostly black population. This analysis suggests that the low transportation diversity in L and ML impacts the zip codes with the majority black populations more than other groups. A similar pattern can be seen in the relationship between drive/carpool and commute time (Figure 4.7c-d). In general, black and Hispanic zip codes have higher commute time. The majority black or white zip codes have the highest commute time and drive/carpool; however, black zip codes have higher commute time when the drive/carpool is the same. Similar to vehicle ownership, these zip codes are from L and ML, indicating that the inequity of access to transportation modes in L and ML affects zip codes with the majority black population the most. Again, the majority of white zip codes with high commute time and drive/carpool are predominantly from L and ML.

In the bus system (Figure 4.7e-f), white zip codes mainly have a lower usage and lower commute time than other groups. Zip codes with majority black and Hispanic populations overall have a high commute time. Furthermore, zip codes of majority black and Hispanic populations are mostly the ones with high bus usage and a high commute time with black zip codes having a higher commute time. Quartile diagram of the bus system shows that zip codes in L and ML rarely have low commute time and the top right side of the diagram (Figure 4.7f) is dominated by zip codes in L and ML. Figure 4.7g that shows metro system usage in race groups indicates that commuters in black and Hispanic zip codes have a higher commute time. Again, black zip codes have a higher commute time compared to other groups. Further, Figure 4.7g reveals that zip codes that have high metro usage and commute time are generally Hispanic and black zip codes regardless of their transportation diversity quartile. Figure 4.7h also shows that since the metro transit is not well developed in L and ML, these zip codes are mostly in the low usage half of the diagram. In general, diagrams in Figure 4.7 indicate that zip codes with a majority black and Hispanic population have higher commute time and are mostly in L and ML. In addition, when these groups within L and ML are compared, white zip codes have a shorter commute time than black and Hispanic zip codes.

4.4.2.6. Commute Mode Distribution and Transportation Diversity

The clustering of zip codes based on their commute mode and the optimal number of clusters are illustrated in Figure 4.8. The map of zip code clusters shows that in general, the cluster groups are very similar to transportation diversity quartiles regarding their spatial distribution. Zip codes in Staten Island, Queens, Bronx, and the southern part of Brooklyn which are in zone A and B are mostly in L and ML of

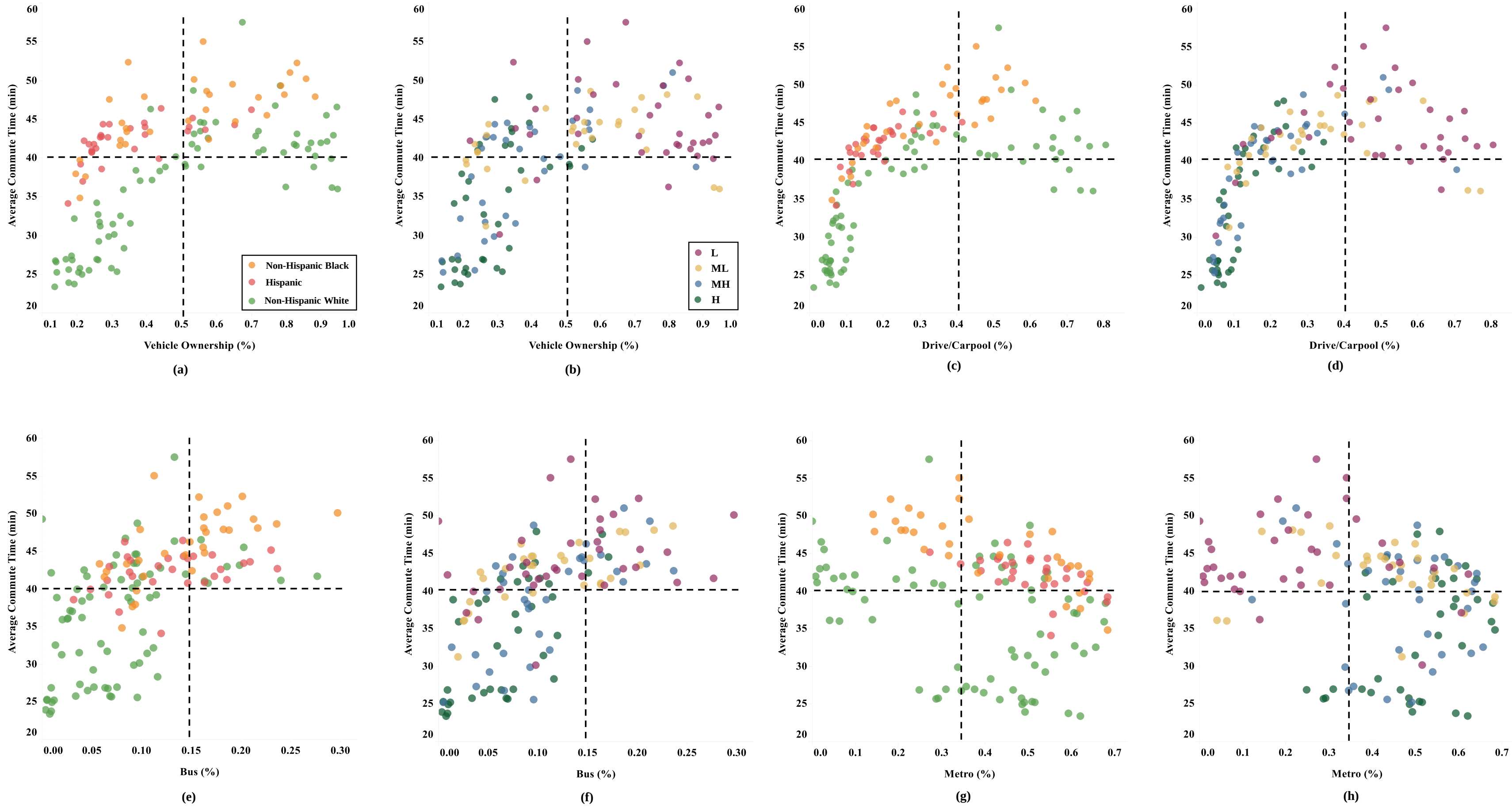

Figure 4.7: Comparison of Zip Codes Based on Race and Hispanic Groups, and Transportation Diversity Quartiles: (a-b) Vehicle Ownership and Commute Time, (c-d) Drive/Carpool and Commute Time, (e-f) Bus and Commute Time, (g-h) Metro and Commute Time

transportation diversity, while zip codes in zones C and D which are located in Manhattan and the northern part of Brooklyn are mainly grouped in MH and H of transportation diversity. A comparison of the four clusters based on transportation diversity, vehicle ownership and commute time is shown in Figure 4.9. This result highlights the similarity between the clusters and quartiles. Higher access to other modes reduces the use of personal vehicles (Papaioannou and Martinez, 2015). Zip codes in zones A and B have lower transportation diversity and in turn, limited equitable access to other transportation modes. This analysis illustrates the relationship between transportation diversity and commute mode choice. Further, given the importance of the transportation system in the travel behavior of individuals, it can be implied that transportation diversity influenced commute mode choice and consequently vehicle ownership and commute time. Albeit, clearly other factors such as land use, population, and availability of jobs are influential too.

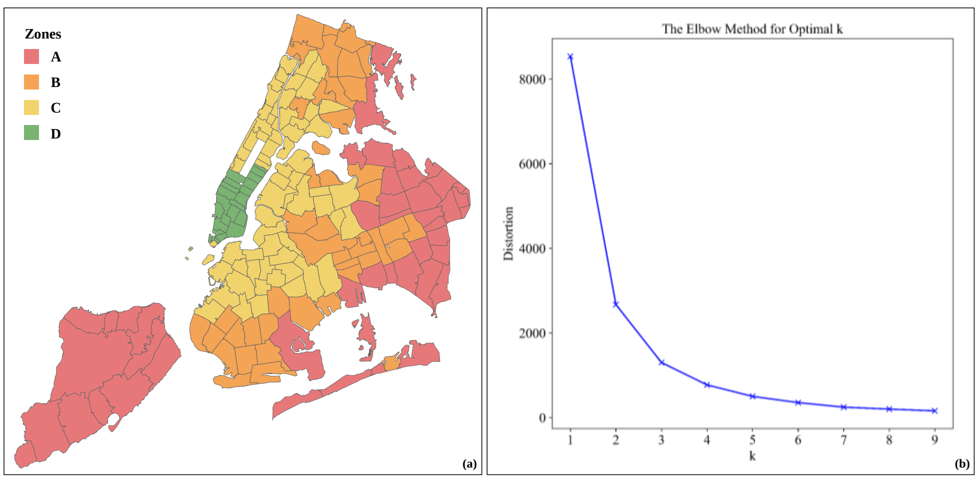

Figure 4.8: (a) Zip Code Clusters, (b) Optimal Number of Clusters

4.5. Discussion

4.5.1. Transport Inequality and Social Exclusion

The results showed the relationship between the equity of access to transportation modes and socioeconomic and transportation related factors. They also suggest that transportation diversity is likely an important element that governs factors such as mode choice and consequently vehicle ownership and commute time. The transportation system has been shown to hinder equitable access to opportunities and services such as jobs, grocery stores, and hospitals. Higher mobility is often associated with higher accessibility. However, imposed vehicle ownership (e.g., Currie and Delbosc, 2009) in low-income households that have limited access to infrastructure and facilities can cause a higher level of mobility due to transport inequity (Markovich, 2013). The short-range activity of high-income individuals was shown in

Lotero et al. (2016). The comparison of vehicle ownership and income in transportation diversity quartiles suggests that the lower income and higher vehicle ownership in L and ML groups is likely an imposed vehicle ownership.

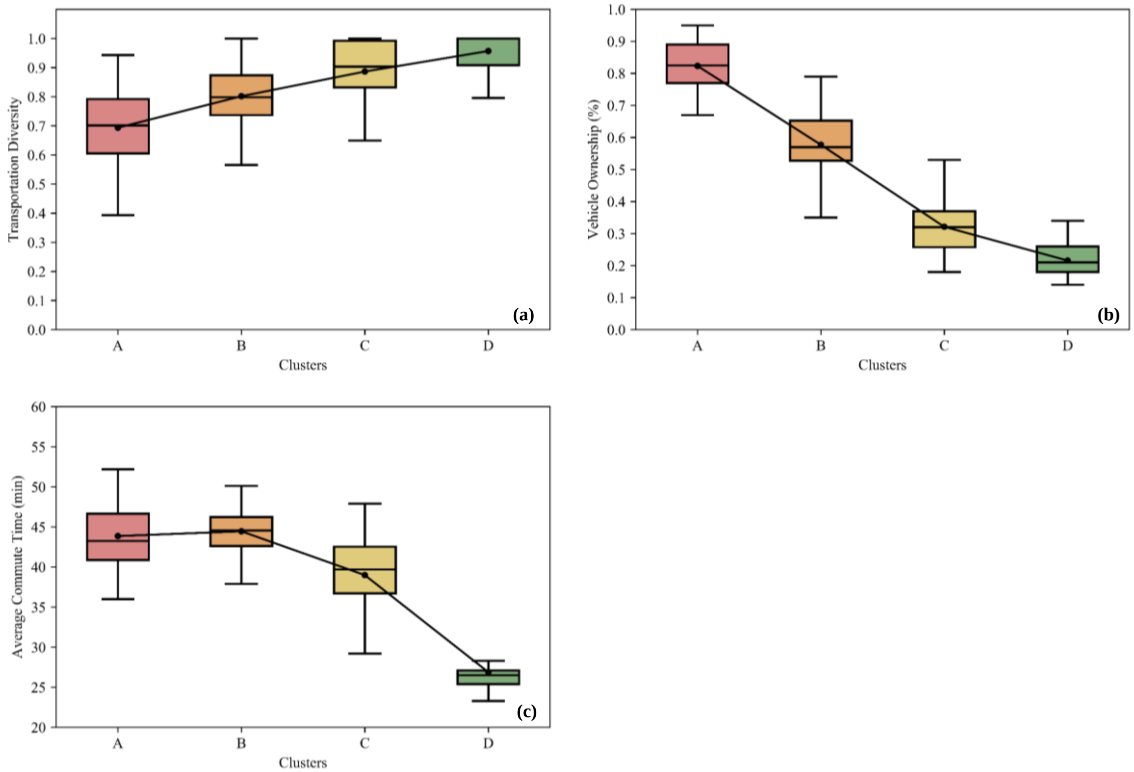

Figure 4.9: (a) Transportation Diversity in Clusters, (b) Vehicle Ownership in Clusters, (c) Commute Time in Clusters

The commute distance of residents in zip codes of NYC is shown in Figure 4.10 in three classes of less than 10 miles, between 10-24 miles and between 25-49 miles from the U.S. Census Bureau Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics. These maps indicate the percentage of the workers of a zip code in each class. The workers who live in Manhattan and Brooklyn have shorter commute distance. Conversely, workers in Staten Island, Queens, and Bronx commute longer distances. The longer commute distance of workers living in these areas is intensified by the lower transportation diversity of these areas. This relationship shows the higher level of mobility in low-income workers compared to high-income workers living in areas with a higher transportation diversity. In addition, it confirms that a higher level of mobility of workers living in areas with a lower transportation diversity is due to transport inequality and limited access to infrastructure and opportunities. The hidden burden of this transport inequity and its negative compounding impacts can be seen in the cost of vehicle ownership, longer commute time, and the cost of time for residents in these zip codes. In other words, due to transit inequity, residents in L and MH zip codes are forced to bear the expenses of owning a car despite their lower income. These expenses aggravate the financial situation of these residents. Additionally, the longer commute time of these residents decreases their available time for other activities compared to those in MH and H and the cost of time lost in longer commutes is higher for residents in L and ML groups. These factors linked with transport inequity contribute to the social exclusion of residents in L and ML zip codes and make it difficult to decrease *poverty* and *inequality* that are two key goals adopted by the United Nations for sustainable development (UN, 2015). This inequality of access to transportation modes not only can cause social exclusion in normal situations, but it could also potentially pose more difficulties in emergency situations when the access to transportation modes is likely reduced by failures in the transportation system.

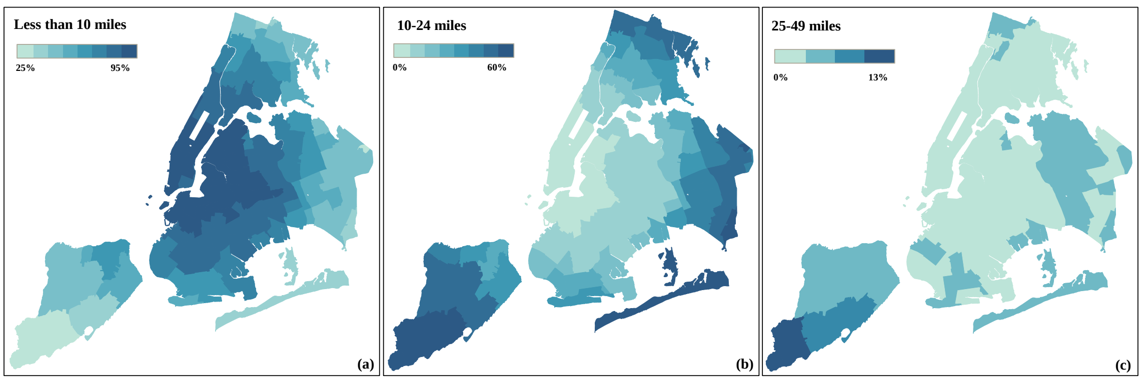

Figure 4.10: Commute Distance Classes: (a) Less than 10 Miles, (b) Between 10 and 24 Miles, (c) Between 25 and 49 Miles

4.5.2. Post-Disaster Transport Equity

If a natural hazard causes disruptions in the transportation system, transport inequity would have a greater impact on the mobility of people living in low diversity zip codes. Rahimi-Golkhandan et al. (2020) analyzed the impact of transportation diversity on mobility patterns in NYC after Hurricane Sandy and showed that residents who live or have activities in zip codes with lower transportation diversity struggled to maintain their mobility patterns and their recovery to pre-Sandy mobility patterns took longer. The reason for the less robustness in mobility patterns and longer recovery time can be attributed to little transport options. Specifically, commuting as a routine mobility need is likely to be impacted in low diversity zip codes due to limited alternative transportation modes and their longer commute distance. The disruption in commute patterns and the difficulty of reaching the workplace after an extreme event can affect employment (Kontou et al., 2017a). Public transit accessibility has been shown to decrease unemployment (Sanchez, 1999). Tyndall (2017) studied the effect of public transit accessibility in NYC after Hurricane

Sandy and found that low accessibility to public transit caused an increase in the unemployment rate. Hajhashemi et al. (2019) investigated the influence of Hurricane Sandy recovery timeline on commuter's travel patterns and post-disaster adaptation. The result of the survey they used reveals that nearly 60% of the commuters who live far from work canceled work. The commute distance maps in Figure 4.10 show that workers with the farthest distance to their workplace live in areas with lower transportation diversity. Therefore, the failure in the less developed transportation system in such areas after Hurricane Sandy left these workers with even more problem for commuting.

A possible gas shortage caused by disturbances like natural hazards can severely affect mobility patterns. For example, (Kontou et al., 2017b) used a survey to analyze the changes in the commute patterns in NYC after Sandy. They reported that restrictions in gas purchase impacted commute patterns. The majority of commutes in L and ML that have low transportation diversity drive/carpool; thus, a disaster-induced fuel restriction can affect these groups as they have limited transport options and rely on personal vehicles for commuting. Since these individuals have a lower income, they are more vulnerable to such events. Telecommuting (Kontou et al., 2017a, 2017b) can be an alternative but requires power and the internet which might also be impacted by the disaster. Furthermore, these individuals generally have a lower income; so, telecommuting might not be a feasible option for their likely low-paid jobs.

FEMA's Individual and Household Program (IHP) that provides financial assistance to individuals and households affected by disasters can be viewed as a proxy for the magnitude of damage. Figure 4.11 shows the major IHP financial help in zip code in NYC after Hurricanes Irene and Sandy that are overlaid on the map of transportation diversity quartiles. For both hurricanes, the zip codes with major IHP assistance are in L and ML. Since major damages have been in areas with less equitable transportation infrastructure, the damaged transportation infrastructure exacerbates the mobility of people in these areas. Zip codes in the Rockaway Peninsula are in the L of transportation diversity. A survey of residents in the Rockaway area four months after Hurricane Sandy (Subaiya et al., 2014) showed that 60% of the households in this area lost their car and 13% lost their jobs and after three months 32% of households still had difficulty buying food. The results of this study also show that people from lower socioeconomic statuses in the Rockaway area were more concerned about buying food from outside of the area, which could partly be due to the deteriorated transportation system. While Rockaway Peninsula was one of the most impacted areas after Hurricane Sandy, the post-Sandy recovery efforts were more focused on areas like Manhattan that show the disproportionate allocation of resources for recovery (Subaiya et al., 2014). This unequal distribution of post-disaster recovery resources could be because of a plan that recognizes areas with a more vulnerable infrastructure system. Thus, improving the diversity of the transportation system in low diversity zip codes not only reduces the transport inequity gap in normal situations, but it can also enhance the resilience of mobility patterns by providing accessible multimodal transportation system.

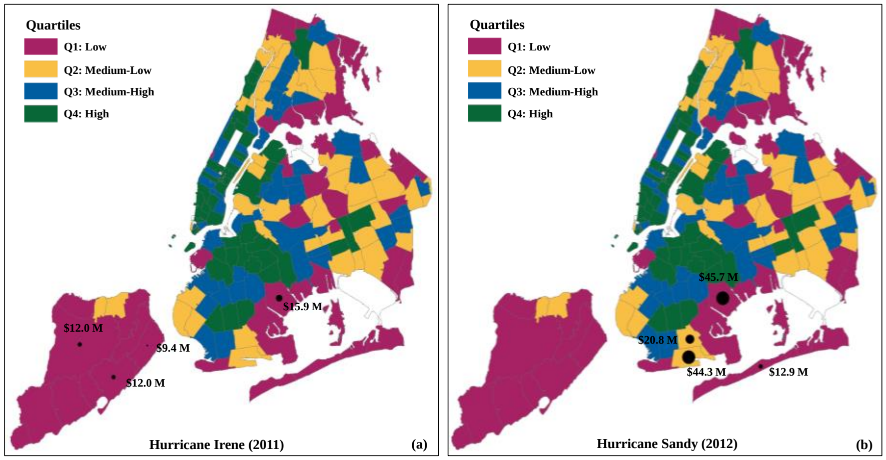

Figure 4.11: FEMA's IHP in Zip Codes: (a) Hurricane Irene, (b) Hurricane Sandy

4.5.3. Transportation Diversity Enhancement

The transportation diversity approach identifies the modes that need to be enhanced in each zip code to improve the equity of access to transportation modes and the resilience of this infrastructure. However, developing all modes in all areas of an urban community is bounded by several constraints that make such improvements impractical. Key constraints include the built environment, demand, policies and regulations, financing, and construction and maintenance (Rodrigue, 2016). The urban structure shapes the network of transportation infrastructure (Gil, 2014). Density, land use mix, street network design, access to destinations, access to the transit system, and demand management (Ewing and Cervero, 2001) are the built environment factors that influence the transportation system and travel behavior (e.g., da Silva and Silva, 2003; Cao et al., 2007; Ewing and Cervero, 2010; Cao et al., 2010; Daisy and Habib, 2015). For example, from the five boroughs of NYC, the Bronx and Staten Island have similar street patterns and the other boroughs — Manhattan, Brooklyn, and Queens — are different (Louf and Barthelemy, 2014). Thus, transportation diversity enhancement in the zip codes of each of these boroughs will be influenced by different built environment challenges that will make the development of certain modes prohibitive. Moreover, low demand for a transportation mode in an area would likely have a slight effect on improving transport equity. Further, the cost of system development and operation could make such improvements infeasible. Therefore, the development or improvement of modes must account for these factors. For instance, if constraints in an area make metro system development impractical, then modifications to bus system such as additional routes or the development of a bus rapid transit system might be viable alternatives to enhance transport equity. Ultimately, the transportation diversity approach highlights the variation in the supply of transportation modes pinpointing the areas and the modes that require improvement; consequently, planners and designers can use this information while taking into account existing constraints when evaluating system modifications.

4.5.4. Limitations

This study has some limitations. First, the equity of access to the transportation system can be influenced by the built environment factors such as land use and urban form. Analyzing the results of this study with land use and urban form data can give more insights on how to improve transport equity. Further, the relationship between transportation diversity, as an indicator of transport equity, and socioeconomic and transport related factors demonstrated the meaningful correlation between transport equity and these factors which could be attributed to transportation system characteristics. However, to inspect the level of impact of transportation diversity on these factors, a casualty analysis is necessary that will be deferred to future studies. Several studies have investigated the causal relationship between the built environment and travel behavior (see Cao et al., 2009). For instance, longitudinal structural equation modeling with control group (e.g., Cao et al., 2007) may be a suitable approach for causal analysis between built environment characteristics and travel behavior (Næss, 2015). This approach can be explored in subsequent studies to investigate the causal relationship between transportation diversity and factors such as vehicle ownership, commute time, and commute mode. Furthermore, factors such as frequency of transit systems and capacity of modes, and conditions of each mode are not included in the equity assessment that will be explored in future studies to incorporate these elements. Further, in this study, we only focused on the supply side of the transportation system. The demand for each mode was not considered since demand could be influenced by transport equity. Transportation equity is dynamic as the supplied service and population density changes over time (Xia et al., 2016). For example, Jou and Chen (2014) examined the usage of public transit, motorcycle, and car in Taiwan and found that improving transit systems decreased car and motorcycle usage. Likewise, Linovski et al. (2018) highlight the socioeconomic disparity in the mode choice over time and concluded that compared to car drivers the income of individuals using bus has decreased in the past few decades while this value increased for rail transit users. Therefore, the changes in transport equity, demand, and socioeconomic factors can be studied over time to analyze the dynamic between transport equity and demand, and the contribution of transport equity in sustainable development.

4.6. Conclusions

The equity of transportation infrastructure can be assessed from several perspectives. All transportation modes contribute to the performance of this infrastructure and enable connectivity and mobility. Further, a well-developed transportation mode can only be fully effective when it is also well distributed to support equal access to service for residents in different areas. Moreover, the functionality of all transportation modes and their complementarity is crucial for the robustness and recovery of the transportation system in response to extreme events such as natural hazards. Thus, identifying the most vulnerable areas in terms of the transportation system and analyzing the socioeconomic factors can give a more comprehensive perspective of transportation equity to incorporate it into urban resilience planning. In this study, we explored the equity of transportation infrastructure by transportation diversity that determines both equal provision and distribution of all transportation modes in different areas.

Measuring the diversity of NYC transportation system identified the areas with the inequity of transport. Based on this spatial equity assessment, we analyzed factors pertaining to socioeconomic status and transportation usage to investigate the relationship between transportation diversity and these factors. This relationship revealed that areas with a less equitable transportation system are generally more deprived which can be relatively associated with the transportation system. In a diverse transportation system, a failure in a mode can be covered by other modes to maintain the performance level of the entire transportation system. It is shown that areas with low transportation diversity can severely be impacted by extreme events. Thus, low transportation diversity not only brings about the inequity of transport in normal situations, but it can also compromise the resilience of the transportation system that might cause more socioeconomic pressure on residents in these areas.

The main contribution of this study is presenting an alternative approach for assessing the equity of access to transportation modes by the provision of transportation modes in different areas as well as the distribution of modes that helps differentiating between the equity of sub-areas within an area. Additionally, transportation diversity considers all transportation modes to have a more comprehensive equity assessment. The results of the transportation diversity identify areas that have transport inequity. Further analyzing the richness and evenness of all modes in these areas would suggest the modes that caused inequity in each area and the diversity metric that needs to be improved in these areas. Moreover, the category assessment of transport equity based on transportation diversity indicated that disadvantaged groups do not necessarily have similar transport equity. The comparison based on transportation diversity classes allowed pinpointing the vulnerable groups that have the least equitable transportation system. Analyzing the relationship between transportation diversity and post-disaster socio-economic impact in NYC highlighted that people living in areas with a lower transportation diversity suffered more from extreme events. This analysis indicates the importance of improving the equity of access to transportation mode in these areas to better serve them in normal conditions and provide a more resilient transportation system to support mobility in case of extreme events. It also provides a means to more effectively and efficiently allocate resources for transportation enhancement plans and prioritize improvements in the areas that have the lowest transport equity and socioeconomically are disadvantaged. Such improvements will, in turn, prompt an equitable resilience enhancement of this infrastructure, enabling people to maintain their routine mobility patterns after such events through alternative transport options and mitigate the socioeconomic issues caused by transportation system failure.

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Chapter 5: Summary, Contributions, and Future Research

5.1. Summary

The research in the three studies aimed to characterize and measure transportation diversity, investigate its impact on post-disaster mobility, and explore the relationship between transportation diversity and socioeconomic factors for equitable resilience planning.

In Study 1, measuring transportation diversity in NYC revealed that the diversity of the transportation system varies across the city and zip codes with the lowest transportation diversity are located in hurricane evacuation zones. Thus, the more vulnerable zip codes to hurricanes have the least diverse transportation systems that can pose more difficulties for mobility in case of a natural disaster. Moreover, transportation diversity pinpointed the modes in each area and the transportation diversity metric in each area that needs improvement. Measuring transportation diversity in this study provided a basis to explore how transportation diversity contributes to the resilience of this infrastructure.

In Study 2, the impact of transportation diversity on post-disaster mobility patterns was explored. The results indicated that after Hurricane Sandy, individuals that lived in or visited zip codes with a lower transportation diversity experienced more difficulty in maintaining their pre-disaster mobility patterns; therefore, the robustness of their mobility resilience was compromised by the low transportation diversity in their primary locations. In addition, the recovery to pre-Sandy mobility patterns took longer for these individuals, so the low transportation diversity also impacted the recovery of their mobility patterns. The results of Study 2 confirmed that transportation diversity supports the resilience of mobility patterns in the wake of a natural disaster.

In Study 3, the transportation diversity approach was employed to quantify the equity of access to transportation modes. The comparison of transport related and socioeconomic factors in zip code quartile groups demonstrated the relationship between transportation diversity and these factors. The results indicated that individuals in zip codes with a lower transportation diversity have higher vehicle ownership and commute time and as transportation diversity increases, vehicle ownership and commute time decline. In addition, driving/carpooling is the dominant mode of commute in these zip codes unlike zip codes with a higher transportation diversity that use transit, bikes, and walk more for commuting. These findings can partly be associated with the equality of access to transportation modes. The results further show that a lower transportation diversity affected poor more than non-poor and black and Hispanic more than white suggesting the role of transportation diversity in social exclusion. The analysis of the impacts of Hurricane Irene and Sandy in NYC indicated that the mobility of individuals in areas with the lowest transportation diversity and transport equity were disturbed more and these individuals experienced greater post-disaster social exclusion. This reinforces the importance of transport equity to mitigate social exclusion in normal situations and after natural disasters. Finally, the results indicate that a transportation resilience planning should consider the physical aspect of the transportation infrastructure along with the socioeconomic factors for more comprehensive, effective, and efficient resilience strategies that prioritize areas with the least developed transportation system that are socioeconomically more deprived.

In summary, the characterization of transportation diversity in Study 1 mainly focused on the physical aspects of this infrastructure. Specifically, the calculation of evenness in Study 1 considered census blocks as likely places of demand for transportation; however, the characteristics of people in these areas were not considered. In Study 2, the dynamics of change in the mobility patterns of people were explored, which highlighted the relationship between transportation diversity and mobility resilience. Indeed, knowledge of travel behavior of people and its relationship with the transportation system is key for improvement planning of this infrastructure. Thus, in Study 3, the relationship between transportation diversity and transportation system usage and user socioeconomic characteristics such as mode split and poverty was examined to link the physical characterization of transportation diversity with travel behavior; this linkage illustrated the likely influence of transportation diversity on transport-related social exclusion.

In practice, decision-makers must consider transportation system constraints when evaluating transportation diversity improvements. Indeed, improving richness by adding more infrastructure might be difficult in some areas due to several factors such as geographic conditions; however, enhancing evenness of the existing transportation modes is likely more pragmatic, at least in the short-term, and such improvements would strengthen mobility resilience and transport equity. Areas with lower transportation diversity have less inherent complementarity between transportation modes. However, decision-makers can plan for augmented complementarities in these areas to mitigate the impact of natural disasters and other system shortcomings on mobility and connectivity. For instance, improving hard shoulders to expand roadway capacity, increasing the frequency of transit services, and adding new bus routes are all practical and potentially cost effective ways of augmenting an existing system.

Furthermore, high transportation diversity in all areas of a community is ideal, but it is likely impractical given the transportation infrastructure constraints. The transportation diversity approach developed in this dissertation was inspired by the biodiversity of ecological systems, so improving transportation diversity for diversity's sake would undermine ecological systems – the very source of this approach. One intent of heightening transportation diversity is to decrease the impact of natural hazards on communities. Yet, building new infrastructure will impact, if not destroy, ecological systems; this could result in higher greenhouse gas emissions that exacerbates climate change that results in more natural hazards. Thus, the pursuit of transportation diversity must also consider sustainability. Modifying the evenness of a transportation system may prove more viable in this regard. This does not mean ruling out improving richness since simply providing service, or expanding it, may be necessary in specific areas. Rather, it suggests that improving the evenness of transportation modes as a "first" objective is likely a more sustainable strategy because it reduces habitat degradation, promotes sustainable transportation, and is economically more feasible than new infrastructure development.

5.2. Contributions and Implications for Transportation and Community Resilience

City-scale transportation resilience assessment methods are typically general; they fail to capture all the important resilience factors and have limited capacity to identify the most vulnerable areas of a city for improvement. The main contribution of Study 1 is a novel approach to characterizing transportation diversity based on the concept of biodiversity. The investigation developed metrics to quantify this resilience factor offering a new technique for evaluating a transportation system. Transportation diversity highlights that a comprehensive transportation resilience assessment should include all transportation modes. Furthermore, transportation diversity suggests that both the provision and distribution of transportation modes are important and identifies the most vulnerable areas of an urban community based on these two factors. Identifying the most vulnerable areas can help advance a more targeted approach to transportation resilience planning. In addition, variability patterns of transportation systems and the inherent and augmented complementarities were characterized in Study 1. The inherent complementarity suggests adaptability to a disturbance through compensation among modes. When the inherent complementarity is not high, system interventions or augmentations can improve its performance; indeed, some systems and regions in a community have more potential for augmented complementarity as a consequence of network structure or capacity adjustments. Analyzing the variability patterns of a transportation system permits understanding the performance of individual modes and the whole transportation system during perturbations such as natural hazard scenarios. The inherent and augmented complementarities establish a baseline to investigate how transportation diversity contributes to compensation among modes amid extreme events or routine disturbance scenarios.

The impact of transportation diversity on post-disaster mobility was analyzed in Study 2 by two methods developed to (a) focus on an individual's frequently visited locations, and (b) take into account the importance of the frequently visited locations by considering the frequency of visits. The approach used in this study overcomes the lack of transportation system data in CDR and social media data and permits an analysis of the influence of a transportation system on mobility patterns after extreme events. In addition, the results helped understand the relationship between transportation diversity and mobility patterns, highlighting the role of mode complementarity on transportation resilience. Further, Study 2 provides the first approach in analyzing the underlying dynamics of change in post-disaster mobility patterns and identifying the influence of the provision and distribution of transportation modes on these changes.

Transportation infrastructure is a sociotechnical system. Thus, transportation resilience plans should consider the technical and physical aspects of this infrastructure along with socioeconomic factors. Building upon Study 1, the transportation diversity approach was used to measure the equity of access to all transportation modes in Study 3. The diversity approach provides an alternative to existing approaches for equity assessment and enhances this evaluation by considering access to all modes. Further, the transportation diversity approach enables distinguishing between the equity of access to modes in sub-regions in an area such as census blocks in a zip code. In addition, since transportation diversity takes into account the provision and distribution of all modes, it identifies the improvements needed in each mode in each area to improve equity of access. The findings in Study 3 suggest that equity of access should include all modes since they support the performance of each other. This enhances the assessment of equity of access to modes in previous studies that largely focused on transit systems. Moreover, considering all modes for equity assessment highlights the importance of equity in supplying all transportation modes to enhance transportation resilience. In addition, there is a strong relationship between transportation diversity and vehicle ownership, commute mode, and commute time highlighting the need for a causal analysis to determine the influence of transportation diversity on these factors. Further, the results indicated that the socioeconomically disadvantaged groups do not necessarily have lower equity of access to transportation modes; albeit, in areas with a low transportation diversity the impact is more significant on majority poor, black, or Hispanic zip codes. Therefore, these groups cannot be considered homogeneous regarding their equity of access to transportation modes. This study also suggests that transport inequity causes greater social exclusion after natural disasters as a failure in the transportation system in areas with a low transportation diversity cripples the already weak transportation system and leaves residents in these areas with even more limited options for their mobility.

5.3. Future Research

Future research can investigate transportation diversity in more detail. The transportation diversity approach developed empirically depicted the relationship between transportation diversity and post-disaster mobility and assessed the equity of access to transportation modes; these investigations provide the basis for further research.

5.3.1. Variability Patterns in Transportation Modes

In Study 2, the positive influence of transportation diversity on mobility patterns was shown. This means that the availability of transportation modes in areas with higher transportation diversity allowed mode complementarity. In other words, the failure in one or more modes in areas with a high transportation diversity was compensated by other available modes. However, the dynamics of these compensations are unknown. In addition, it is not clear how each mode reacts to a disturbance (component variability) and how the entire transportation system responds to it (aggregate variability). Analyzing the variability patterns of a transportation system to different natural disaster scenarios or a natural disaster with different intensities will help identify the response of individual modes and the entire transportation system to such disturbances. Such an analysis determines the sensitivity of the system to various disturbances with different intensities. This allows characterizing the variability patterns of a transportation system for more detailed transportation resilience planning. Further, it will assist in analyzing the role that transportation diversity plays in modal complementarities and compensatory dynamics. The inherent and augmented complementarities can mitigate the impact of a natural disaster or a routine disturbance on a transportation system. However, a transportation system might experience a change in the travel behavior of people due to system disruptions or their routine life such as changes in the travel mode, travel schedule, or the places they visit. These travel behavior changes will likely amplify the impact of a natural disaster or another type of disturbance on the transportation system and how modal complementarities alleviate these impacts. Therefore, these travel behavior changes should be included in the modeling of transportation infrastructure and natural disaster scenarios.

5.3.2. Influence of Micro-Mobility on Mode Complementarity and Smart Mobility

Characterizing transportation diversity in NYC demonstrated that the distribution of transportation modes (evenness) is as important as the provision of modes (richness). A low evenness in an area can cause issues such as first/last mile which can impact mode complementarity, intensify equity of access to transportation modes, and decrease the resilience of the transportation system to natural hazards. Implementing modes of micro-mobility such as bike-sharing and scooter-sharing as well as mini-buses and shuttles can potentially fill the gap of a low provision and distribution of transportation modes and enhance mode complementarity. Coupling the data of mobility of these micro-mobility modes with the smart card data of transit modes, GPS data of cars, and potentially ride-sharing data provides a rich dataset to assess the influence of micro-mobility on mode complementarity and smart mobility. Such an analysis provides a basis for an agent-based model to explore the role of micro-mobility during extreme events.

5.3.3. Transportation Diversity and Urban Structure

The work in this dissertation was inspired by the concept of diversity in ecological systems. Diversity is a key factor in ecological resilience and higher diversity promotes higher stability. However, ecological systems have natural and anthropogenic constraints that could hinder higher biodiversity (Maskell et al., 2013), although higher diversity promotes higher stability. For example, the way an ecosystem is assembled limits the similarity between species (McPeek, 2019). Other hypotheses highlight the influence of the total energy in an environment (Currie 1991) and the niche space (Hutchinson 1959, MacArthur 1970) in limiting higher diversity. As discussed in Study 3, a transportation infrastructure is bounded by similar constraints found in ecological systems such as demand, resources, and the built environment that influence developments and improvements in this infrastructure. Therefore, pragmatic improvements in transportation diversity should take into account these contextual limitations. One of the main constraints of transportation infrastructure is the structure of the built environment. The organization of cities is often considered as hierarchical or having different spatial scales (Buhl et al., 2006) such as regional, urban, neighborhood, block, and street (Williams, 2014). Urban areas can be analyzed through their physical form which is defined by three physical elements: (1) buildings and open spaces, (2) plots, and (3) streets (Moudon, 1997), which have different spatial scales. Diverse combinations of these elements form various urban structures (Oliveira, 2016). Cities are composed of these three elements with different combinations (Levy, 1999) or a mosaic of units with different structures that vary in size, complexity, heterogeneity of elements, and functional use (Gordon, 1984). The built environment also influences the shape of infrastructure networks, particularly, transportation infrastructure (Gil, 2014). There is ample evidence on the relationship between the built environment and travel behavior (e.g., Van Acker et al., 2008; Wells and Yang, 2008; Daisy and Habib, 2015). Investigating the relationship between transportation diversity and the structure of the built environment can reveal how transportation diversity is influenced by the built environment. Improvements in transportation diversity will be constrained by the built environment's structure. Thus, understanding the relationship between transportation diversity and urban structure would be useful in transportation diversity enhancement planning.

5.3.4. Additional Opportunities to Apply the Transportation Diversity Approach

The transportation diversity approach in this dissertation was measured at the scale of a zip code. However, this approach is flexible, so it can be applied at larger or smaller spatial scales. This feature permits analyzing the transportation diversity of a community at different spatial scales such as an entire city, districts, neighborhoods, Public Use Microdata Areas (PUMAs), and census tracts. Further, this feature allows comparing different communities or cities based on their transportation diversity; these characterizations might then be linked with other factors such as congestion, air quality or economic productivity indicators. Moreover, a comparative study of the transportation diversity approach and other approaches quantifying accessibility to transportation modes would further reveal the advantages and disadvantages of the transportation diversity approach. Certainly, such an analysis at various spatial scales could demonstrate the similarities and differences between approaches. Transportation infrastructure experiences both “pulse” disturbances caused by traffic congestion, construction work, public events, and manmade disasters and “press” disturbances caused by natural disasters or pandemics. The focus of this dissertation was on natural disasters. However, the influence of transportation diversity on managing pulse disturbances as well as pandemics could be explored to understand how varying levels of transportation diversity impact routine events in a community as well as less other threats to the safety and security of its residents, such as the COVID-19 pandemic.

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