SAFETY EFFECTS OF MULTIMODAL INFRASTRUCTURE AND ACCESSIBILITY IN URBAN TRANSPORTATION SYSTEMS

by

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ABSTRACT

The interest in multimodal transportation improvements is increasing in cities across the U.S. Investing in multimodal infrastructure benefits the portion of urban population that is unable to drive due to a variety of reasons such as personal preference, age, and affordability. It is also well known that active transportation such as walking, biking, and taking transit, can improve public health due to increased physical activity, and reduce traffic congestion by reducing the average person's delay. While improved multimodal infrastructure and accessibility attracts new users, it can possibly increase their exposure to risk from crashes. In urban areas where the "safety in numbers phenomenon" does not exist, nonmotorized user vulnerability becomes a predominant risk factor when they are involved in a crash, even at lower vehicle speeds.

This dissertation aims to explore the factors that are associated with safety outcomes in urban multimodal transportation systems, and develop methods that can be used to estimate safety effects of multimodal infrastructure and accessibility improvements. Using Chicago as a case study, a comprehensive dataset is developed that significantly contributes to the existing literature by including socio-economic, land use, road network, travel demand, and crash data. Area-wide analysis on the census tract level provides a broader perspective about safety issues that multimodal users encounter in cities. The characteristics of a multimodal transportation system are expressed through the presence of multimodal infrastructure, street connectivity and network completeness, and

accessibility to destinations for multimodal users. A set of statistical areal safety models (SASM) based on both frequentist and Bayesian statistical inference is applied to estimate the factors that are associated with total and severe vehicular, pedestrian, and bicyclist crashes in urban multimodal transportation systems.

The results show that the current safety evaluation methods need to acknowledge the complexity of multimodal transportation systems through the inclusion of diverse factors that may influence safety outcomes, particularly for more vulnerable users. The methods developed in this research can further be used to expand the current practice of evaluating multimodal transportation safety, and planning for city-wide investments in multimodal infrastructure and improved accessibility, while being able to estimate the expected safety outcomes.

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ACRONYMS

SASM	Statistical Areal Safety Modeling
GLM	Generalized Linear Models
GAM	Generalized Additive Models
FBH	Full Bayes Hierarchical Models
SE	Socio-Economic
DVMT	Daily Vehicle Miles Traveled
HSM	Highway Safety Manual
AASHTO	American Association of State and Highway Transportation Officials
TRB	Transportation Research Board
MAUP	Modifiable Areal Unit Problem
AADT	Average Annual Daily Traffic
VMT	Vehicle Miles Traveled
WMT	Walk Miles Traveled
BMT	Bike Miles Traveled
STP	Space-Time Prism
AMELIA	A Methodology Enhancing Life by Improving Accessibility
GIS	Geographic Information System
DOT	Department of Transportation

CMAP	Chicago Metropolitan Agency of Planning
CTA	Chicago Transit Authority
NHTS	National Household Traveler Survey
ADT	Average Daily Traffic
MUTCD	Manual on Uniform Traffic Control Devices
FHWA	Federal Highway Administration
OD	Origin Destination
GTSF	Google Transit Feed Specification
ACS	American Community Survey
NB	Negative Binomial
KA	Severe (Fatal and Incapacitating Injury Crashes)
MCMC	Monte Carlo Markov Chain
CAR	Conditional Autoregressive Model
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
DIC	Deviance Information Criterion
CBD	Central Business District

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CHAPTER 1

INTRODUCTION

Transportation shapes the cities, which in return require transportation as the engine of their economic, environmental, and social development. This interaction between cities and their transportation systems is continuous, where the change of one always requires further change of the other. Neglecting this relationship may lead to transportation problems commonly faced by urban environments today, mostly resulting from urban policies that favor one mode over the other modes of transportation (Jacobs, 1961; Mumford, 1961; Vuchic, 1999).

Today, as the population living in the cities continues to increase, transportation and mobility are central to sustainable urban development. The concept of "smart cities" requires transportation system where "interaction is possible in any direction and at any distance" and "streets are not an end in themselves…they are a means towards an end" (Jacobs, 1961, p. 186; Lynch, 1960, p. 89). Over the course of several decades, these concepts that tie cities and transportation together have slowly been transformed into policies that prioritize the inclusion of all urban street users.

As cities across the U.S. increase their interest in multimodal transportation investments and providing accessibility to multimodal options for all users, there is a particular concern regarding the safety effects of these changes, particularly for more vulnerable road users. The benefits of improving multimodal infrastructure and accessibility range from better health outcomes through the use of active transportation and reduced air pollution, to better mobility for those who cannot afford driving (United Nations [UN] HABITAT, 2014). There is a general understanding that improved multimodal transportation systems may lead towards resolving multiple long-term issues related to sustainability and efficiency of travels in urban environments.

This movement towards more active and diverse transportation options in cities was followed by the development of policy and guidelines for multimodal transportation, and the need to extend existing evaluation methods to account for the presence of different modes and their impacts on transportation performance. Improved access to multimodal transportation attracts new users of alternative transportation modes, and safety of multimodal users is still a topic that requires further research. Initiatives for creating more sustainable transportation systems are gaining attention on the international scale, and the need to reduce fatal road crashes remains in the focus of that effort. Safety emerges as a global issue as the UN General Assembly declared the "UN Decade of Action for Road Safety 2011-2020" supported by 100 world countries, as "nearly 1.3 million people are killed on the world's roads each year" (World Health Organization, 2010).

In cities across the U.S. that are developing or improving their multimodal transportation features, the assessment of safety outcomes of improved multimodality is still challenging. The methods of measuring the success and performance of multimodal transportation systems are in the early stage of development, particularly in the area of multimodal safety evaluations.

Research Problem Statement

In urban environments, where multimodal transportation thrives, the relationship between access to multimodal transportation and safety is complex. Transportation funding programs require that investments primarily focus on transportation performance, including establishing quantitative transportation safety targets. With this need to quantify safety outcomes, evaluation methods need to account for additional factors associated with multimodal safety in urban environments.

As cities invest in multimodal infrastructure, accessibility for all users is improving, which is a desirable outcome. However, with these improvements, the exposure of multimodal users to conflicts with motorized users also increases, and the effects on multimodal safety need to be examined. Transportation practitioners would benefit from being able to estimate the expected safety effects of investments in multimodal transportation and improving multimodal accessibility. In the short-term sense, this knowledge would contribute to safety performance-based decision making, while the long-term benefits would contribute to safety planning efforts and system-wide improvements for multimodal users. The major impediments to gaining this knowledge are the following existing limitations:

1) Data comprehensive enough to capture the complexity of multimodal transportation systems in urban environments, while considering system-wide effects as well as information on factors that potentially have a direct influence on safety outcomes;
2) Measures that use the appropriate data to quantify the success of implemented multimodal features in terms of their ability to provide access to opportunities for

all users as well as users' activity and potential to be involved in conflicts that may result in crashes;

3) Methods that draw from complex data and developed measures to estimate safety effects for multimodal users, while dealing with the challenges which may arise in extensive datasets, being flexible enough to be useful to both researchers and practitioners, and enabling transferable application among different scales and locations.

The opportunities to address these challenges for advancing knowledge on urban multimodal safety are increasing with the emerging number of data sources on multimodal users choices and activities, the paradigm shift in transportation performance measurement towards more sustainable performance indicators, and the need to put the emphasis on the safety of nonmotorized users as their vulnerability becomes a predominant risk factor with the enhancement of multimodal transportation options.

Research Objectives

The goal of this research was to explore the factors that influence multimodal safety outcomes in urban transportation systems, particularly focusing on the effects that improved multimodal infrastructure and accessibility have on safety outcomes for pedestrians, bicyclists, and private vehicle users. The defined research goal was developed through three major objectives that align with the previously explained research problem statement. These major research objectives were defined as the following:

1) Develop a dataset consisting of spatially aggregated data to include multimodal crash outcomes in urban environments, while capturing system-wide effects that

are associated with crashes according to the existing urban safety studies, as well as detailed information about multimodal infrastructure;

2) Determine how multimodal users exposure can be represented, and develop measures that may serve as the indicators of the level of success of multimodal transportation system as well as the potential surrogate measures of exposure, using the collected data;
3) Explore and apply a set of statistical areal safety modeling (SASM) methods that will capture both system-wide effects and measures of multimodal presence in urban environments, in order to estimate crash outcomes for pedestrians, bicyclists, and private vehicle users.

Following these objectives, the City of Chicago was selected as the analysis location due to its developed complete streets initiatives and extensive multimodal transportation network features. A dataset was developed to allow for a system-wide analysis selecting a census tract as the level of data aggregation. Aggregating the data in this way provided a broader perspective about safety issues that multimodal users encounter in cities. The system-wide effects captured in this manner include socio-economic features, land use characteristics, road network, travel demand, and crashes. In this research, multimodal safety outcomes are defined as 1) the expected number of total and severe vehicle-only (vehicular crashes); 2) the expected number of total and severe crashes involving pedestrians (pedestrian crashes); and 3) the expected number of total and severe crashes involving bicyclists (bicyclist crashes). Severe crashes included fatal and severe injury crashes for these three types of users.

Following the defined research objectives, several options were considered to represent the exposure of multimodal users, as explained in the Methodology chapter. In addition, measures that represent the level of access to multimodal transportation options, including data on multimodal infrastructure and measures of multimodal connectivity and accessibility, were developed to serve as proxies or surrogates for multimodal exposure.

The final part of the methodological approach in this research was using a set of SASM methods to estimate vehicular, pedestrian, and bicyclist total and severe crashes as a function of variables used to represent system-wide effects and measures of access to multimodal transportation. The SASM methods were based on frequentist statistical approach, including generalized linear (GLM) and generalized additive (GAM) models, and Bayesian statistical approach used in Full Bayes Hierarchical (FBH) models. These different SASM methods were used as a form of validation of the estimated crash outcomes for multimodal users in urban environments.

This approach resulted in the ability to incorporate new variables that may influence the safety of vulnerable transportation users into the SASM methods, explore different SASM methods in terms of their ability to capture the system-wide effects and issues that may arise in modeling spatially collected data, and use the estimated relationships and provide recommendations for the development of safety evaluation methods for multimodal users in urban environments. The research methodology was designed to provide some insights to questions related to the variety of factors that may influence urban safety in terms of both crash frequency and severity, the relationship between access to multimodal transportation and safety, the methods that can be used to successfully evaluate urban safety for different user and crash types, the expected number of crashes under the given set of multimodal transportation features, and recommendations about safety improvements in urban multimodal transportation systems. The focus of this research was on the methodology, acknowledging that data from other urban environments of various sizes should be collected in order to verify transferability of findings from this study.

Conceptual Framework

Figure 1 presents the conceptual framework that serves as the core theoretical hypothesis of this research that was used to develop the dataset, measures, and research methodology. The core hypothesis is that areal units of analysis with different levels of access to multimodal transportation, different levels of multimodal exposure, and different system-wide characteristics are expected to have different multimodal crash outcomes. Previous research on transportation mode choice addresses the relationship between multimodal accessibility and exposure, influenced by system-wide effects such as socio-economic (SE) features and land use patterns, leaving the statistical modeling of this relationship beyond the scope of this research, but still acknowledged by the conceptual framework. Key groups of variables and measures for each element of the conceptual framework are also presented in Figure 1. Multimodal accessibility is represented through the variables that should capture the physical presence of multimodal infrastructure (e.g., bus lanes and stops, bike lanes, and bike racks), overall destinations accessibility for a variety of modes, and network completeness in terms of the physical street network share that serves multiple modes. Multimodal exposure is represented through Daily Vehicle Miles Traveled (DVMT), trips generated by pedestrians and bicyclists, commuter work trips by mode, and points of conflict between different modes.

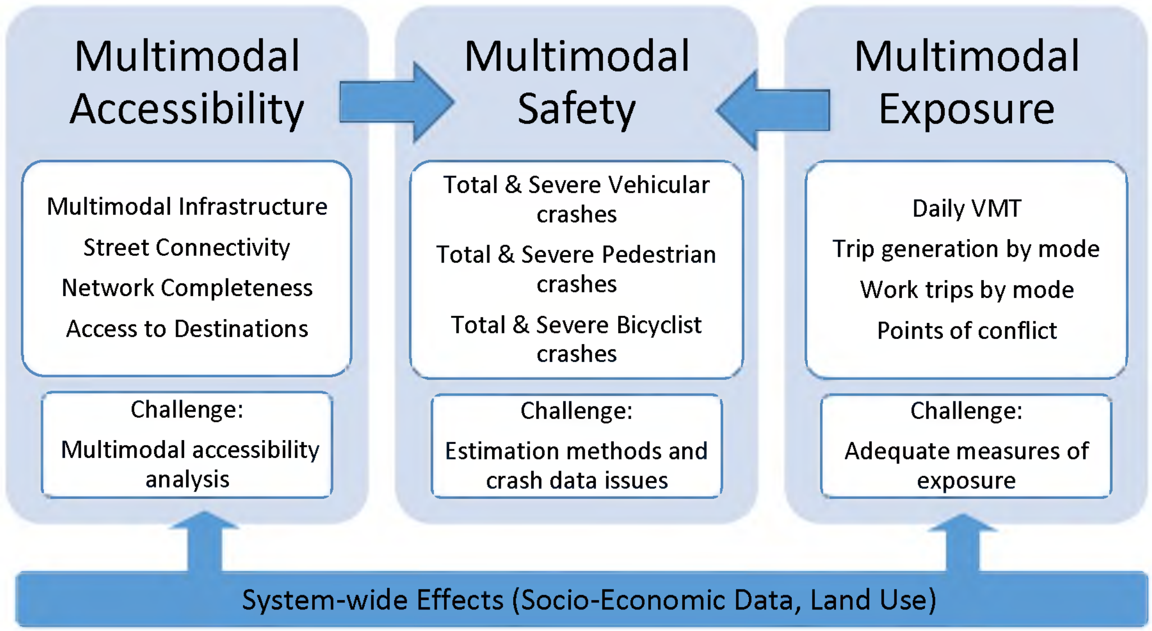


Figure 1 Conceptual Framework

System-wide effects are provided through SE variables and land use characteristics. Multimodal crash outcomes are represented as defined in the research objectives section of this chapter. As previously stated, the conceptual framework served to develop the methodological approach that estimates the expected number of total and severe vehicular, pedestrian, and bicyclist crashes on the areal analysis level of census tract units in the City of Chicago.

Dissertation Outline

This dissertation consists of six chapters. The first chapter introduces the research problem, defines the research questions including the conceptual framework, and outlines the proposed dissertation chapters. The second chapter presents the literature review focused on urban multimodal transportation safety, areal safety studies, and the representation of multimodal exposure and accessibility, summarizing the gaps in the existing research and including the role that this research could play to fill in those gaps.

The third chapter introduces the methodology, including data collection, variables, measures, and SASM methods used to estimate the expected number of crashes for multimodal users. Chapter 4 presents the results of the crash data analysis, starting from preliminary model specifications to final "best models" by crash type. Chapter 5 is focused on the interpretation of results presented in Chapter 4. Major contributions of this research, recommendations for future research efforts, and research limitations are provided in the final chapter.

CHAPTER 2

LITERATURE REVIEW

This chapter provides the review of previous research conducted in the area of urban multimodal transportation safety. The chapter then continues to explain how areal safety analysis is used to explore transportation safety for multimodal users, including the levels of data aggregation, and the variety of effects captured in areal safety studies. Measures of multimodal exposure and accessibility that exist in the literature are addressed, including previous research on relationships between multimodal exposure, accessibility, and safety. The chapter also covers the review of the methodological approaches applied in areal safety studies.

Multimodal Transportation Safety

Transportation mode choice and the presence of multimodal infrastructure are among the factors that could influence the future of road safety (Hauer, 2005). Crashes involving pedestrians and bicyclists, or vulnerable road users, have become an international concern (Wei, Feng, & Lovegrove, 2012), especially in urban environments where these road users' vulnerability if involved in a crash is a predominant risk factor (Wegman, 2006). The Highway Safety Manual (HSM) (American Association of State and Highway Transportation Officials [AASHTO], 2010) recognizes that "increasing the availability of mass transit reduces the number of passenger vehicles on the road and therefore a potential reduction in crash frequency may occur because of less exposure" (Transportation Research Board [TRB], 2010). Availability and access to multimodal transportation options in urban environments is likely to play a key role in the way safety is estimated and evaluated in these environments for motorized and nonmotorized transportation modes.

While the majority of the existing quantitative methods in road safety focus on vehicular traffic as the most dominant mode of transportation, evaluation of non-motorized safety and related impact factors has been occurring on the zonal and regional levels (Quddus, 2008; Siddiqui, Abdel-Aty, & Huang, 2012; Washington et al., 2006; Zeng & Huang, 2014). There are several reasons why road safety in general is explored on this "macroscopic" level. It is quite common that safety-influencing factors such as roadway and roadside geometrics, pavement conditions, and traffic control are best explored on the segment or intersection-level (TRB, 2010), but there is an increasing interest among researchers to explore some other area-wide factors that can be addressed in spatial analysis (Aguero-Valverde, 2013). Also, the current crash modification factors (CMFs) have "methodological drawbacks" due to the fact that applied modeling techniques do not account for spatio-temporal heterogeneity exhibited by crashes (Aguero-Valverde, 2013; Chen & Persaud, 2014; Huang & Abdel-Aty, 2010; Karlaftis & Tarko, 1998; Li et al., 2013; Plug, Xia, & Caulfield, 2011). Some other applications of crash modeling, such as identifying crash risk hotspots, network screening, and safety planning, are becoming more relevant with legislative requirements to incorporate multimodal safety performance goals into long-term planning processes (Anderson, 2009; Coll, Moutari, & Marshall, 2013; Hauer, 2005; Jiang, Abdel-Aty, & Alamili, 2014;

Montella, 2010; Nicholson, 1998; Park & Young, 2012; Persaud, Lyon, & Nguyen, 1999; Plug et al., 2011; Pulugurtha, Krishnakumar, & Nambisan, 2007; Siddiqui, Abdel-Aty, & Choi, 2012; Vieira Gomes, 2013; Washington et al., 2006; Yiannakoulias, Bennet, & Scott, 2012). These initiatives also lend themselves to analysis at a spatial level in some cases.

Areal Safety Studies

New applications of crash models and the exploration of additional factors that could impact traffic safety of a variety of users has led to the development of spatial modeling techniques that analyze crashes on a selected level of spatial analysis units (Aguero-Valverde, 2013; Vanderbulcke, Thomas, & Panis, 2014; Wang & Kockelman, 2013). The first areal safety studies appeared about a decade ago, focusing on country-wide or state-wide data, disaggregated to different spatial units and providing general indications of factors associated with crash occurrences (Aguero-Valverde & Jovanis, 2006; Noland & Quddus, 2004; Yannis, Papadimitriou, & Antoniou, 2008). Since then, several attempts have been made to apply similar statistical crash modeling methods in urban environments, both in the U.S. (Moeinaddini, Asadi-Shekari, & Shah, 2014; Ukkusuri et al., 2012; Wang & Kockelman, 2013) and Europe (Quddus, 2008).

Crash data in areal studies are aggregated within traffic analysis zones (Siddiqui, 2012), neighborhoods (Wang & Kockelman, 2013), census-based units (Noland & Quddus, 2004; Quddus, 2008), or counties (Aguero-Valverde & Jovanis, 2006; Flask & Schneider, 2013; Li et al., 2013; Yannis et al., 2008). Regional safety modeling may raise the issue of the Modifiable Areal Unit Problem (MAUP), which could cause changes in statistical inference if spatial analysis units change, and can be handled by reducing the number of analyzed regions (Xu et al., 2014). Spatial aggregation of crash data may also lead to ecological fallacy, when the relationship between aggregated variables is attributed to established aggregation methods, the effect which may be corrected by using lower levels of aggregation (Davis, 2002). If traffic analysis zones are used to aggregate the data, there are indications that "internal" and "near boundaries" crashes need to be treated separately (Siddiqui et al., 2012). The existing evaluations at various levels of spatial aggregation show that some analysis units such as census tracts are more reliable than the others in terms of providing more repeatable estimation results (Ukkusuri et al., 2012). Procedures to conduct intersection- and segment-level analysis to identify high-risk sites with a potential for safety improvement have been well-documented (e.g., Wang & Abdel-Aty, 2006; Yu et al., 2014;), but a higher level of spatial aggregation, such as that reported in this research, can be used to account for area-wide factors that may influence safety outcomes in multimodal environments.

Previous areal safety studies focused on both motorized (Aguero-Valverde, 2013; Li et al., 2013; Siddiqui et al., 2012) and nonmotorized crashes (Wang & Kockelman, 2013; Quddus, 2008; Shankar et al., 2003), accounting for variables that somewhat represent the availability of alternative transportation modes (Wang & Kockelman, 2013; Yannakoulias et al., 2012; Quddus, 2008; Schneider, Ryznar, & Khattak, 2004). These research efforts were focused primarily on vehicle-only crashes, with the explanatory variables limited to roadway mileage, estimated average speeds, and socio-economic data (Castro et al., 2013; Siddiqui et al., 2012; Wang et al., 2009). Several recent studies have incorporated estimates for pedestrian crashes by including land use-related variables (Ukkusuri et al., 2012; Wang & Kockelman, 2013). Relatively few studies have dealt with crashes involving bicyclists (Siddiqui et al., 2012; Yannakoulias et al., 2012). Limited numbers of these studies focused on urban environments, and accounted for more detailed features of multimodal street networks (Moeinaddini et al., 2014; Quddus, 2008).

The Role of Exposure and Surrogate Measures

A typical concern in multimodal transportation safety analysis is determining the adequate exposure variables, and this has been addressed by using both surrogate and conventional exposure variables depending on data availability. The exposure variables in existing areal safety studies include variables such as population (Ukkusuri et al., 2012), presence of jobs as trip generators (Noland, 2014), network attributes and land use data (Shankar et al., 2003), estimated walk miles traveled for pedestrian crashes (Lee & Abdel-Aty, 2005; Wang & Kockelman, 2013), estimated bicycle traffic (Vanderbulcke et al., 2014), length of road (Noland & Quddus, 2004; Quddus, 2008; Zeng & Huang, 2014), and vehicle miles traveled (Aguero-Valverde & Jovanis, 2006; Li et al., 2013). Previous spatial analyses of crashes focused on both motorized (Aguero-Valverde, 2013; Li et al., 2013; Siddiqui et al., 2012) and nonmotorized crashes (Quddus, 2008; Shankar et al., 2003; Wang & Kockelman, 2013), accounting for variables that somewhat represent the availability of alternative transportation modes (Quddus, 2008; Schneider et al., 2004; Wang & Kockelman, 2013; Yiannakoulias et al., 2012).

The importance of exposure variables as crucial elements of risk assessment in crash prediction models has been recognized in safety research for over two decades (Qin, Ivan, & Ravishanker, 2005; Zhang, 2008). Measures of exposure were primarily related to traffic flow and the amount of road travel, with an assumed linear relationship between the exposure and risk (Zhang, 2008). As crash modeling methods advanced, new ways to define exposure emerged, and the relationship between the exposure and risk has been redefined as more complex, multidimensional concept that can be decomposed in terms of both road users and vehicle movements (Elvik, 2009; Zhang, 2008).

The concept of exposure originates from epidemiology and it is essential in road safety studies, as it relates to the opportunities for conflicts that may occur between different users, and result in a crash outcome (Lam, Loo, & Yao, 2014). The term "exposure" as related to road safety dates back to the 1970s when exposure was defined as the "number of opportunities for accidents" of a certain type within a given time and in the given area. The definition of exposure has varied since to account for different locations, users, and measures. A very detailed overview of the way exposure was defined over years is provided in (Elvik, 2015).

According to (Elvik, 2015) measures of exposure can be categorized as follows:

1) Activity-based measures of exposure represent the sum of users that may be exposed to crashes. These measures are usually continuous variables that include Average Annual Daily Traffic (AADT), Vehicle Miles Traveled (VMT), the number of vehicles entering the intersection approach, Walk Miles Traveled (WMT), and Bike Miles Traveled (BMT).
2) Event-based measures of exposure represent the total number of events within a given time in the defined area that may result in crash outcomes. These measures are different from the more traditional continuous summary measures based on users activity, and include the number of potential conflict points, the number of intersection turning movements, and the number of lane changes. Exposure as an

event is defined as the "occurrence of any event in traffic limited in space and time that represents a potential for an accident to occur by bringing road users close to each other in time and/or space or by requiring the road user to act to avoid leaving the roadway".

3) Behavior-based measures of exposure represent users behavior that may lead to higher exposure to crashes. These measures became possible as real-time monitoring technology became available to enable measurements such as the time spent following, pedestrian crossing behavior, pedestrian gap acceptance, and drivers characteristics.

The linear relationship between exposure and risk has been rejected over time (Hauer, 1995), and previous research explains how this is due to the human ability to learn from experience (Elvik, 2009). As the amount of travel increases, the propensity to be in a crash is expected to decrease, because of the human learning process (Elvik, 2009). The rate of fatalities is also expected to decrease as a function of motorization level (Smeed, 1949). Similar "laws of accident causation" include the assumption that higher crash rates are associated with more rare events, higher crash complexity, and more limited cognitive capacity (Elvik, 2009).

Theoretical relationships between crash risk and exposure commonly use the term "crash rates." The expected number of crashes can be estimated as the product of exposure measures and risk factors only when exposure and risk are independent. However, operationally and conceptually, it is always expected that exposure to risk is somewhat related to risk, which renders the assumption of the independent relationship biased. This conclusion, as well as the existence of the composite measures of exposure, raised issues with using crash rates to quantify road safety. Unlike the "observed crash frequency," which is the term used to refer to the historic crash data, crash rates refer to the number of crashes in relation to a particular measure of exposure. When crash rates are used, the number of total, fatal, or injurious crashes is divided by different exposure measures such as the population size, the number of licensed drivers, the number of registered vehicles, or the number of miles/kilometers driven (Shinar, 2007). The U.S. Department of Transportation uses fatalities per million VMT to set traffic safety goals, as the number of crashes per total VMT is the most common crash rate used. However, the value VMT can only be estimated, and is not perfectly accurate (Shinar, 2007). VMT as a summary measure of exposure that is commonly used, is sometimes criticized in the literature as the average value of VMT used to predict crash models can rarely be considered close to the value of traffic flow near the time of crash occurrence (e.g., on the annual level) (Mensah & Hauer, 1998). To compensate for these limitations of using VMT as the measure of exposure, it is recommended to analyze safety using multiple years of data.

In terms of multimodal exposure and safety, two concepts are defined in the existing literature: "safety in numbers" and "hazard in numbers." Safety in numbers concept implies a decline in risk as exposure increases, while hazard in numbers refers to the opposite effect when the number of crashes increase even more as the volumes increase. Some researchers claim how both effects, safety and hazard in numbers, may co-exist in the same dataset, recommending further that the count of the road users number rather than rate is used as a measure of exposure in road safety. There is also evidence that higher numbers of nonmotorized users result in lower likelihood of these users being injured in crashes, as motorists adjust their behavior in the presence of walking and biking (Elvik, 2013; Jacobsen, 2003).

As exposure measures progressed from the activity-based to event and behavior-based, the measurement process became more complex. Exposure measures also become more challenging to obtain as the transportation users group of interest changes from the exposure of vehicle occupants to the exposure of multimodal users. Collecting highly accurate data on walking and biking remains a challenge, even though significant improvements have been made over time. Theory of accessibility has previously been used as a proxy for exposure variables in road safety studies. Trip generation elements, including estimations of productions and attractions and estimates based on gravity theory, were used to quantify the amount of travel within the defined units of spatial analysis (Lee & Abdel-Aty, 2013; Noland & Quddus, 2004; Vandenbulcke et al., 2013;). With the often limited data on nonmotorized users activity, and the link between multimodal accessibility and multimodal exposure, there is a need to further explore if measures of accessibility can help overcome the gap in urban multimodal safety research due to lack of information on exposure.

Measures of Multimodal Accessibility

With the limitations of the exposure measures related to multimodal users, and the growing potential of urban data on multimodal infrastructure and access to transportation options, there is a need to further explore whether measures that represent multimodal accessibility can help overcome gaps in urban multimodal safety research in terms of multimodal trip distances and opportunities for conflicts. Measuring accessibility for different modes of transportation is a challenging task, and this field has been developing for over four decades, but studies that explore the relationship between accessibility and safety are rare.

While current policy makers still use transport system metrics that are mobility oriented, partially because they are the most available, these performance metrics are excluding some crucial components of urban transportation systems (TRB, 2003). Accessibility emerges as the measure that captures more than the speed of travel, emphasizing the benefits of the transportation system users. It relates to both transportation and land use, as it quantifies how many destinations an individual can reach using the given mode of transport within the available time (Handy & Niemeier, 1997).

The first challenge in accessibility measurement is to define accessibility. While it is generally defined as the opportunity to approach, enter, and interact (Burns, 1979; Engwicht 1993; Koenig, 1980), in terms of transportation, accessibility definitions are more precise. In transportation systems, accessibility is the ease of reaching goods, services, activities, and destinations (Alba & Beimborn, 2003; Cervero, 2005; Litman, 2012). The transportation element of accessibility reflects how 'easy' travel is or could be between points in space, while the spatial element of accessibility characterizes the attractiveness of a trip destination (Handy, 1993). Access can be affected by many factors, such as the location of adequate employment options, availability and affordability of travel options, and the attractiveness and diversity of opportunities. This is why measuring accessibility is a complex task (Litman, 2011).

Several types of accessibility measures related to transportation are developed in the existing research. Cumulative accessibility measures evaluate accessibility in terms of the number of opportunities or activity locations that can be reached within the given travel time from a defined reference location (Black & Conroy, 1977; Handy & Niemeier 1997). Accessibility as a cumulative measure is a function of proximity, connectivity, and mobility, and as such, is very useful in transportation planning practice (Handy, 2002).

Gravity-based accessibility measures assign specific weights to the opportunities depending on the distance, travel time, and cost required to reach those opportunities or activity locations. With gravity-based measures, accessibility increases with proximity and affordability of opportunities, and decreases as those opportunities become more distant and their costs increase. The available literature emphasizes two disadvantages of these measures, as they require assigning weight to a wide range of destinations, and there is a need for an impedance factor that represents distance, travel time, and cost of the weighted opportunities (El-Geneidy & Levinson; 2006; Hansen, 1959; Papa & Coppola, 2012; Scheurer & Curtis, 2007).

Utility-based accessibility measures incorporate traveler preferences, which affect the weight of opportunities in terms of access. These measures calculate the utility of the chosen opportunity relative to the utilities of alternative opportunities (Ben-Akiva & Bowman, 1998; Ben-Akiva & Lerman, 1979; El-Geneidy & Levinson, 2006; Geurs & Eck, 2001).

Some measures related to network connectivity in urban areas are also good indicators of accessibility, since denser, better connected networks make destinations easier to reach and increase the number of reachable destinations in general. One such measure is the connectivity index, the number of network links divided by the number of network nodes (Ewing, 1996). Higher connectivity indices improve accessibility up to a certain point, but it does not always guarantee the optimal transportation performance (Alba & Beimborn, 2005; Tasic et al., 2015). The challenge in utilizing a connectivity index as an indicator is that there is always a need to balance the level of connectivity in order to optimize transportation performance by increasing the number of nonmotorized and transit users while avoiding congestion.

The composite accessibility measure incorporates temporal constraints in addition to spatial constraints for a more complex measurement approach (Kwan, 1998; Miller, 1999; Wu & Miller, 2001). As public transit has unique characteristics among other modes, due to its spatial and temporal constraints, using composite space-time accessibility measures is appropriate for developing transit accessibility indicators. One of the most powerful techniques for space-time accessibility measurements is the space-time prism (STP). The STP-based accessibility measures determine a "feasible set of locations for travel and activity participation," considering spatial and temporal constraints that affect individual's behavior (Kwan, 1998). Some earlier STP-based accessibility measures had the disadvantage of treating travel time as static rather than dynamic. After empirical research proved that temporal constraints have a significant impact on an individual's ability to reach desired destinations, the STP-based accessibility measurement methods have been updated to account for this (Kwan, 1998; Miller, 1999; Wu & Miller, 2001). The STP-based measures incorporate the spatial distribution of destinations, uncertainty of origin and destination choices, travel time variability as a consequence of transportation network configuration, time needed to participate in various activities at various destinations, destination availability in terms of temporal constraints or maximum available travel time, and static and dynamic traveler delay (Miller, 1991).

Broadening the scope of accessibility to include a wide array of destinations and non-auto modes such as walking, cycling, and transit has been previously proposed as a much needed aim among planning initiatives (Tal & Handy, 2012). Even though a well-known transportation planning concept, for a long time, accessibility has been evaluated using auto-based measures (Handy & Clifton, 2001). The best accessibility measurement method should be chosen based on the purpose and a situation that requires such measurement (Handy & Niemeier, 1997).

Accessibility for Nonmotorized Modes

The most recent advancements in open-source tools for walkability ratings brought attention to the importance of pedestrian accessibility measurements. A large number of transportation app developers today focus on developing the best methods to score walkability of an area and inform pedestrian users about the shortest, safest, and most attractive walking routes in urban environments.

One of the most applied tools for scoring urban walkability is Walk Score, based on awarding points to each address depending on distance to destinations. Walk Score uses a distance decay function combined with density indicators (e.g., population density, block length, intersection density) to grade walkability on a scale of 0 to 100, giving the locations within 5-minute walking distance the highest score. Similar to Walk Score is an application developed to measure the attractiveness of routes for bicyclists, called Bike Score.

Some other similar apps are also developed for measuring walkability, such as Walkonomics which uses eight criteria (including road safety and fear of crime) to inform users about the fastest and most attractive routes to destinations. Clean Air Asia initiative also developed a Walkability app, which is based on citizens' walkability audits and provides authorities with citizens' inputs. All these applications were developed because today, the transportation industry understands that practitioners need to know how feasible walk trips are to become users' choice, whether they lead to actual final destinations or are simply integrated in a multimodal trip. These efforts towards quantifying the quality of pedestrian access acknowledge that every trip begins and ends with a pedestrian trip, and every bicyclist, transit user, or driver is a pedestrian in the first place.

In terms of pedestrian accessibility analysis for scientific purposes, several efforts were made towards software development, mostly based on GIS. One such effort is A Methodology for Enhancing Life by Improving Accessibility (AMELIA), developed by the Center for Transportation Studies at University College London to assess the impact of transportation on social inclusion. Another software tool, Accession, was developed by Citilabs and the United Kingdom Department for Transport, but it is recognized that it handles pedestrian accessibility poorly, mostly due to lack of data (Achuthan, Titheridge, & Mackett, 2004).

The prerequisite for good pedestrian accessibility measurements are data (Chin et al., 2007; Foda & Osman, 2010; Iacono, Krizek, & El-Geneidy, 2010). It is very challenging, and in the first place time consuming, to collect data about pedestrian networks, which is why most of the studies opt for using street centerline as a proxy for pedestrian network.

Further, data about crosswalks and sidewalks are very difficult to obtain. A study by (Chin et al., 2007) compared street network versus pedestrian network in terms of connectedness, using three measures: pedshed, link node ration, and pedestrian route directedness. The results indicated that connectivity in conventional neighborhoods (curvilinear street network) improved up to 120% when pedestrian networks were accounted for. Previous research findings indicate that it is important to account for the actual pedestrian network when measuring pedestrian accessibility and connectivity (Tal & Handy, 2012).

Another challenge related to acquiring pedestrian data is in obtaining the information about movements and destination choices, primarily based on need and utility for pedestrians. Even in highly walkable areas, where mixes of land uses and density are high, pedestrian trips might not be the choice because destinations that are easy to walk to might not be destinations where users are interested in going. Previous studies that introduce pedestrian accessibility measurements are based on urban form features (Cambra, 2012; Rendall et al., 2011). One of the studies deals with energy consumption, where high active mode accessibility means that the transportation system is served with minimal energy input (Rendall et al., 2011). The majority of the developed pedestrian accessibility measurements are based on cumulative opportunity measures, sometimes with the inclusion of impedance to form a gravity-based model, unlike accessibility models for private vehicles or public transit where more complex space-time dynamics is included in measurement concepts.

Transit Accessibility

Transit is a unique mode of transportation because of the way it is constrained in terms of space and time. In terms of space, it requires transit stop facilities and special road design treatments, while in terms of time, transit follows specifically scheduled timetables. These spatial and temporal components determine the accessibility of public transit systems. Transit accessibility indicates how easy it is for an individual to reach a desired destination using public transit. It is important for the existing transit riders, as an indicator of the service quality, and for the potential riders as well, as it might be a factor in their mode choice (Moniruzzaman & Paez, 2012).

Access to transit is a precondition for all the efforts taken towards multimodal transportation systems. Whether an individual will use transit or not depends on many factors, including their value of time and available time budget, transit fare price, and ratio of car/transit utility (Taylor, 2008). However, in order for transit to be considered as an option in mode choice at all, there has to be a feasible transit route leading from given origin to desirable destination within the available time frame.

Public transit is considered to be a feasible travel choice when transit stops are accessible to and from trip origins/destinations (spatial coverage), and when transit service is available at times that one wants to travel (temporal coverage) (Coffel, 2012; TRB, 2003). Transit accessibility determines the attractiveness of transit as a mode choice. How accessible transit stops are depends on whether the transit users are walking, biking, or driving to their nearest stop. The primary factor affecting pedestrian access is distance to transit stops. Based on the assumed average walking speed of about 4ft/s, 5 minutes of walking to transit stops is considered to be acceptable in urban areas, or about quarter of a mile in terms of walking distance (AASHTO, 2004; TRB, 2003). Location and spacing between transit stops have a significant impact on transit service performance and user satisfaction, as they not only ensure reasonable accessibility but influence travel time as well (Google, 2013; Miller, 1999). Measuring “the ease of access” to transit services in terms of space-time constraints is important for evaluation of the existing services, travel demand forecasts, and decision making related to transportation investments and land use development (AASHTO, 2004; Coffel, 2012).

Accessibility, Exposure, and Safety

Previous studies clearly indicate that the amount of exposure for all modes of transportation depends on accessibility. The indicators of accessibility, in terms of both access to destinations and access to transportation infrastructure, influence traveler behavior including mode choice and the amount of travel by different modes.

The primary choice of transportation mode is found to be associated with the availability of multimodal infrastructure, the proximity of desired destinations, and general utility calculated through costs of transport and destination attractiveness. The comparison of similar “accessibility” conditions between the U.S. and countries that have higher shares of alternative transportation users, however, showed that it is especially important to combine physical accessibility to destinations with utility-related measures in order to encourage multimodal transportation in the U.S. (Ben-Akiva & Lerman, 1985; Bhat et al., 2000; Buehler, 2011; Handy, 2002).

The existing research consistently finds strong relationships between accessibility and the amount of travel by different modes. The indicators of accessibility and street connectivity impact the amount of VMT, and as the number of destinations within walking distance increases the propensity to walk also increases while the VMT and fuel consumption decrease. The fundamental characteristics of the street network such as street connectivity, network density, and street patterns are found to be significantly associated with the choice of transportation mode (Cervero & Kockelman, 1997; Ewing & Cervero, 2001; Handy, 1993; Marshal & Garrick, 2010).

The existing literature recognizes the complexity of the relationship between accessibility and safety, as well as the need for further research on this topic (Kim & Yamashita, 2010; Mondschein, Brumbaugh, & Taylor, 2009; Sathisan & Srinivasan, 1998). A study based on 3 years of crash data from Hawaii that used binomial logistic regression to model the relationship between accidents and accessibility found that the indicators of accessibility are associated with increases in various accident types in terms of severity and mode of transportation. In addition to considering the demographic variables, accessibility was represented using road length, bus stops, bus route length, number of intersections, and number of dead ends. Data were spatially disaggregated using uniform grid cells, and the authors indicated the need to use accessibility indices that would take into account travel time and mobility options.

Another study, also based on data from Hawaii, used structural equation modeling to establish causal relationships between accessibility and accident severity (Kim, Pant, & Yamashita, 2011). Other impact factors such as human factors, vehicle type, road conditions were included in the models based on 3 years of crash data disaggregated by uniform grid cells using ArcGIS. Accessibility was represented using total street length, total bus route length, number of intersections, and number of dead ends in the grid. The authors found that accessibility was associated with the reduction of the expected number of severe crashes, refining the findings from the previous study based on the same dataset. The authors further explain that decreased crash severity in better accessible locations makes sense as more accessibility can be associated with lower driving speeds. This conclusion somewhat indicates that accessibility has different relationship with crash frequency and crash severity, as confirmed in studies that link road safety to land use characteristics.

Studies that link land use to road safety include some indicators of accessibility in their analysis. These studies acknowledge human-vehicle-roadway factors as the key factors that contribute to each accident, but are based on the fact that the built environment (and environment in general) leads to particular interactions between the drivers, creating certain driving habits and travel behavior that eventually impacts safety outcomes (Kim & Yamashita, 2006; Kim & Yamashita, 2007). The so-called "secondary variables" indirectly impact traffic safety, and the research that emphasizes the importance of these variables is growing. Relationships have been found between the development type and intensity and road crashes, indicating that simple differentiation between urban and rural areas does not completely capture the impacts of land use on safety (Kim et al., 2006). The indicators of accessibility in these studies are also categorized among the "D variables" (density, diversity, design, destination accessibility, access to transit, parking) in the urban planning literature (Ewing & Cervero, 2001). Destination accessibility as one of the seven "D variables" is defined as the "relative ease of accessing jobs, housing, and other attractions within the region" (Ewing & Dumbaugh, 2009). This group of studies suggests that the strong association between destination accessibility and VMT might indicate that highly accessible areas in urban centers may have lower numbers of fatal crashes than highly accessible areas in suburbs (Ewing, Pendall, & Chen, 2003; Ewing, Schieber, & Zegeer, 2003; Ewing & Dumbaugh, 2009).

Other Relevant Variables in Areal Safety Studies

The majority of the existing areal safety analyses include some kind of SE variables and find them to be significant for area-wide safety outcomes (Aguero-Valverde & Jovanis, 2006; Chen, 2013; Flask & Schneider, 2013; Kim et al., 2013; Li et al., 2013; Noland & Quddus, 2004; Siddiqui et al., 2012). These studies found that the increase in the expected number of crashes is associated with the increase in population, while the findings on the relationship between income level and the expected number of crashes were contradictory (Aguero-Valverde & Jovanis, 2006; Noland & Quddus, 2004; Siddiqui, 2012).

Several existing research studies include land use variables in safety outcome evaluations, particularly studies that focus on spatial analysis in urban multimodal environments (Cho, Rodriguez, & Khattak, 2009; Lee & Abdel-Aty, 2013; Polugurtha et al., 2013; Shankar et al., 2003; Ukkusuri et al., 2012; Wang & Kockelman, 2013). Land use type and land use mix were found to be significantly correlated with area-wide crashes, especially when the effect on nonmotorized crashes is estimated (Polugurtha et al., 2013). Residential areas are usually associated with fewer crashes when compared to commercial land uses (El-Basyouny & Sayed, 2009).

Crash Analysis Methods in Areal Safety Studies

The majority of the areal road safety studies found that it is appropriate to consider spatial correlation among analyzed entities in crash prediction models (Aguero-Valverde, 2013; Castro, Paleti, & Bhat, 2013; Quddus, 2008; Siddiqui et al., 2012; Wang, Quddus,

& Ison, 2009; Zeng & Huang, 2014). More recent research involves using Bayesian rather than classical statistical inference to develop spatial models for motorized and non-motorized crashes at various levels of spatial aggregation (Aguero-Valverde & Jovanis, 2006; Huang & Abdel-Aty, 2010; Miaou & Lord, 2003; Miranda-Moreno, Labbe, & Fu, 2007). As concluded in the previous studies, Fully Bayesian models are either consistent with negative binomial models (Aguero-Valverde & Jovanis, 2006) or outperform models that do not account for the multilevel structure of crash data (Huang et al., 2009; Siddiqui et al., 2012; Wang & Kockelman, 2013). Robustness and transferability of multilevel models applied in safety analysis are issues that are still scarcely addressed (Huang & Abdel-Aty, 2010). These models may be complex for estimation and may not be easily transferable to other datasets. The results, particularly related to the underlying spatial correlation, may also be difficult to interpret (Lord & Mannering, 2010).

While some of the previous studies handled spatial correlation among analysis units by applying Bayesian models, there are studies that opt for less complex modeling approaches that rely on classical statistical inference. These studies use Geographically Weighted Poisson Regression (Li et al., 2013; Xu et al., 2015), or suggest considering negative binomial models with fixed and random effects to account for spatial and/or temporal disturbance "spillover effects" in the data (Noland & Quddus, 2004; Shankar et al., 1998; Wang et al., 2009). In the case where correlation among observations is expected due to spatial or temporal proximity, models with random and fixed effects may be considered. Spatial correlation might occur when data from the same regions "share unobserved effects" (Lord & Mannering, 2010). In such cases, models with fixed effects would account for unobserved heterogeneity by using indicator variables for defined regions, while models with random effects account for unobserved heterogeneity across spatial or temporal units with the assumption that these effects have certain distributions over the spatial/temporal units of analysis (Hausman & Taylor, 1981; Lord & Mannering, 2010). Several previous studies have used fixed and random effects to handle unobserved spatial and temporal correlations in crash data (Johanson, 1996; Shankar, 1995; Miaou & Lord, 2003; Noland & Quddus, 2004; Porter & Wood, 2013).

Generalized Additive Models (GAM) have been used in relatively few published crash studies (Li, Lord, & Zhang, 2009; Xie & Zhang, 2008). The two safety studies using GAM that were identified for this literature review focused on the complexity between the crash outcomes and explanatory variables (e.g., AADT). One of the studies incorporated a smooth function as a cubic regression spline into the additive models, and concluded that GAM outperformed generalized linear models (Xie & Zhang, 2008). The other study used GAM to incorporate interaction terms into crash modification factors, concluding that this approach adequately captured the interactions between geometric design and operational features (Li et al., 2009). Other disciplines, such as ecology and epidemiology, have used GAM in spatial analysis, taking advantage of the ability of smooth functions to account for random spatial effects and spatial correlation in the data (Schmidt & Hurling, 2014; Wood, 2006).

Summary of Literature

Based on the reviewed literature on urban multimodal transportation safety, this study primarily fills in the research gaps in terms of the data used to estimate areal safety models resulting from this research. While previous studies attempt to include area-wide effects and the presence of multimodal infrastructure, this study captures the complete presence of infrastructure dedicated to all four modes: vehicles, transit, pedestrians, and bicyclists. In addition, area-wide effects considered in the previous areal safety studies, such as SE data and land use characteristics, are also considered in this analysis.

Further, the measures that characterize general access to multimodal transportation options for various transportation users are expanded in this study, to include not only the indicators of street connectivity, but also network completeness that captures the presence of complete streets on the area-wide level, and multimodal accessibility measures that capture access to destinations. Particularly measures of accessibility are developed on a very fine-grained level, to capture the ability of pedestrians, and bicyclists to access destinations, as well as the ability of transit users to access both transit service and destinations while accounting for spatio-temporal variations. These additional measures that capture the access and the effectiveness of multimodal infrastructure, contribute to the estimated areal safety models, as a proxy for multimodal users exposure and the opportunities to be involved in crashes, representing trip opportunities, distances and potential conflicts. These measures also contribute to the exiting literature on measuring multimodal accessibility, as previous studies did not measure nonmotorized accessibility on a scale as large as presented in this research, while this is one of the first studies to incorporate spatio-temporal variations in transit service into the measurement of transit accessibility.

Looking at the methodologies applied in previous road safety studies, particularly areal studies and studies that focus on multimodal transportation, both frequentist and Bayesian statistical inference are used to estimate statistical safety models. Areal safety studies that focus on more than one user type are rare, with a particularly low number of studies focusing on pedestrians, and even lower number of studies focusing on bicyclists as vulnerable users. While Bayesian methods have gained a lot of attention over the previous decade, this study explores in details methods based on frequentist inference, and their potential to serve for areal crash estimation. In addition to GLM, the GAM approach is implemented, that has previously been used in very few segment-based road safety studies, and has not been explored in areal safety studies.

The data, measures, and methods presented in this research are developed to fill some of the existing research gaps in multimodal transportation safety in urban environments, and contribute to research and practice efforts focused on designing safer and more accessible multimodal transportation systems.

CHAPTER 3

METHODOLOGY

This chapter describes the methods used to accomplish the research goal and objectives related to exploring the factors that are associated with the multimodal transportation safety outcomes in urban environments, as defined in the Introduction. Methodology described in this chapter is based on the conceptual framework provided in Figure 1. The sections of this chapter include the general approach to research methodology development, the data collection, description of data, variables, and measures, and the SASM methods applied in crash estimation process.

Data collection is described in details, including the site selection, the sources of data, and the way data were aggregated and used for the purpose of crash estimation by using SASM methods. Variables used in the analysis are divided into four major sections covered in this chapter. First, crash data are described, including characteristics of total and severe crashes for vehicles, pedestrians, and bicyclists. Second, variables that represent multimodal exposure are provided. Third, potential exposure surrogates through the representation of access to multimodal transportation are provided. Fourth, variables that represent system-wide factors that are found to be associated with crash outcomes in the existing research are described. The final section of this chapter is dedicated to the description of SASM methods, their application to estimate the expected number of crashes for multimodal users, and statistical model diagnostics.

Research Design

The SASM models were estimated using multimodal crash outcomes as the response variables; and variables and measures representing exposure, access to multimodal transportation, and system-wide effects that may influence safety as the explanatory variables. The following equation represents the general formulation of SASM methods used to safety as a function of multiple explanatory variables:

$$Areal\ Safety = f(Multimodal\ Exposure + Multimodal\ Access + System\_wide\ effects) \quad \text{Equation (1)}$$

The SASM framework for estimation of the expected crash number by type and severity provided in Equation 1 primarily acknowledges the complexity of urban multimodal transportation systems and the variety of factors that may influence safety in these environments. The expected number of crashes was estimated on the areal level in terms of total and severe crashes for vehicles, pedestrians, and bicyclists.

After establishing the general crash estimation framework, the next research step was to determine the location where urban multimodal safety was explored, and to determine the level of data aggregation. The review of literature served to establish the gaps in current multimodal safety research in urban environments, define the research goal and objectives, and establish data needs in order to proceed with the data collection. After establishing the data needs and considering the potential data sources, data were collected from various sources and aggregated, as will be explained in the following section of this chapter.

The data collection and aggregation process resulted in obtaining variables representing crashes, exposure, and area-wide effects that may influence multimodal safety. In addition, obtained data were utilized to develop measures of access to multimodal transportation, from the presence of multimodal infrastructure, to multimodal network connectivity and accessibility. These measures were used as the additional proxies or surrogates for the multimodal exposure in terms of trip opportunities, distances, and potential for conflicts.

Five SASM methods were applied to estimate safety outcomes for multimodal users, following the framework from the Equation 1. These SASM methods were evaluated in terms of the model specifications, the ability to capture spatial correlation in the data due to the spatial aggregation, and the overall model goodness of fit. This research method design resulted in recommendations for the future multimodal safety evaluation methods in urban environments.

Data Collection

The key elements in the data collection for this research included identifying data needs, selecting the analysis site, and determining the areal unit of analysis that was used to aggregate the data. The site selection and data collection and organization were conducted to acknowledge the growing potential of urban data, accounting for a broad array of data sources in urban multimodal transportation systems. Thus the concepts of Big Data and Open Data played a significant role in the dataset development, as the analysis site was selected to explore the potential of the inclusion of Open Data in the dataset, and to allow for the dataset expansion in the future as Big Data on multimodal transportation users activities are becoming more and more available.

Site Selection

The search for data involved various cities, mostly from the U.S. and Europe, with diverse transportation options in their urban environment, and with solid data sources available for urban multimodal research. Since the research methodology was designed to conduct areal analysis, the most useful for this purpose were available Geographic Information System (GIS) databases, or other datasets that include spatial information.

The City of Chicago Department of Innovation and Technology maintains a very detailed database on transportation and urban environment features. Chicago's robust data portal was established in 2010 and hosts over 900 datasets with information on various services in the city, in tabular, GIS, and API formats. The portal is developed to enable residents to access government data and utilize them to develop tools that can improve the quality of life in the city. This is currently one of the "largest and most dynamic models of open government in the country" (Thornton, 2013). In addition to improving the decision making process by merging various data sources and developing an Open Data platform, the City of Chicago is also invested into developing new ways to generate and collect urban data.

Apart from the major efforts to develop high fidelity open source data platforms, Chicago is also known for its extensive multimodal transportation system. The City has developed complete streets design guidelines (City of Chicago, 2013), with "Make Way for People" initiative that converts underutilized "excess asphalt" street spaces into active public spaces with purpose to increase safety, encourage walking, and support community development. Chicago has invested in bicycling infrastructure to become one of the best major U.S. cities for biking with over 200 miles of on-street bike lanes.

The City of Chicago is also known for its active safety research not only vehicles but bicyclists and pedestrians as well, and a very extensive transit system. Chicago is the first major city in the U.S. to adopt a city-wide policy for the investments in safety countermeasures that would reduce pedestrian crashes, as a part of the national "Vision

Zero Network" initiative. All factors described above made Chicago a valid case study for the purpose of this research.

Data Sources

This study combined data from several sources, including open data and data obtained from multiple transportation agencies, to develop a comprehensive framework for the analysis of the relationship between multimodal transportation features and safety in urban transportation systems. Data collection included crashes, multimodal transportation features, road network features and traffic conditions, land use data, socio-economic characteristics, and analysis of spatial features to select the adequate spatial units of analysis. Data were obtained from the Illinois Department of Transportation (DOT), Chicago Metropolitan Agency for Planning (CMAP), Chicago Transit Authority (CTA), City of Chicago, U.S. Bureau of Census, as well as the available open data platforms supported by the City of Chicago. Table 1 shows the data sources used to collect the data and develop the dataset for this research.

Table 1 Data Sources, Descriptions, and Formats

Data	Source	Year	Format
Crash records	Illinois DOT, Chicago Crash Browser	2007-2012	csv
Socio-economic characteristics	U.S. Bureau of Census, ACS 5-Year Estimates	2008-2012	csv
Land use	Chicago Metropolitan Agency for Planning	2010	shp
Road network	City of Chicago	2012	shp
Travel demand model	Chicago Metropolitan Agency for Planning	2010	csv, shp
Other traffic volume data	Illinois DOT	2014	csv
L Train lines, stops and ridership	Chicago Transit Authority	2012	csv, shp
Bus lines, stops and ridership	Chicago Transit Authority	2012	csv, shp
Bike lanes and bike racks	City of Chicago	2012	shp
Sidewalk	City of Chicago	2012	shp
Commuter trips to work by means	U.S. Bureau of Census, ACS 5-Year Estimates	2008-2012	csv
Spatial units of analysis	City of Chicago	2012	shp

Spatial Analysis Units and Data Aggregation

In order to capture multiple factors that could impact crashes in urban environments, collected data from Chicago were spatially aggregated. Determining the level of spatial data aggregation is an important step in this study, as the choice of spatial analysis units could significantly impact the outcomes and types of conclusions that can eventually be drawn. The choice of the data aggregation unit ultimately depended on the desired level of detail in the final dataset and the data availability. For Chicago, a wide range of spatial units was considered, including four planning regions and seven planning districts, 50 wards, 77 communities, 228 neighborhoods, more than 800 census tracts, more than 2000 census blocks, and traffic analysis zones.

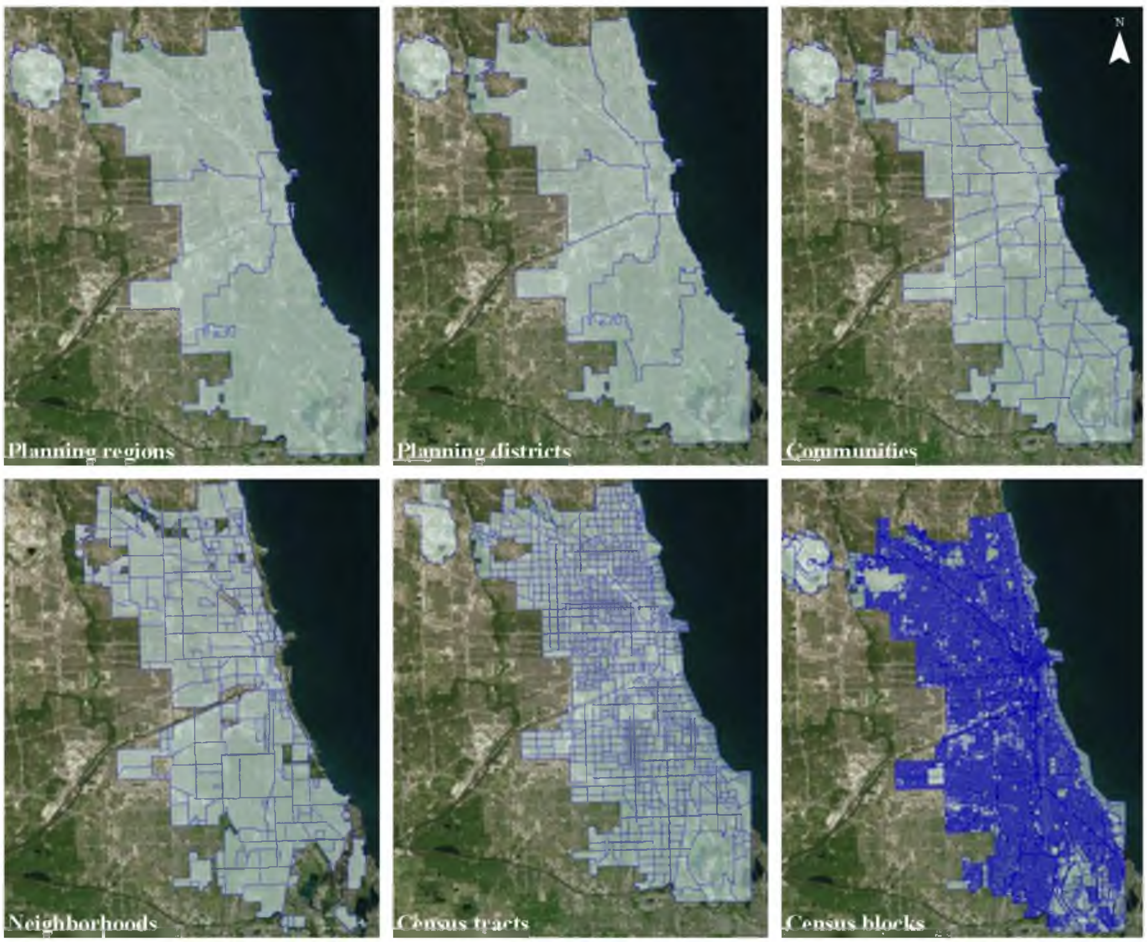
There are always trade-offs when selecting the appropriate unit of analysis in areal safety studies. Compromises in selecting a unit of analysis will often be made on account of data availability. Another compromise must be considered between the accuracy of the data and the ease of comparison between units of analysis.

Planning regions and districts, or the Central, South, North, and West Side, were too large areas for this type of analysis, covering both land uses and parts of the urban transportation systems that are too diverse to be aggregated for the dataset formulation. Since 1923, the city has been divided into 50 wards led by the City Council representatives. However, it was not recommended to use wards for city areas comparison, especially over a period of time, since the wards are redistricted every 10 years related to the population.

Communities in Chicago refer to the work of Social Science Research Committee at the University of Chicago, which has unofficially divided the City of Chicago into 77 community areas. Census data are tied to community areas, and they serve as a basis for a variety of urban planning initiatives on both local and regional level. Communities are well defined and static, and they were a potential candidate for areal analysis units. Each community, however, contains one or more neighborhoods, and in some cases, the character of the community was hard to determine due to the number and variety of neighborhoods. There are 228 neighborhoods in the available GIS database, but the shape and size of these neighborhoods has been varying over time as real estate development was changing. So the neighborhoods were not the ideal starting point for this type of analysis.

Census tracts are small statistical county subdivisions with relatively permanent geography that are updated each decade under the initiative of the U.S. Census Bureau. Census tracts are supposed to be somewhat homogeneous and ideally have around 1200 households (perhaps 2000-4000 people), but, in Chicago, population varies from 0 up to 16,000. Census tracts in the city of Chicago have remained nearly constant since the 1920s, but the numbering system has changed. Census tracts in the suburbs have changed a great deal over the years, in most cases by splitting. There were 876 census tracts in Chicago according to the 2000 census. Census blocks correspond closely to blocks that any urban resident would identify. Only limited data are available at the block level, and some figures are suppressed to prevent identification of individuals.

Based on the previous discussion, census tracts were selected as the areal units of analysis for data aggregation and SASM methods application in this study. Census tracts were the most appropriate for spatial analysis in this case due to the data coverage and availability, and the convenient link to SE characteristics, which have proven to be relevant for safety outcomes. The ranges of spatial units numbers used in the available literature indicated that census tracts would be appropriate as well. After merging the data needed for the analysis, and eliminating some census tracts due to missing data in the geocoding process, a total of 801 census tracts remained in the dataset. Figure 2 provides the illustration and the descriptive statistics for the spatial units of analysis considered in this analysis, including the selected census tract areas.



Area	Obs	Mean	Std. Dev.	Min	Max
Census Tract Area in miles squared	801	.3025424	.4834481	.003204	8.355789

Figure 2 Spatial Units of Analysis Considered in This Study with the Description of Census Tract Area as the Selected Unit of Analysis

Response Variables

Crash data for Chicago were available from the Chicago Crash Browser and the Illinois DOT. The Chicago Crash Browser is an online database that maps all pedestrian and bicyclist crashes in the city. It is an interactive map that allows the choice of a search radius, output type (either graph or text), and address in Chicago, for pedestrian and bicycle crash search. The Browser right now includes Chicago crash data for the period between 2005 and 2012, with crash records where a pedestrian or a bicyclist was the first point of impact by an automobile. These records were collected by corresponding law enforcement and maintained by the Illinois DOT. Chicago Crash Browser interactive map primarily served for preliminary crash data exploration for nonmotorized user crashes.

After using the open-source data to determine the adequate crash data availability for multimodal users and confirm that Chicago is the appropriate case study, the Illinois DOT served as a main source of crash data for the period from 2005 to 2012. A total of 764,261 crash records were included in this database, with crashes that involved only motorized and both motorized and nonmotorized users. The obtained crash records included crash coordinates, county, city, and township codes where crash has occurred, year, month, day, and hour when the crash has occurred, vehicle occupant information, crash severity information, horizontal and vertical alignment, cross section, road functional classification, traffic control, pavement condition, weather and light condition, primary and secondary crash causation events, and collision type. These two data sources provided very detailed information about crashes that have occurred in Chicago over the period of 8 years. Response variables in this research were identified to differentiate between safety outcomes for motorized and nonmotorized users, as well as safety outcomes in terms of frequency and severity. The response variables that this research was focused on included:

- Total vehicle-only crashes (vehicular crashes, all types and severities)
- Fatal and severe injury vehicle-only crashes (severe vehicular crashes, all types)
- Total crashes involving pedestrians (pedestrian crashes, all severities)
- Fatal and severe injury crashes involving pedestrians (severe pedestrian crashes)
- Total crashes involving bicyclists (bicyclist crashes, all severities)
- Fatal and severe injury crashes involving bicyclists (severe bicyclist crashes)

Crashes were aggregated across the defined 8-year time period (2005 - 2012), and then disaggregated using the defined areal units of analysis, census tracts in the City of Chicago. Table 2 provides the initial descriptive statistics for total and severe crashes for a variety of users. This dataset enabled the exploration of pedestrian and bike crashes separately, as well as consideration of various levels of crash severities, providing information for potential future research efforts. Spatial distribution of crashes is provided in Figure 3, while Figure 4 shows histograms and q-q plots of crash data.

Table 2 Descriptive Statistics for Road Crashes

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
All_Crash	Total Crashes	801	393.109	371.431	6	4298
KA_Crash	Total Fatal and Sever Injury Crashes	801	10.516	10.446	0	114
VehCrash	Vehicle-only Crashes	801	375.176	354.534	5	3920
Veh_KA	Vehicle-only Fatal and Severe Injury Crashes	801	8.004	8.465	0	71
PedCrash	Crashes Involving Pedestrians	801	17.750	22.528	0	481
Ped_KA	Fatal and Severe Injury Crashes Involving Pedestrians	801	2.131	2.555	0	41
BikeCrash	Crashes Involving Bicyclists	801	9.528	13.178	0	172
Bike_KA	Fatal, and Severe Injury Crashes Involving Bicyclists	801	0.783	1.293	0	12
NMCrash	Nonmotorized Crashes	801	27.278	32.640	0	653
NM_KA	Nonmotorized Fatal and Severe Injury Crashes	801	2.914	3.331	0	53

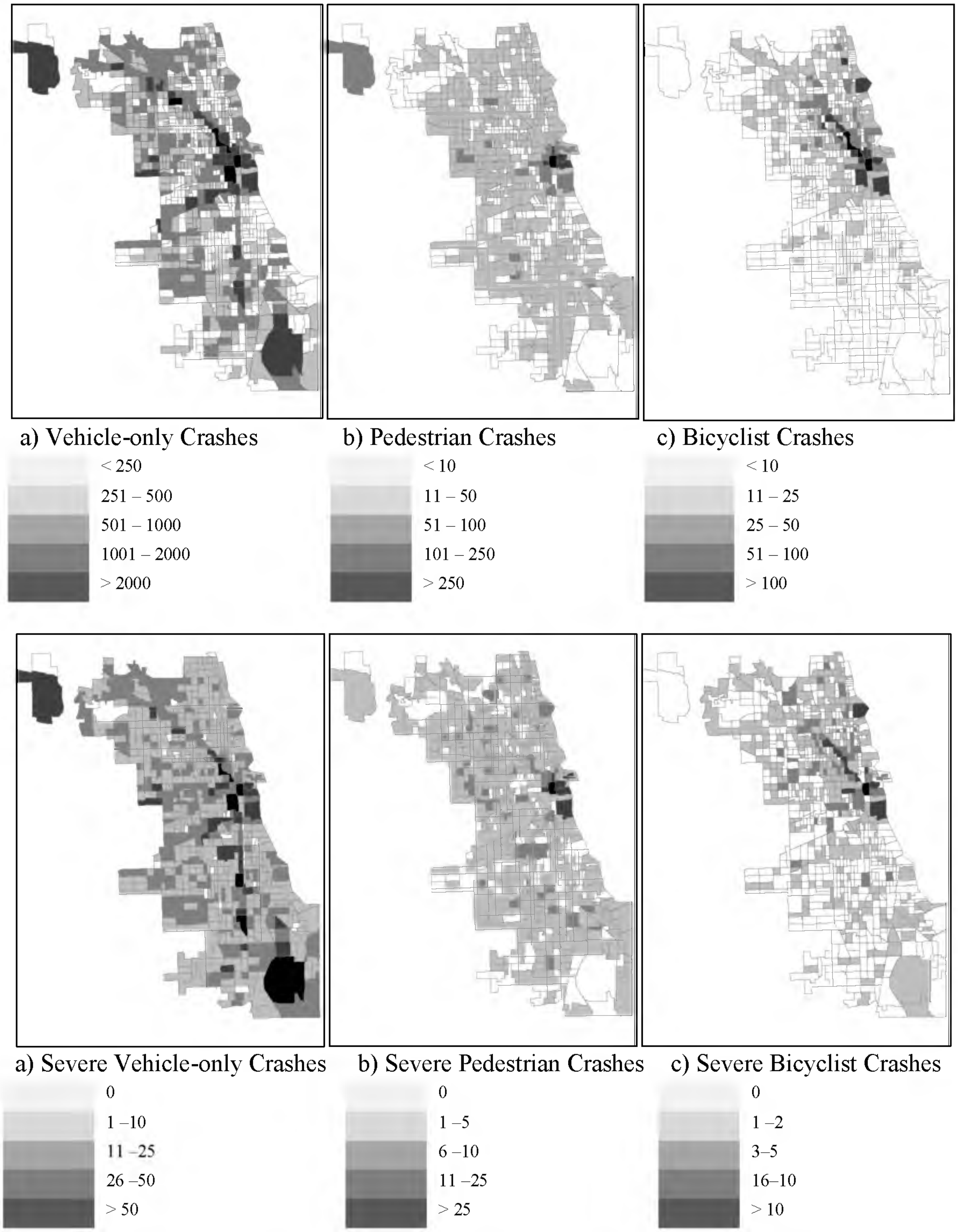


Figure 3 Spatial Distribution of Crashes by Census Tract in Chicago for Time Period from 2005 to 2012

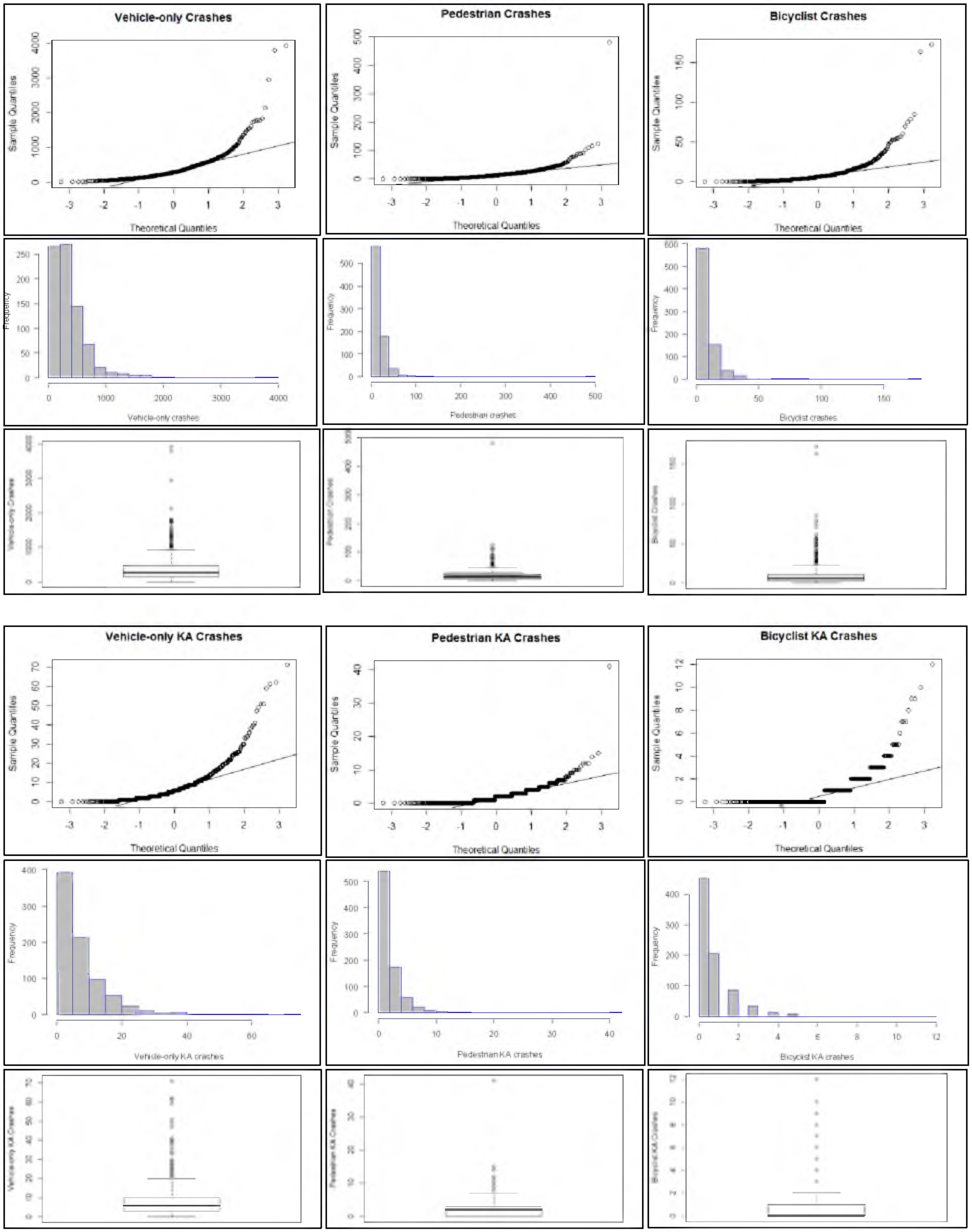


Figure 4 Normal Q-Q Plot, Histograms, and Box Plots for Vehicle-only, Pedestrian, and Bicyclist Total and Severe (KA) Crashes, Respectively

Measures of Exposure

This research primarily used measures of exposure that are defined as the activity measures that provide an indication about the number of users that may be exposed to crashes (Elvik, 2009). Multiple options were explored to determine the measures of exposure for vehicular, pedestrian, and bicyclist users, and the adopted measures needed to be appropriate for applying SASM methods on the census tract level. These activity-based measures of exposure were used in the SASM models in such a way that it was assumed that no crashes would occur if there was no exposure.

The challenges of determining adequate variables that would represent vehicular traffic volumes and speeds at spatial units' level are recognized in previous research (Noland & Quddus, 2004; Quddus, 2008). The information about traffic volumes and conditions is typically used to develop exposure variables vehicular users (Elvik, 2010; Hauer, 1995). Several sources of traffic volume data were considered to represent the vehicular exposure on the census tract level. The value of VMT can be estimated based on the National Travel household Survey data (NTHS), where VMT is based on trip distance reported by driver, trip units represented by the number of blocks which are further converted to miles, and the number of private vehicles. VMT estimated in this manner largely depends on the trip distance that household drivers report in the survey, and does not provide adequate road network coverage for the entire Chicago area. An alternative source of traffic volume data maintained by Chicago DOT is "Chicago Traffic Tracker", a city-wide real-time traffic information system. The traffic tracker includes real-time speed measurements, current outlook on traffic congestion with hourly projections for up to 12 hours ahead, Average Daily Traffic (ADT) counts from the year 2006, signals, red-light cameras, speed cameras, and downtown pedestrian counts from the year 2007. The traffic tracker is constantly updated, and allows the selection of a specific corridor, intersection, and landmark where volume counts are collected. If this research was conducted on the intersection or road segment-level of analysis, traffic tracker would have been the optimal source of volume data. Since the tracker provides coverage for only certain portions of road network, the network-wide vehicular volumes would likely be estimated using the available volumes, introducing the additional source of error in the data. In order to provide vehicular volume data for the entire road network, the most recent Chicago Air Quality Conformity Analysis conducted by CMAP was used. This study by CMAP was completed in the first quarter of 2014, and submitted to Federal Highway Administration (FHWA). For the purpose of this study, the vehicular volumes for road network segments in Chicago were estimated using the data from the travel demand model, specifically the results of traffic assignment. The way dynamic traffic assignment is performed involves link volume estimation, while accounting for travel survey data, accessibility analysis for a variety of modes, and as close as possible calibration of the assignment to match the actual volume counts. The CMAP analysis reflects the 2010 Census data, and the analysis years are 2010, 2015, 2025, 2030, and 2040. Data for the analysis year of 2010 are most suitable for the purpose of this study. The dataset includes trip generation inputs and outputs by traffic analysis zone, person trips productions and attractions, network assignment including vehicular and transit assignment, and detailed link volume data. Using this CMAP study, DVMT for each census tract were calculated, based on the validated traffic assignment volumes for the year 2010 and the available road network segment lengths.

Obtaining the data related to nonmotorized users measures of exposure is even more challenging than obtaining vehicular users exposure data. Volume count data are rarely available for pedestrians and bicyclists, so the exposure measures for these two modes are usually replaced with surrogates or estimated. This research used two primary sources of data for pedestrian and bicyclist exposure in the form of activity-based exposure measures: the percentage of commuter trips to work by different modes were extracted from the ACS U.S. Census data, and the estimated number of pedestrian and bicyclist trips generated in Chicago based on the CMAP travel demand model. The U.S. Census ACS 5-year data provided the estimates for the percentages of commuter work trips by means of transportation for drive-alone trips, carpool, public transit, walking, and trips by other means of transportation for the period from 2008-2012, providing alternative information on mode choice on the census tract level. The CMAP trip generation model was based on the data for the year of 2010, just as in the case of traffic assignment model used to obtain the values of DVMT on the census tract level. As commuter trips to work account for only a portion of total daily trips (usually up to 25 %), the estimated pedestrian and bicyclist trips from the CMAP trip generation model were used as the primary measure of pedestrian and bicyclist exposure. Generated pedestrian and bicyclist trips are estimated for trip generation subzones defined by CMAP, which represent the quarter-sections of traffic analysis zones. Trips generated within each subzone were aggregated on the census tract level to obtain the summary of generated pedestrian and bicyclist trips for each of the 801 census tracts. Descriptive statistics for exposure measures are provided in Table 3.

Table 3 Descriptive Statistics for the Road Network, Traffic, and Multimodal Transportation Variables

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Road	Total Length of Roads, miles	801	6.278	3.910	0.142	30.762
Road_d	Road density, miles/miles squared	801	0.005	0.001	0.000	0.009
EXPY	Expressways, % of street network	801	0.219	0.601	0.000	4.302
EXPY_d	Expressways Density, miles/miles squared	801	0.000	0.000	0.000	0.004
Art	Arterials, % of street network	801	0.924	0.790	0.000	7.675
Art_d	Arterials Density, miles/miles squared	801	0.001	0.000	0.000	0.003
Exp_Art	Expressways and Arterials, % of street network	801	1.143	1.115	0.000	11.976
Coll	Collectors, % of street network	801	0.876	0.668	0.000	4.668
Coll_d	Collectors density, miles/miles squared	801	0.001	0.001	0.000	0.008
Street	Other Streets, % of street network	801	3.848	2.694	0.000	15.096
Street_d	Other Streets Density, miles/miles squared	801	0.003	0.001	0.000	0.006
Alley	Named Alleys, % of street network	801	0.000	0.000	0.000	0.000
Alley_d	Named Alleys Density, miles/miles squared	801	0.000	0.000	0.000	0.000
BikeLane	Total Length of Bike Lanes, miles	801	0.679	0.723	0.000	6.163
Bike_d	Bike Lane Density, miles/miles squared	801	0.001	0.000	0.000	0.003
BusRoute	Total Length of Bus Routes, miles	801	1.541	2.559	0.000	39.980
Bus_d	Bus Route Density, miles/miles squared	801	0.001	0.001	0.000	0.017
Ltrain	Total Length of L Train Lines, miles	801	0.147	0.353	0.000	4.411
Ltrain_d	L Train Line Density, miles/miles squared	801	0.000	0.000	0.000	0.001
Sidewalk	Total Sidewalk Area, feet squared	801	287.382	198.201	0.000	1,131.373
Sidew_d	Sidewalk Density, ft2/ft2	801	0.044	0.016	0.000	0.159
Intersect	Total Number of Intersections	801	37.803	27.800	0.000	163.000
Inter_d	Intersection Density, per mile squared	801	153.904	57.948	0.000	714.460
Connect	Connectivity Index, intersections/mile of road	801	5.798	1.531	0.000	16.232
Signals	Total Number of Signalized Intersections	801	3.759	4.637	0.000	77.000
Signal_P	Signalized Intersections, %	801	0.123	0.141	0.000	1.333
BusStops	Total Number of Bus Stops	801	13.104	9.099	0.000	75.000
BusStopD	Bus Stops Density, per mile squared	801	59.606	33.500	0.000	312.110
LStops	Total Number of L Train Stops	801	0.091	0.325	0.000	2.000
LStopD	L Train Stops Density, per mile squared	801	0.000	0.000	0.000	0.000
BikeRacks	Total Number of Bike Racks	801	6.446	11.394	0.000	220.000
BikeRackD	Bike Racks Density	801	35.256	50.513	0.000	480.397
DVMT	Daily Vehicle Miles Traveled	801	40,563.580	57,246.750	8.057	522,024.400
Ped	Pedestrian Trips Generated	801	47.715	103.345	1.191	1581.315
Bike	Bicyclist Trips Generated	801	2.511	5.439	0.062	83.227
DriveAlone	Drive-alone Trips to Work, %	801	50.186	15.522	0.000	86.300
Carpool	Carpool Trips to Work, %	801	9.511	6.560	0.000	39.500
Transit	Transit Trips to Work, %	801	27.506	12.956	0.000	79.100
Walk	Walk Trips to Work, %	801	0.603	3.156	0.000	35.000
OtherMeans	Trips to Work by Other Means, %	801	2.542	2.942	0.000	21.300
WorkHome	Work Home, %	801	4.058	3.296	0.000	21.300
TT_min	Average Travel Time to Work, minutes	801	34.019	6.303	0.000	56.500

Measures of Multimodal Accessibility

Based on the reviewed literature, the common measures of exposure in road safety do not completely capture the presence of multimodal users in urban environments and their opportunity to be involved in a crash. The main limitations of activity-based measures of exposure is the lack of ability to represent the traveling distances and the opportunities for conflicts on the network-wide level. Indicators from accessibility theory are sometimes used to improve the representation of multimodal exposure and capture the presence of multimodal transportation options and the overall access to multimodal infrastructure. The measures of accessibility are incorporated in long-term transportation planning, and it is considered that they impact the amount and nature of travel that occurs on various levels. This research uses the combination of traditional activity-based measures of exposure and multimodal accessibility indicators, in order to develop SASM estimates and explore how multimodal infrastructure and accessibility features relate to safety on the areal level. These measures of "multimodal accessibility" were developed in three categories, to include the following:

1) Multimodal transportation infrastructure availability and connectivity
    - Road mileage, density, and functional classification
    - Intersections number, density, and signal control
    - Sidewalk length and density
    - Bike lane length and density
    - Bike racks presence and density
    - Transit lines length and density
    - Transit stops presence and density
2) Street network completeness

- Percent of network that is complete (e.g., serving all four modes)
- Percent of network serving more than one mode (e.g., drive and walk)

3) Multimodal accessibility
    - Pedestrian accessibility
    - Bicyclists accessibility
    - Transit accessibility

Multimodal Transportation Infrastructure and Connectivity

Road network mileage and functional classification variables are included in the reviewed literature, mostly as proxies for exposure. Road network data are provided by the City of Chicago open database. Data files take the form of digital geospatial polyline features of road centerlines in Chicago. This dataset was originally created in 2010, and updated in 2013. The available data files include the information about direction, street name, street type, status code (e.g., closed to traffic, private), address range, road class values, one-way streets, FIPS codes for municipalities, “from” and “to” elevation levels, “from” and “to” intersecting street segments, segment length, and dates when the features were created, edited, and updated. The information from this dataset was used for further network mileage calculations and street class codes. To account for the diversity of the road network in Chicago in terms of capacity and speeds, the percentages of road network categorized according to functional classes was determined. The intersection numbers, densities, and the percentage of signalized intersections were also calculated for each of the analyzed census tracts. The calculation of network connectivity-related variables that mostly related to densities of multimodal facilities was conducted following the GIS protocols from the previous walkability studies (Oakes, Forsyth, & Forsyth, 2012; Schmitz, 2007; Tressider, 2005).

Variables related to multimodal transportation features in Chicago were an important addition to the dataset, as they are rarely present in the previous research. These variables represent access and availability of multimodal transportation options on a census tract level, including public transit, biking, and walking facilities. The City of Chicago and Chicago Transit Authority provide the data on bus lines and bus stops, bike lanes and bike racks, sidewalks, and parking zones. Indicators of density for bus lanes, bike lines, and sidewalks were also developed and included in the dataset.

Figure 5 provides the visualization of multimodal infrastructure in Chicago that was included in the dataset. The initial descriptive statistics for road network, traffic, and multimodal transportation data is provided in Table 3.

Network Completeness

Additional variables included in the SASM analysis as exposure surrogates relate to street network completeness. Apart from capturing the presence of multimodal infrastructure, multimodal users activity, and access to destinations, variables related to network completeness indicate how different modes relate to each other in urban space, and how multimodal networks are layered in the city. Specifically, network completeness shows what percent of street network on the census tract level serves all four modes (private automobile, public transit, biking, and walking), as well as what types of users are served on those parts of the street network that are not "completed".

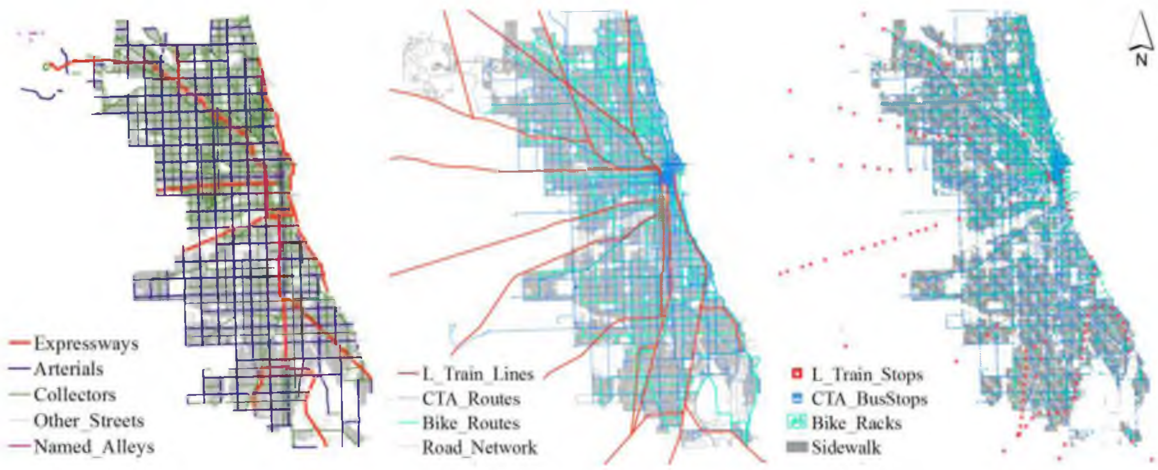
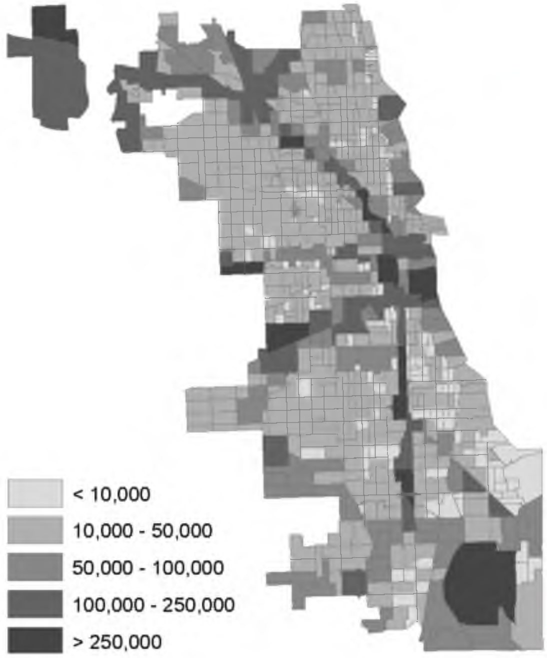


Figure 5 Roadway Network and Multimodal Facilities

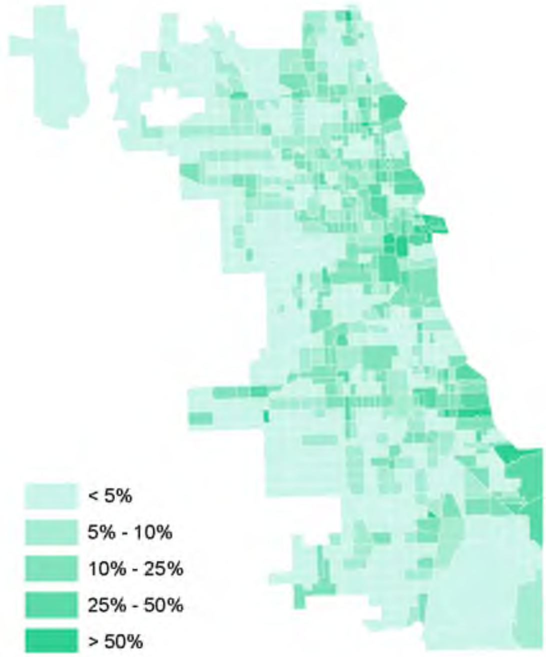
This inclusion of network completeness rather than street completeness in the analysis provided the opportunity to compare the safety benefits of streets serving all modes versus streets that are strategically prioritizing single mode while not excluding other modes in terms of access on the network-wide level. The idea of "complete networks versus complete streets" was previously discussed by the Congress for New Urbanism, where transportation planners and urbanists concluded that it may be more beneficial to plan for accessibility for all users on the network-wide level, rather than insisting on complete streets even when they are not the most feasible design solution. Table 4 shows variables included in this research to capture network completeness. Figure 6 shows spatial distribution of DVMT and the percentage of street network serving all four modes in each census tract.

Table 4 Descriptive Statistics for Network Completeness

Variable	Explanation	Obs	Mean	Std. Dev.	Min	Max
NC_Car	Network Serving Cars only (%)	801	0.030	0.076	0	0.543
NC_Car_W	Network Serving Cars and Pedestrians (%)	801	0.577	0.286	0	1.000
NC_CarWT	Network Serving Cars, Pedestrians and Transit (%)	801	0.438	0.930	0	1.000
NC_Car_WB	Network Serving Cars, Pedestrians and Bicyclists (%)	801	0.061	0.078	0	0.528
NC_Car_WTB	Network Serving All Modes (%)	801	0.085	0.143	0	1.000



Daily Vehicle Miles Traveled



Percentage of Network Completed

Figure 6 Spatial Distribution of DVMT and the Percentage of the City of Chicago Street Network Serving All Four Modes

Accessibility can simply be defined as the ability to reach spatially distributed activities within a defined time frame, and it measures the quality of the connection between origins and destinations. So in transportation, accessibility can be defined in terms of origins or destinations by asking one of the two following questions:

- How many destinations can we reach from a specific origin?
- From how many origins can we reach a specific destination?

Although there is a wide range of performance measures available in the literature, measuring accessibility is a challenge because guidelines that link the types of accessibility measures to their practical application are still not established. In transportation performance measurement, the implementation of any newly developed measures is difficult because it needs to be tailored to fit into more traditional performance evaluation processes. In addition, accessibility in transportation varies across the modes of transport, and while access for all modes is a function of infrastructure features, nonmotorized modes are much more sensitive to the way activities are distributed in space than motorized modes. This research develops cumulative accessibility measures for nonmotorized modes, and composite accessibility measures for transit mode.

Accessibility for Pedestrian Mode

The accessibility measurement approach for nonmotorized modes is based on a previous, smaller scale case study, used to quantify pedestrian and bicyclist accessibility (Tasic, Musunuru, & Porter, 2014). For both pedestrian and bicyclist modes, a specific destination is considered accessible if there is a connection between the origin and destination, if that connection is within a defined distance, and if it is reachable within a defined time frame. So the approach developed here recognizes that accessibility is provided gradually. The first step is to have points of interest, or origins and destinations as they are referred to here, and to provide infrastructure that links the defined origins and destinations in a manner appropriate for a particular mode of transport. The factors that determine whether the link or a connection between origin and destination is appropriate for the specific mode are determined based on the existing Manual on Uniform Traffic Control Devices (MUTCD) standards and AASHTO guidelines. If the connection between origin and destination is feasible for a particular mode, the second step in providing accessibility is deciding how far origins and destinations are from each other. The third step is adding a temporal dimension to accessibility by incorporating the speed and obtaining travel time for feasible connections and distances for given transportation modes. Temporal accessibility is especially relevant from transportation users' perspectives (Beeco & Brown, 2013). In transportation systems, people tend to think in terms of time it takes to get to desired destinations, or the acceptable travel time (Mahmasanni, Abdelghany, & Kraan, 1998). This way of thinking in terms of time is created due to transportation systems' inherent time variability. Traveling the same distances does not always take the same amount of time. This variability depends on the environment, geometric design features, mode of transportation, amount of traffic, and modal diversity in general. Variability in travel time for equal distances is larger in urban environments where multiple transportation modes are present, it is larger on roadway segments with grades and curves than on the straight level segments, and there is more variability for modes that can achieve higher speeds and travel longer distances. Therefore, both spatial and temporal dimensions are important for accessibility measurements, and which one is more important depends on the application of those measurements (e.g., whether it is deployed for spatial allocation of activities or trip planning) and the presence of characteristics that contribute to time variability across equal distances. Based on the previous discussion, the accessibility criteria for the quality of connections, the distance between origin and destination, and the time needed to reach the destination are different for different modes. The approach, assumptions, and calculations proposed to measure accessibility in the described Chicago case study network are further expanded for pedestrian and bicycle modes.

The first step in a pedestrian accessibility assessment was to define the potential origins and destinations in a study area of Chicago. Although data aggregation on the census tract level was adopted in this study, origins and destinations were defined on a much higher level of aggregation, to capture the actual scale of pedestrian movements in Chicago. As the most recent land use data for the year of 2010 became available in the form of parcel data, this very detailed dataset was used to define pedestrian origins and destinations. Land use parcel data were first cleaned to eliminate parcels that refer to vehicular right of way. Then, land use parcels were divided into eight categories (residential, commercial, institutional, industrial, transportation/parking, agriculture, open space, and vacant/under construction). All land use parcels were used as both origins and destinations for pedestrian trips in the city. This resulted in total of 136,134 origins defined for pedestrian trips, and just as many destinations. Defining each land use parcel as both an origin and a destination, rather than simply defining centroids in each of 801 census tracts, made the computational process very exhaustive, but significantly contributed to more precise measurements of pedestrian accessibility. To author's knowledge, no previous studies measured pedestrian accessibility at a city-wide scale using such high level of data aggregation in terms of trip origins and destinations. More recent transit accessibility studies used data aggregated at the census block level, also providing very detailed measurement of accessibility to jobs, but pedestrian accessibility measurements were not the objective of this research (Owen & Levinsom, 2014).

In addition to defining adequate origins and destinations, another challenge in calculating pedestrian accessibility was to properly define pedestrian network in the city. The available sidewalk area data were used to edit the street network of Chicago and include only those streets in Chicago that have sidewalk in the pedestrian accessibility analysis. This is a standard way of manipulating the street network data to ensure that freeways and ramps are excluded from the final pedestrian network (Forsyth, 2012). This approach, however, does not account for all pedestrian paths in the city, as some pedestrian routes that cut through parks and public spaces were not incorporated in the shortest path search between the origins and destinations. While excluding the off-street pedestrian paths from the analysis could be a limitation for this study, using the entire street-based pedestrian network provided a good approximation for the possible pedestrian routes in the city.

For the defined origins and destinations, an origin destination (OD) matrix was created for all possible OD combinations with the following questions assessed for each pair:

- Is there a feasible walking connection between origin and destination?
- Is the distance between origin and destination adequate for pedestrians?
- Is the time needed to reach the destination adequate for pedestrians?

To answer the first question, possible connections between each O-D pair were identified as uninterrupted paths between an origin and a destination, on the terrain appropriate for pedestrians, with AASHTO guidelines for the adequate path width of 4.67ft (AASHTO, 2004). One-quarter mile and half a mile distances were adopted as the criterion for acceptable walking distances as suggested by the AASHTO Guide for Planning and Design of Pedestrian Facilities (AASHTO, 2004). The distances between origins and destinations were measured using ArcGIS network analyst tools and calculating shortest paths for pedestrians. By applying MUTCD guidelines for average pedestrian speed of 4 feet per second to this distance, the one-quarter mile distance criterion suggests that visitors are not willing to walk more than 10 minutes to reach their destination (MUTCD, 2009). Pedestrian speeds range from 2.5 feet per second to 6 feet per second, and the average pedestrian speed is usually related to the age of the population in the observed area. The pedestrian speed of 4 feet per second was used to determine travel times between origins and destinations. Several time buffers were used to account that pedestrians might be willing to walk longer to certain destinations, including time frames from 5 minutes to 30 minutes walking time with 5 minute increments (MUTCD, 2009).

This study primarily measured cumulative pedestrian accessibility defined as the total number of destinations accessible to pedestrians within the defined time frames for all the origins located within a particular census tract. In the case of cumulative measures, the same weight is used for all destinations, acknowledging this as a limitation that should be addressed in potential future research efforts, as all destinations do not have the same level of attractiveness, and visitors might be willing to walk longer to some destinations than others. In order to standardize the variables, as census tracts vary in size and population, the cumulative number of destinations accessible for pedestrians was divided by the total number of destinations within each census tract. Cumulative number of opportunities for pedestrians was calculated as following:

$$Ped_{dk} = \frac{\sum_i \sum_j \{d_{ij} \in N | o_i \in N_k, T_{ij} \leq T\}}{N_k} \qquad \text{Equation (2)}$$

Where:

Ped_{dk} – total number of accessible destinations in census tract k

d_{ij} – destination j accessible from origin i

N – total number of destinations

o_i – origin i within census tract k

N_k – total number of destinations within census tract

T_{ij} – time needed to reach destination j from origin i

T – available time budget (5, 10, 15, 20, 25, or 30 minutes)

Figure 7 shows the cumulative pedestrian accessibility, calculated by using the Equation 2 for the defined time frames of 5, 10, 15, 20, 25, and 30 minutes of the assumed acceptable walking time. As expected, census tracts with the highest number of destinations accessible within the defined time frames are mostly located in city center and the North side of the city, as these areas have higher densities and more developed pedestrian networks. Some census tracts on the South side also show higher cumulative pedestrian accessibility, mostly where current multimodal infrastructure investments are concentrated. In addition to cumulative pedestrian accessibility, weighted accessibility is also calculated by incorporating the travel time impedance function into the equation for cumulative accessibility measures:

$$Ped_{ak} = \frac{\sum_i \sum_j \{d_{ij} \in N | o_i \in N_k\}}{T_{ij}} \qquad \text{Equation (3)}$$

Where:

Ped_{ak}– weighted pedestrian accessibility in census tract k

d_{ij} – destination j accessible from origin i

N – total number of destinations

o_i – origin i within census tract k

N_k – total number of destinations within census tract

T_{ij} – time needed to reach destination j from origin i

Figure 7 shows the spatial distribution of destinations accessible within the given walking time in the City of Chicago. Both weighted and cumulative pedestrian

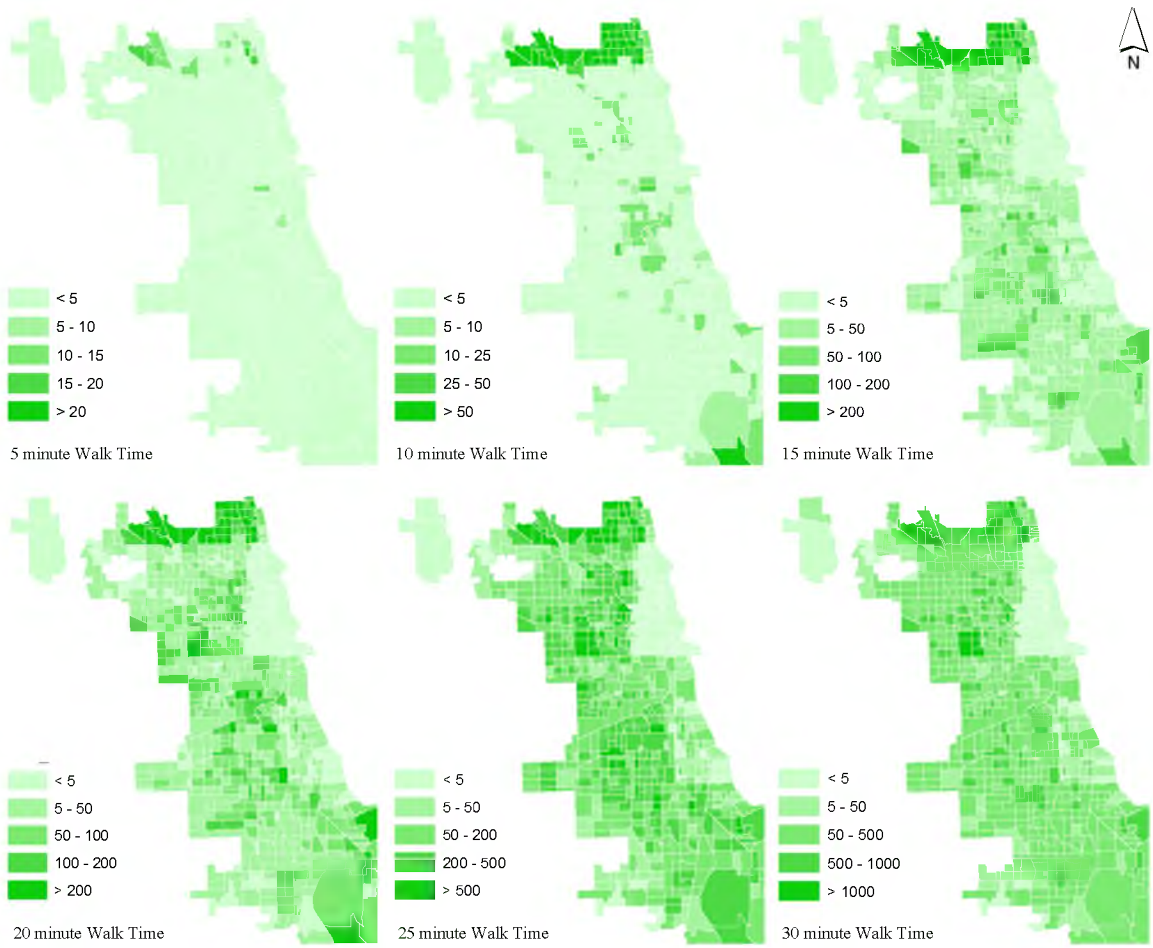


Figure 7 Destinations Accessible Within the Given Walking Time

accessibility calculated in described manner were used to estimate crash outcomes for nonmotorized transportation users in Chicago.

Accessibility for Bicyclists

Accessibility for bicyclists in each census tract was computed similar to pedestrian accessibility, but with different standards for the acceptable biking distances and travel times. The origins again were defined using all land use parcels (without the parcels referring to vehicular right of way areas) in Chicago, and the destinations were defined in the same way as origins.

Defining destinations and origins like this enabled building OD matrices from each land use parcel to all other land use parcels in Chicago. In order to be considered accessible for biking, there should be an uninterrupted connection between the origin and destination, the origin and destination should be within the acceptable distance, and the destination should be reached within the acceptable travel time for bicyclists.

A connection was defined as an uninterrupted path between an origin and a destination, on the terrain appropriate for bicyclists, but this time with AASHTO guidelines for adequate operating spaces for bicyclists (AASHTO, 2012). Based on the reviewed literature, acceptable biking distance was defined as 3 miles (Dill, 2008). An average biking speed of 15 miles per hour was used for average biking speed as suggested by the AASHTO Guide for Planning and Design of Bicycle Facilities (AASHTO, 2012). ArcGIS network analyst tools was used to calculate shortest paths between origins and destinations for bicyclists, while adopting the identified criteria and including weights for intersections along the paths. As for the acceptable biking time for most of the cyclists traveling from an origin to a destination, times of 15, 30, 45, and 60 minutes were adopted. Cumulative number of opportunities for bicyclists were then computed by using the following equation:

$$Bike_{dk} = \frac{\Sigma_i \Sigma_j \{d_{ij} \in N | o_i \in N_k, T_{ij} \leq T\}}{N_k} \qquad \text{Equation (4)}$$

Where:

$Bike_{dk}$ – total number of accessible destinations by bike in census tract k

d_{ij} – destination j accessible from origin i

N – total number of destinations

o_i – origin i within census tract k

N_k – total number of destinations within census tract

T_{ij} – time needed to reach destination j from origin i

T – available time budget (15, 30, 45, and 60 minutes)

The cumulative number of destinations accessible for bicyclists was divided by the total number of destinations within the census tract. Based on the described measures of non-motorized accessibility, for each census tract in the dataset, it was possible to extract the percent of destinations accessible for pedestrians and bicyclists. Figure 8 shows the spatial distribution of cumulative bicyclist accessibility in Chicago. When compared to Figure 7, Figure 8 shows significantly higher census tract cumulative accessibility for bicyclists than for pedestrians, due to obvious differences in the amount of time users are willing to spend walking and biking. Even the highest considered biking time budget of 60 minutes does not render the entire area of the city highly accessible for bicyclists, particularly some census tracts alongside the lake Michigan. As expected, the downtown area as well as census tracts along the so-called "diagonal" avenues in Chicago show a high number of destinations reachable by bike. Similar as for pedestrian accessibility, weighted bicycle accessibility is calculated (please see Table 5 for results) by using the following equation:

$$Bike_{ak} = \frac{\sum_i \sum_j \{d_{ij} \in N | o_i \in N_k\}}{T_{ij}} \qquad \text{Equation (5)}$$

Where:

$Bike_{ak}$ – weighted bicyclist accessibility in census tract k

d_{ij} – destination j accessible from origin i

Figure 8 Destinations Accessible Within the Given Biking Time

N – total number of destinations

o_i – origin i within census tract k

N_k – total number of destinations within census tract

T_{ij} – time needed to reach destination j from origin i

This particular approach for nonmotorized accessibility was adopted to not only differentiate between the two modes, but to also clarify that even with high level of overall network connectedness, accessibility for nonmotorized modes might still be limited. This accessibility limitation might occur if the network of pedestrian and bicyclist facilities is disconnected with many interruptions and segments for vehicular mode only, then due to large distances between origins and destinations, and finally due to any traffic conditions that might cause delay for pedestrians and bicyclists on the way to their trip destinations.

Transit Accessibility

The framework for measuring transit accessibility adopted here has previously been applied on a smaller scale (Tasic, Zhou, & Zlatkovic, 2014). The methodology for transit accessibility measurement builds upon the traffic and transit data from the case study network, and uses transit network as well as Google Transit Feed Specification (GTFS) to perform transit accessibility measurements by calculating the number of accessible transit stops from each census tract centroid as a defined origin, as well as the total number of destinations that can be accessed by walking from the accessible transit stations. The methodology considers network features, acceptable walking time, available time budget, transit schedule variability, and spatial constraints as impact factors in accessibility measurements.

The City of Chicago road network with nodes, links, census tracts, transit network, and transit stations, imported as GIS shapefiles, was used as a basis for transit accessibility calculations. Transit accessibility, is defined as the average daily number of destinations reachable by transit from each census tract, using both walking and transit routes, constrained by spatial characteristics of the case study network and temporal dimension determined by transit service and traffic characteristics. In order to execute transit accessibility measurements, the transit stations within census tract areas are defined as trip origins, while all land use parcels in the city were considered as potential destinations. Transit lines and stations data available from CTA were combined with Chicago GTFS to provide the information on spatial and temporal distribution of transit services. The GTSF from Google includes the following (Google Transit Feed Data, 2014):

- Calendar that specifies when service starts and ends, including the days of the week when service is available
- Calendar dates with possible service exceptions
- Routes or groups of trips displayed to riders as single service
- Shapes or rules for representing transit routes on the maps
- Stop times or arrival and departure times for each individual trip
- Stops or passenger pick up and drop off points
- Trips or sequences of stops for each route

Particularly important for our accessibility measurements were the stop time records, that include a sequence of stops along each trip. Each stop time record contains required data such as trip identification, arrival and departure time, stop identification, and stop sequence. These data were used to determine how many times within each 15-minute period over the course of one day is each transit station accessible within the various combinations of time needed to walk to/from a transit station and time needed for a trip by public transit. A total of 11,664 transit stations with up to 123 stop time records per station were included in the analysis that resulted in average daily accessibility to destinations by transit on the census tract level.

While the resulting measures of transit accessibility appear similar to those of pedestrian and bicyclist accessibility, using the data on transit stop time and transit schedule helped to incorporate daily temporal variations of transit service into census tract-level transit accessibility measurements. This inclusion of time-dependent transit availability dynamics is the key difference between accessibility measurements for non-motorized modes and transit mode, as transit travel times to destinations vary with both space and time.

The idea to combine spatial and temporal changes in transit service in transit accessibility measurements is rooted in the composite space-time accessibility measures based on Miller's STP concept (Miller, 1999; Miller, 2011; Wu & Miller, 2001). The STP is a set of locations in space and time that are accessible to an individual, given the locations and duration of fixed activities, time budget, and transportation speeds. The STP-based accessibility measures account for both individual sequence of trips and spatio-temporal constraints, calculating the amount of space that an individual can reach at specific combinations of times and locations.

In the case of public transit, travel times are not only affected by traffic conditions, but also by the time needed to access the transit stop, waiting time which depends on familiarity with the timetable, potential stops and transfers, and the time needed to reach the destination from the final transit stop. The accessibility models were developed based on the dynamic potential path calculations, but also to account for pedestrian connectivity, transit stop accessibility, and scheduled service variability as elements that specifically relate to transit mode. Instead of using a simple, radius-based service coverage, the actual transportation network was used. Walk to transit was adopted as the mode used to access transit stations. Calculations and assumptions for different space-time constraints, applied to compute average daily number of destinations accessible by transit is as follows:

$$PT_k = \sum_i \sum_j \sum_t \frac{d_{ij}(walk) + d_{ij}(transit) \cdot f_{it}}{nt} \qquad \text{Equation (6)}$$

Such that:

$o_i \in N_k$

$T_{ij} = t_{ijwalk} + t_{ijtransit} \leq T$

Where:

$\mathrm{PT_k}$ – daily average number of destinations accessible by transit in census tract k

$\mathrm{d_{ij}(walk)}$ – destination j accessible from transit station i by walking

$\mathrm{d_{ij}(transit)}$ – destination j accessible from transit station i by transit

$\mathrm{f_{it}}$ – frequency of transit stop time records at station i during time period t

(time period "t" in this case is a 15-minute period)

nt – total number of time periods t within a working day

N – total number of destinations

T_{ij} – time needed to reach destination j from transit station i (min)

t_{ijwalk} – total walk time included in the trip between station i and destination j

(acceptable walking time includes 5, 10, 15, and 20 minutes in this case)

$t_{ijtransit}$ – total time spent in public transit between station i and destination j

(acceptable time spent in public transit does not exceed 120 minutes)

T – available time budget (up to 120 min)

In order to implement the framework given in Equation 6, for each census tract, the number of destinations accessible by public transit combined with walk trips to and from each destination is summarized for all transit stations within the census tract. The defined origins and destinations with the public transit network of Chicago were uploaded in ArcGIS platform for a shortest path calculations between each OD pair for all determined constraints related to acceptable time budget. Shortest path is calculated between transit stations and destinations accessible within 20-minute walk distance and pairs of transit stations located within 120 minutes distance traveled by transit regardless of the number of transfers. The accessible number of destinations is then calculated as a sum of all destinations accessible by combining walking and public transit within 120 minutes of travel time budget. This measure of accessibility is calculated for each 15-minute time period during the daily period of the public transit service, resulting in time variable transit accessibility for each census tract over the course of a working day. Based on these results, the average transit accessibility is then computed for each census tract.

Weighted transit accessibility is also calculated, using the approach similar to the one used for nonmotorized accessibility, based on the travel time impedance:

$$PT_{ak} = \frac{PT_k}{\sum_i \sum_j t_{ijwalk} + t_{ijtransit}} \qquad \text{Equation (7)}$$

Where:

PT_{ak} – weighted transit accessibility in census tract k

PT_k – daily average number of destinations accessible by transit in census tract k

t_{ijwalk} – total walk time included in the trip between station i and destination j

$t_{ijtransit}$ – total time spent in public transit between station i and destination

Evaluating public transit is always more complex than any other mode of transportation, and selecting adequate accessibility measures is also a challenge. Several factors that impact space-time constraints were included in transit accessibility analysis. Service variability refers to the frequency of transit service and service span in general. Walking distance is the acceptable walking distance to transit stops. Available time budget defines the time that individual has to access activity locations from the given trip origin.

Table 5 shows the variables that capture transit accessibility and were selected to be included in crash statistical modeling described in the following chapter. Transit stop frequency as a result of the daily transit schedule in Chicago is provided in Figure 9. The total number of transit stop time records in Chicago ranges between a 1000 and 2000 stops for all transit stations within each 15-minute period over the course of a day. This variation in stop frequency influences overall city-wide transit accessibility, in addition to the influence that other factors such as walking time and transit travel time have on the ability to reach destinations by transit.

Table 5 Descriptive Statistics for Variables Capturing Destination Accessibility

Variable	Explanation	Mean	Std. Dev.	Min	Max
Total_Dest	Total number of destinations in the census tract	185	109	0	690
Ped_D5	Total number of destinations accessible within 5 minute walk time	0	2	0	26
Ped_D10	Total number of destinations accessible within 10 minute walk time	10	40	0	476
Ped_D20	Total number of destinations accessible within 20 minute walk time	56	101	0	1143
Ped_A5	Pedestrian weighted accessibility within 5 minute walk	0.00	0.00	0.00	0.00
Ped_A10	Pedestrian weighted accessibility within 10 minute walk	0.00	0.00	0.00	0.00
Ped_A20	Pedestrian weighted accessibility within 20 minute walk	0.00	0.00	0.00	0.01
Bike_D15	Total number of destinations accessible within 15 minute bike time	589	655	0	4610
Bike_D30	Total number of destinations accessible within 30 minute bike time	2379	2749	0	19140
Bike_D45	Total number of destinations accessible within 45 minute bike time	7524	9083	0	62956
Bike_D60	Total number of destinations accessible within 60 minute bike time	13462	17977	0	134399
Bike_A15	Bicyclist weighted accessibility within 15 minute walk	0.00	0.00	0.00	0.03
Bike_A30	Bicyclist weighted accessibility within 30 minute walk	0.02	0.02	0.00	0.13
Bike_A45	Bicyclist weighted accessibility within 45 minute walk	0.05	0.06	0.00	0.43
Bike_A60	Bicyclist weighted accessibility within 60 minute walk	0.09	0.12	0.00	0.91
Transit_D30	Total number of destinations accessible by transit within 30 minutes	565	408	0	2798
Transit_D60	Total number of destinations accessible by transit within 60 minutes	1088	772	0	5035
Transit_D90	Total number of destinations accessible by transit within 90 minutes	1657	1173	0	7645
Transit_D120	Total number of destinations accessible by transit within 120 minutes	2197	1567	0	10341
Transit_A30	Weighted transit accessibility within 30 minutes of travel time	4.49	8.38	0.00	187.64
Transit_A60	Weighted transit accessibility within 30 minutes of travel time	8.60	15.91	0.00	361.33
Transit_A90	Weighted transit accessibility within 30 minutes of travel time	13.05	23.99	0.00	547.27
Transit_A120	Weighted transit accessibility within 30 minutes of travel time	17.34	32.54	0.00	751.93

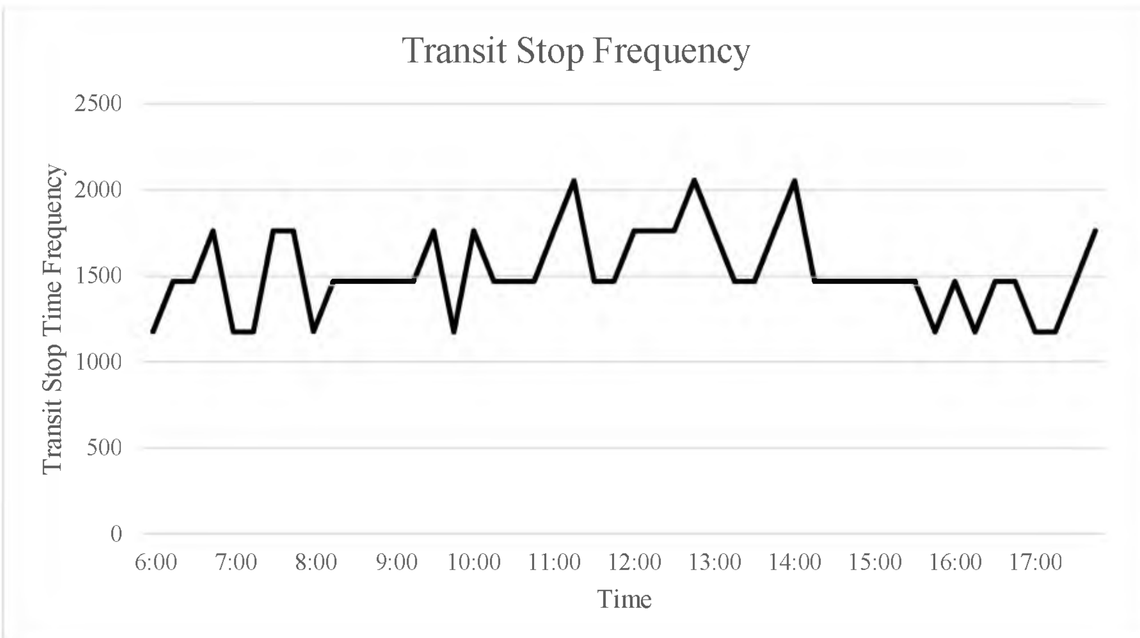


Figure 9 Daily Changes in Transit Stop Frequency by Station on the Census Tract Level

Accessibility between each pair of transit stations in the city was calculated as a part of average accessibility calculations for public transit mode. These results are provided in Figure 10, for different amounts of travel time budget. The percent of accessible transit stations is then extracted as a ratio of transit station pairs accessible within a given time over the total number of transit station pairs. As expected, the percent of accessible transit stations increases as the users travel time budget increases. This is further confirmed with the results provided in Figure 11, where transit accessibility dependence on the acceptable walking time is given, and the results provided in Figure 12 where transit accessibility varies with different amounts of the acceptable travel time spent in transit. Incremental accessibility change is given in Figure 13 to show the combined effect of changes in time spent on walking to and from a transit station, and time spent in public transit, on the percent change in transit accessibility. All these and other factors that may influence transit accessibility in urban environments are explained in a more detailed manner in a previous study (Tasic et al., 2014). For the purpose of this research, it was important to consider a wide range of potential variables that may have the influence on safety outcomes, particularly nonmotorized safety outcomes in urban environments. All calculated variables related to transit accessibility, however, were not included in the final statistical models, and this will further be explained in the Results chapter.

Figure 14 shows spatial distribution of the average daily transit accessibility on the census tract level. The results show relatively good coverage of the entire city by transit service, where the downtown area of Chicago has the best access to destinations by transit, as expected.

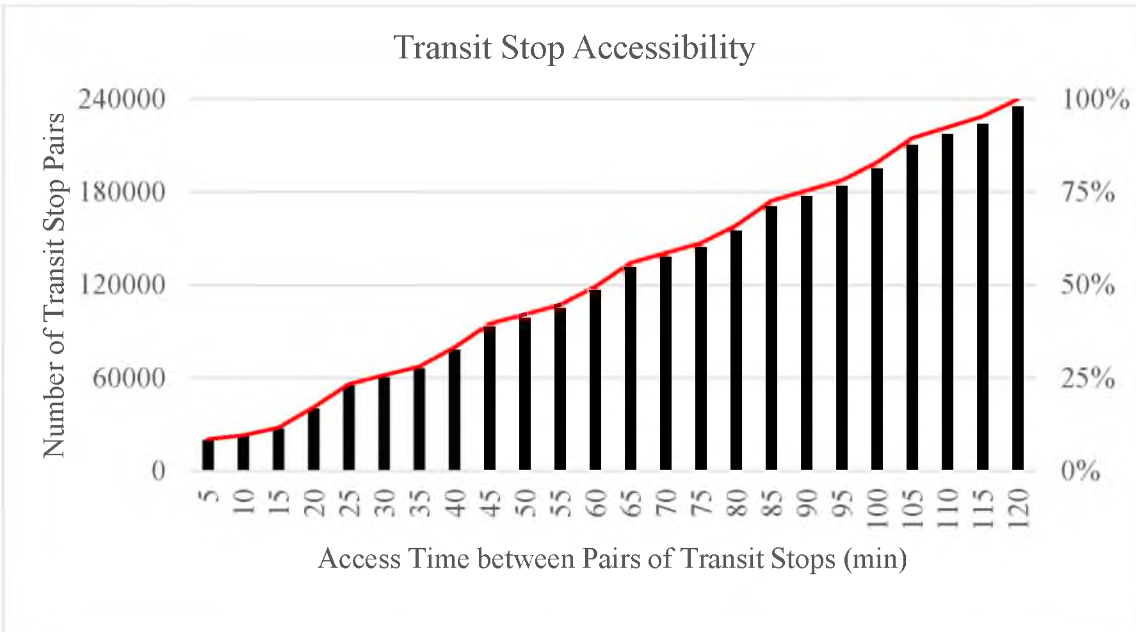


Figure 10 Number and Percentage of Transit Stops Accessible Within the Given Amount of Time Budget

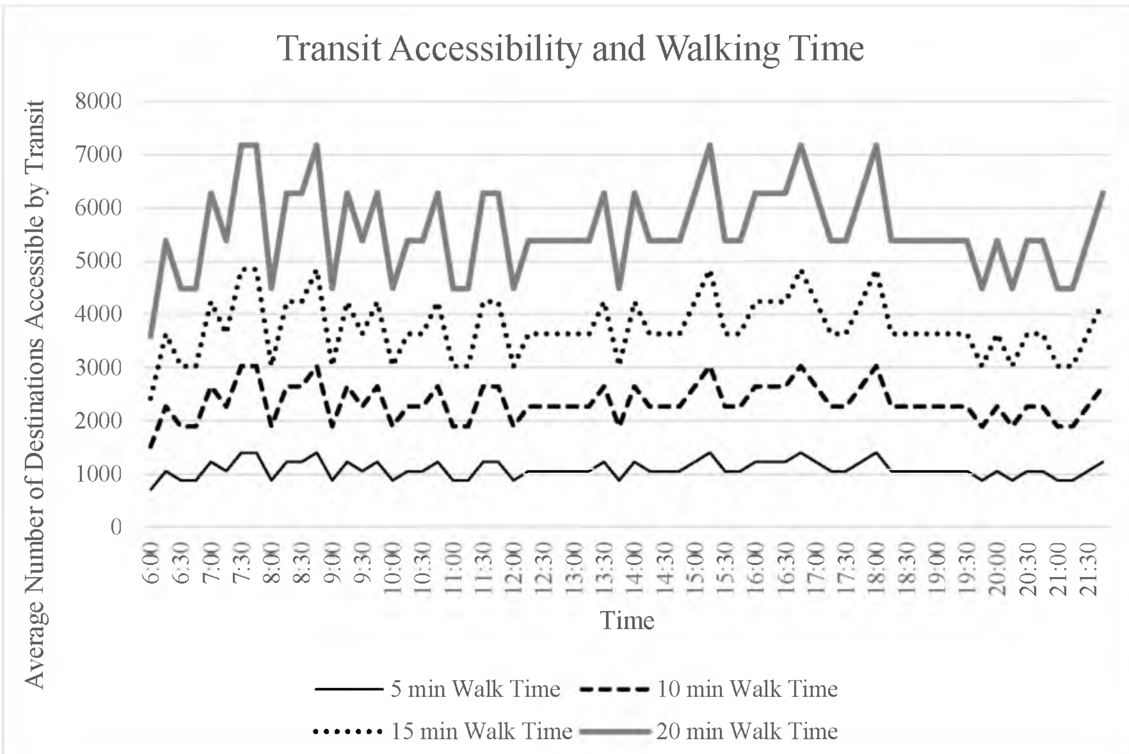


Figure 11 Daily Variations of Transit Accessibility for All Census Tracts Dependent on Preferred Walk Time Within the 60-minute Available Time Budget

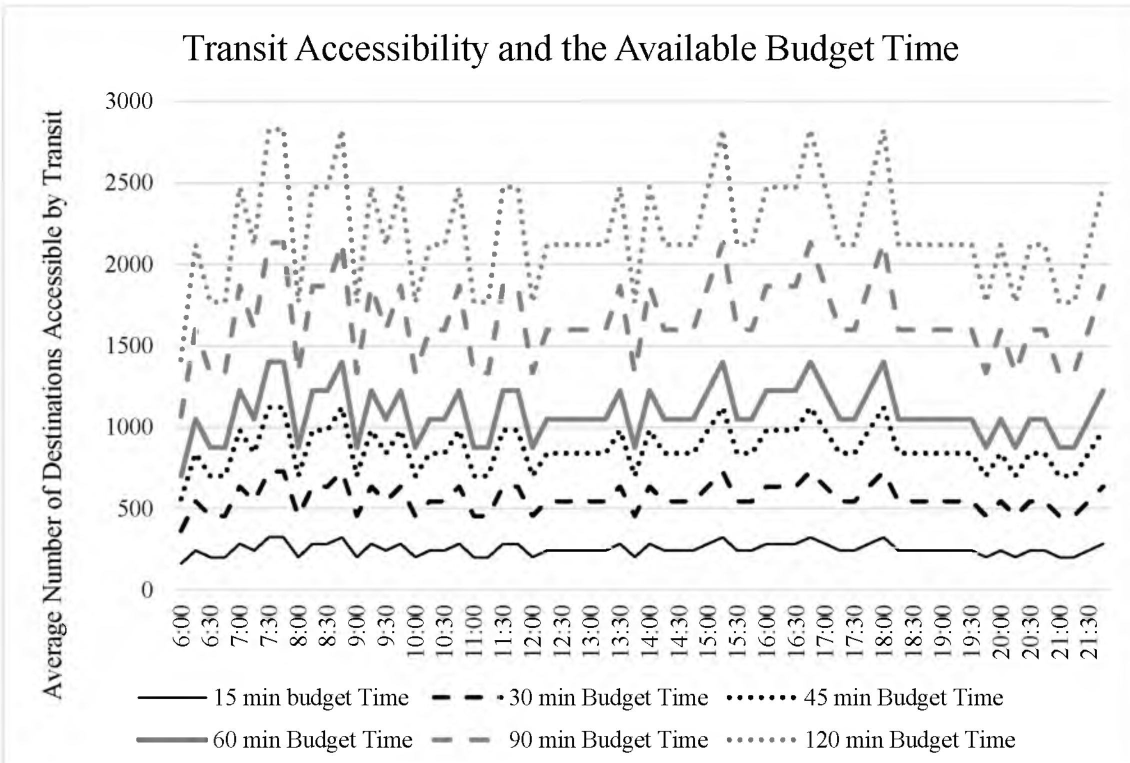


Figure 12 Daily Variations of Transit Accessibility for All Census Tracts Dependent on the Available Budget Time Within the 5-minute Walk from the Transit Stations

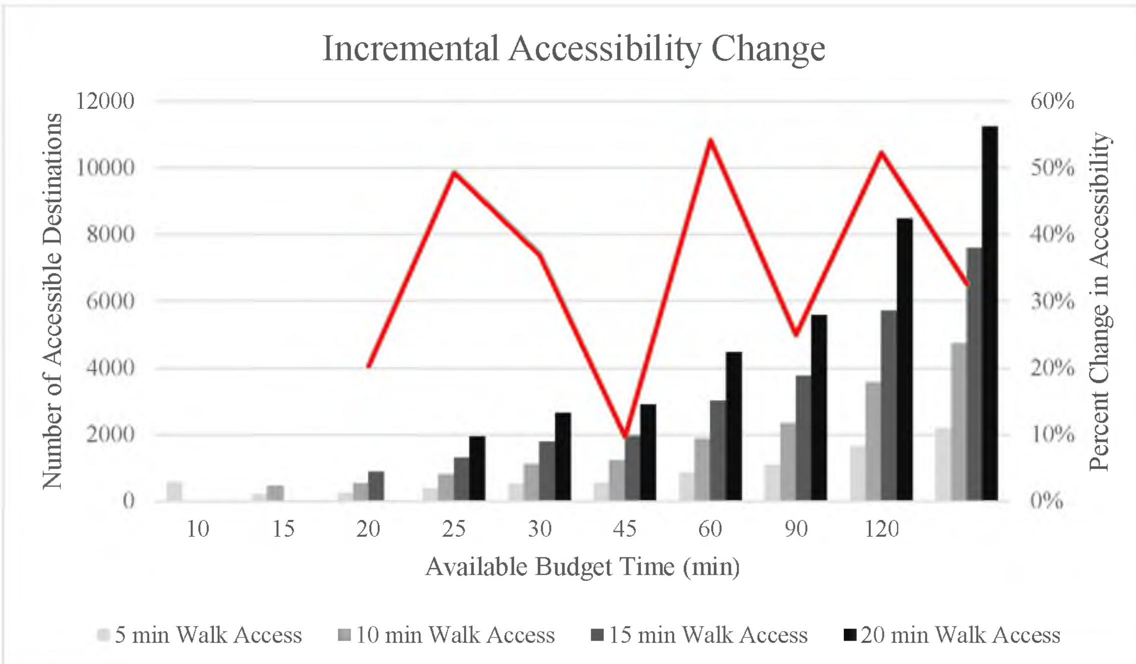


Figure 13 Incremental Change in Transit Accessibility Depending on the Available Time Budget and Walking Distance

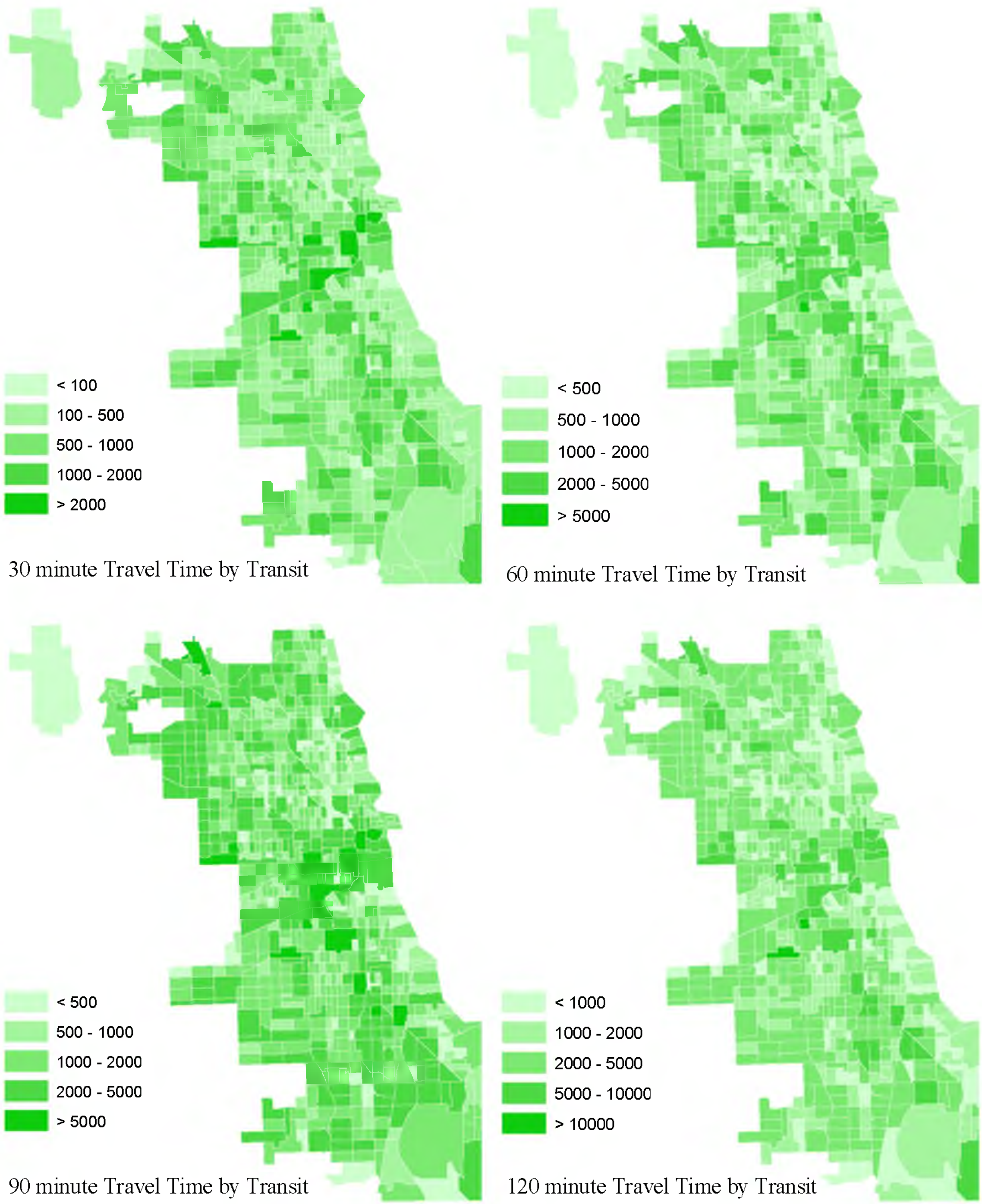


Figure 14 Destinations Accessible Within the Given Travel Time by Transit

When comparing these results to bicyclist accessibility, the number of destinations accessible by bike appears higher than the number of destinations accessible by transit, due to the fact that average time-dependent rather than total cumulative accessibility was calculated for transit. While the developed accessibility indicators provide the basis for a general multimodal accessibility indicator, calculation of such an indicator would require making assumptions about user preference in terms of mode choice that are not strongly supported by the data available in this study. As previously stated, the goal of the developed indicators is to improve the way multimodal exposure is captured in the safety prediction models, and development of a single indicator of multimodal accessibility remains a part of future research efforts.

Explanatory Variables Representing System-wide Effects

Additional explanatory variables were developed using the available data on SE characteristics and land use data to capture the system-wide effects that may influence multimodal safety outcomes in urban environments. The final dataset included roughly 100 variables considered in the SASM analysis.

Socio-Economic Variables

The SE variables were drawn from the American Community Survey (ACS) 5-year estimates of SE and household characteristics for each census tract in the City of Chicago (U.S. Bureau of Census). The ACS data were aggregated on the census tract level, allowing for a convenient extraction of variables of interest, without any need for the additional data manipulation. The selection of the SE variables from the extracted ACS data was based on the revised literature on traffic safety modeling in general, and traffic safety modeling of spatially collected data.

The ACS provides single-year and multiyear estimates of SE and housing characteristics of an area over a specific time period. The ACS collects survey information continuously nearly every day of the year and then aggregates the results over a specific time period: 1 year, 3 years, or 5 years. The data collection is spread evenly across the entire period represented so as not to over-represent any particular month or year within the period. Single-year data are more current, while multiyear data are more reliable because of the larger sample size.

The primary uses of ACS estimates are to understand the characteristics of the population of an area for local planning needs, make comparisons across areas, and assess change over time in an area. Factors that guide users to determine which ACS estimate to use where both single year and multiyear estimates are available include intended use of estimates, precision of estimates, and currency of estimates. For small geographic areas such as census tracts, 5-year ACS estimates are the only option, as single-year and 3-year estimates are unavailable.

Both availability and accuracy of SE data from the ACS 5-year estimates influenced the decision to use these estimates from the period from 2008 to 2012 and develop the SE variables for the purpose of this research. The ACS 5-year data included population, social, economic, and housing estimates on a variety of levels, and for this study, data are extracted for the Illinois counties Cook and Du Page, for census tracts that belong to Chicago. Figure 15 presents the spatial distribution of population density and unemployment in Chicago. Descriptive statistics for SE variables is provided in Table 6.

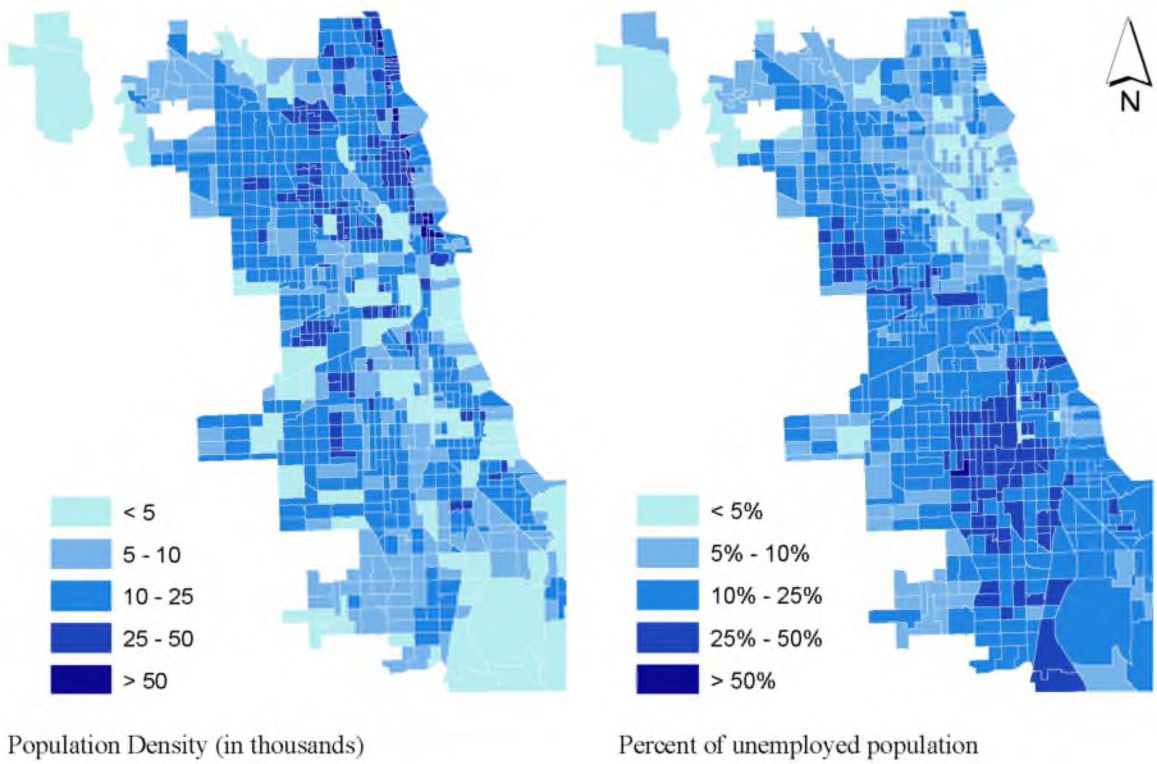


Figure 15 Spatial Distribution of the Population Density and the Percent Unemployed Population in Chicago (U.S. Census ACS 5-Year Data, 2008 - 2012)

Table 6 Descriptive Statistics for the SE Variables

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Population	Population Size	801	3.402	1.741	0.000	15.740
Pop_Dens	Population Density per mile squared	801	18.203	20.206	0.000	485.019
Employed	Percent of Employed Population	801	6.759	18.955	0.000	86.000
Unemploy	Percent of Unemployed Civil Population	801	14.970	9.459	0.000	51.000
Total_HH	Total Number of Households	801	1,296.553	786.911	0.000	9,180.000
HHI_Med	Median Household Income	801	48,201.260	24,220.910	0.000	155,500.000
HHI_Mean	Mean Household Income	801	65,296.570	35,266.030	0.000	211,891.000
FamI_Med	Median Family Income	801	62,689.660	40,894.530	0.000	233,702.000
FamI_Mean	Mean Family Income	801	82,579.100	59,415.360	0.000	394,284.000
PerCapInc	Average Income per Capita	801	27,786.690	20,029.490	0.000	131,548.000
HH	Total Number of Households	801	1,296.553	786.911	0.000	9,180.000
HHSize	Average Household Size	801	2.707	0.709	0.000	5.560
FamSize	Average Family Size	801	3.446	0.620	0.000	5.200
HHPop	Population in Households	801	3,336.594	1,717.642	0.000	15,544.000
ED9	No High School Degree, %	801	9.644	10.061	0.000	51.900
ED9_12	Some High School, %	801	10.460	7.166	0.000	38.400
EDHigh	High School Degree, %	801	23.717	11.402	0.000	58.600
EDSomeCol	Some College, %	801	18.898	8.292	0.000	48.700
EDAssoc	Associate Degree, %	801	5.477	3.236	0.000	34.600
EDBach	Bachelor's Degree, %	801	18.820	14.157	0.000	70.200
EDGrad	Graduate School Degree, %	801	12.483	12.291	0.000	63.900
EDHighPlus	More than High School Degree, %	801	79.396	15.181	0.000	100.000
EDBachPlus	More than Bachelor's Degree, %	801	31.303	25.240	0.000	96.900
HousUnits	Number of Housing Units	801	1,506.150	890.775	0.000	10,906.000
HousOcc	Occupied Housing Units, %	801	84.862	11.109	0.000	100.000
NoVeh	Households with no Vehicles, %	801	26.537	15.118	0.000	89.400
Veh1	Households with 1 Vehicle, %	801	43.589	9.508	0.000	81.300
Veh2	Households with 2 Vehicles, %	801	22.558	11.544	0.000	59.100
Veh3plus	Households with 3 or more Vehicles, %	801	6.814	5.648	0.000	26.900

Land Use Variables

Land use has emerged as an important factor to consider in any type of transportation analysis, particularly in urban environments. CMAP provided land use data for this research, in the form of digital geospatial polygon parcel data that indicate land use in northeastern Illinois.

Numerous GIS reference layers and several internet resources are used to support the land use inventory that is updated periodically. This research initially used land use data for the year 2005, which were available as polygon data that did not account for the right of way. After the initial research proposal, new land use data for the year 2010 became available for the analysis. Land use data from 2010 are parcel-based, account for the transportation right of way, and represent more accurate details on how land use is distributed spatially in Chicago. Therefore, this research used the most recent land use data for 2010 from CMAP. Land use variables are given in Table 7. Land use diversity was calculated as the total number of different land uses within each census tract, where eight categories of land uses were established: residential, commercial, institutional, industrial, transportation, agriculture, open space, and vacant (under construction). Land use entropy (Figure 16) is a measure of land use balance developed and used in previous studies (Wang and Kockelman, 2013; Cervero and Kockelman, 1997), and calculated as:

$$Entropy = -\sum_{i=1}^{n} \frac{p_i \cdot ln(p_i)}{ln(n)} \qquad \text{Equation (8)}$$

Where:

p_i - the proportion of land use “i" in the census tract area

n - the maximum number of land uses in census tract (in this case n = 8)

Table 7 Descriptive Statistics for Land Use Variables

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
LUDiv	Total number of land uses	801	5.916	1.012	1.000	8.000
Entropy	Land use entropy	801	0.472	0.123	0.015	0.802
ResidI	Indicator of residential land use	801	0.996	0.061	0.000	1.000
Resid	Proportion of residential land use	801	0.381	0.160	0.000	0.745
CommercI	Indicator of commercial land use	801	0.989	0.105	0.000	1.000
Commerc	Proportion of commercial land use	801	0.072	0.060	0.000	0.404
InstI	Indicator of institutional land use	801	0.948	0.223	0.000	1.000
Inst	Proportion of institutional land use	801	0.093	0.138	0.000	0.985
IndustryI	Indicator of industrial land use	801	0.958	0.202	0.000	1.000
Industry	Proportion of industrial land use	801	0.084	0.117	0.000	0.869
TranspI	Indicator of transportation land use	801	0.891	0.311	0.000	1.000
Transp	Proportion of transportation land use	801	0.054	0.092	0.000	0.969
AgricI	Indicator of agricultural land use	801	0.006	0.079	0.000	1.000
Agric	Proportion of agricultural land use	801	0.000	0.000	0.000	0.012
OpenI	indicator of open space land use	801	0.600	0.490	0.000	1.000
Open	Proportion of open space land use	801	0.038	0.097	0.000	0.869
VacantI	Indicator of vacant land under construction	801	0.909	0.288	0.000	1.000
Vacant	Proportion of vacant land under construction	801	0.046	0.069	0.000	0.520

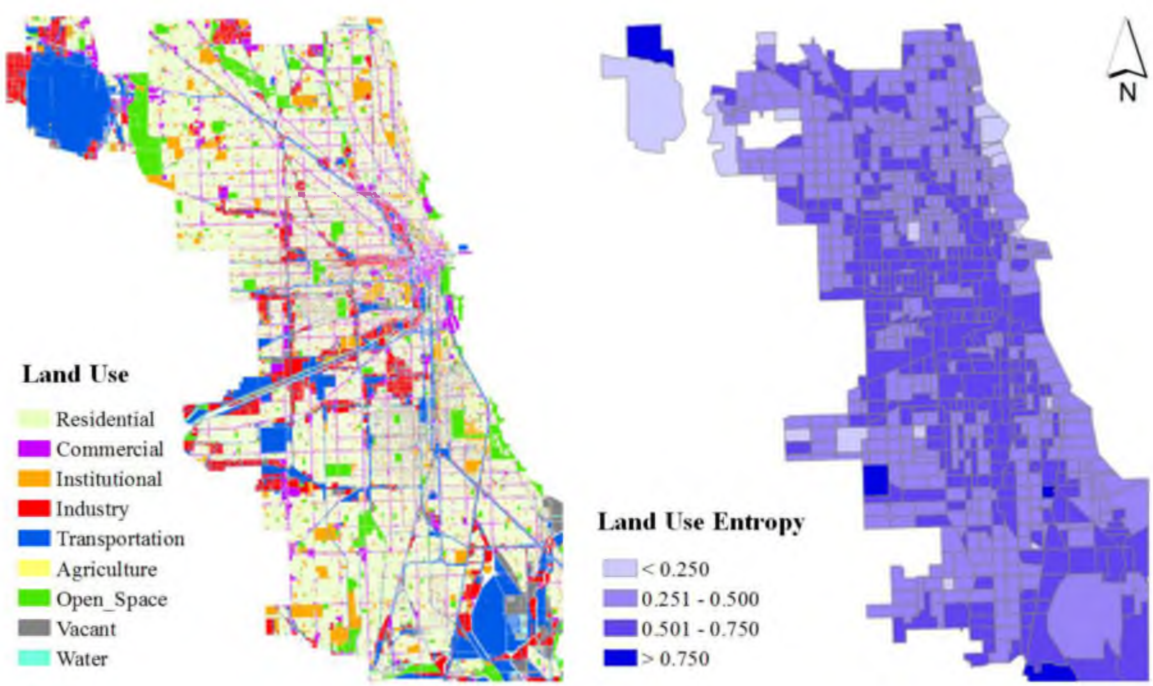


Figure 16 Land Use Parcels and Land Use Entropy in Chicago

Statistical Areal Safety Modeling Methods

This section of the Methodology chapter is focused on explaining the SASM methodology used to estimate multimodal crash outcomes on the census tract level using the dataset from Chicago based on the variables described in the previous sections of this chapter. The chapter includes the framework used for the application of SASM methodology, the description of five different SASM methods, and the diagnostics used to evaluate these methods. As shown in Figure 17, the application of SASM methods for the previously defined response and explanatory variables started from the traditional crash prediction models, and expanded to frequentist and Bayesian methods that account for spatial effects potentially present in the data. Due to the fact that data are spatially collected and aggregated, adequate tests for spatial auto-correlation were conducted. The combination of R, STATA, and ArcGIS was used to execute the SASM methodology presented in this section.

Frequentist Approach to Crash Modeling

There are two main approaches to statistical inference used to model crash data over the previous decade, frequentist and Bayesian. The key difference between these two approaches in in the way unknown parameters are defined and estimated. When frequentist statistical inference is used, it is assumed that data are a repeatable random sample, the hypothesis is fixed (either true or false), and parameters are considered to remain constant during the sampling process. This inferential approach is called frequentist because it is focused on the expected frequency with which the data will be observed, given the defined hypothesis.

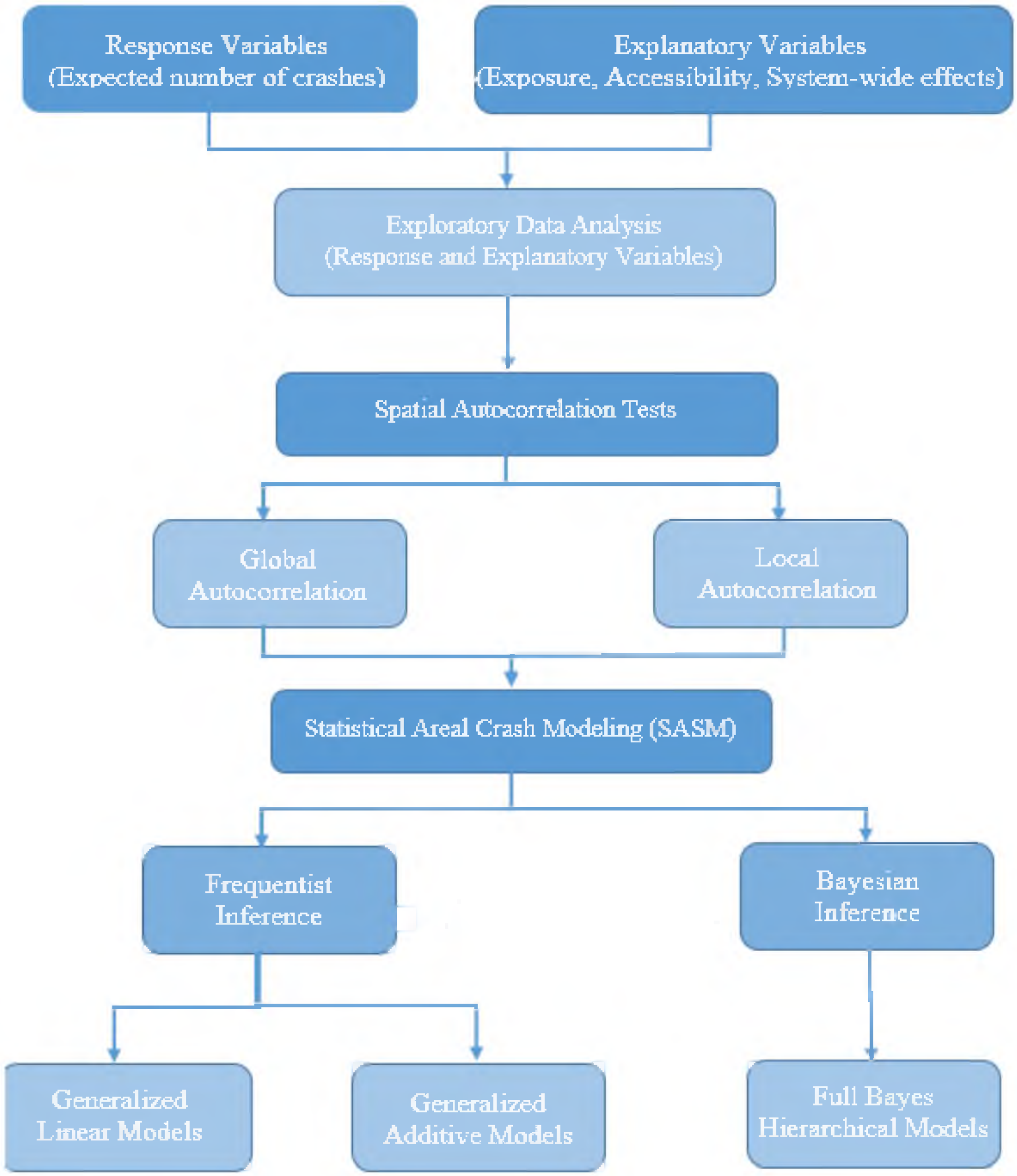


Figure 17 Flowchart of Crash Data Analysis Process

Bayesian approach uses probability to describe the unknown parameters, recognizing the uncertainty that exists in the knowledge about the parameters that should be estimated. Unlike the frequentist approach, Bayesian statistics is focused on determining the probability of the hypothesis, given the observed data, so while data are considered to be fixed, hypothesis is considered to be random.

Areal safety studies have been conducted using both frequentist and Bayesian estimation methods. Particularly over the last 10 years, Bayesian statistics became predominant in SASM, due to limitations of frequentist methods to capture spatial autocorrelation and heterogeneity of crash data. This research was conducted using both frequentist and Bayes SASM. While previous studies mostly use frequentist approach based on GLM, this study also explored the potential of GAM to capture the unobserved shared effects between analyzed areas (census tracts). In addition, Full Bayes Hierarchical (FBH) were also used to see if the estimated parameters obtained from both frequentist and Bayesian inference are comparable in terms of values and significance levels.

As crash data are positive count data, the primary statistical modeling approach based on frequentist inference is Negative Binomial (NB) regression, as a more general variation of Poisson regression which can account for overdispersion often present in crash data (Hilbe, 2007). The NB model includes an error term, ε_i, for which the exponent, $\exp(\varepsilon_i)$, follows a gamma distribution with parameters (1, α), where α is the overdispersion parameter. The general form of Negative Binomial model is (Hilbe, 2007):

$$\theta_i = e^{(\beta_0 + \beta_1 \ln(\text{Exp1}_i) + \beta_2 \ln(\text{Exp2}_i) + \sum_j \beta_j x_{ij} + \varepsilon_i)} \qquad \text{Equation (9)}$$

Where:

θ_i - expected number of crashes for census tract "i"

β_0- intercept

β_i - coefficients quantifying the effect of the "j" explanatory variables characterizing census tract "i" on θ_i

Exp1 and Exp2 – measures of exposure in census tract "i"

x_i - a set of "j" explanatory variables that characterize census tract "i" and influence θ_i

ε_i - disturbance term corresponding to census tract "i"

In the NB model provided in Equation 10, the variance in the number of crashes is: $\theta_i + \alpha_i \theta_i^2$. The provided general form of the NB model from the Equation 10 can further be expanded to capture SASM of the expected number of crashes for vehicular, pedestrian, and bicyclist users:

$$\theta_{veh\_i} = e^{(\beta_0+\beta_1 \ln(DVMT)+\beta_2 \ln(\text{Road})+\sum_j \beta_j x_{ij}+\varepsilon_i)} \quad \text{Equation (10)}$$

$$\theta_{ped\_i} = e^{(\beta_0+\beta_1 \ln(DVMT)+\beta_2 \ln(Ped)+\sum_j \beta_j x_{ij}+\varepsilon_i)} \quad \text{Equation (11)}$$

$$\theta_{bike\_i} = e^{(\beta_0+\beta_1 \ln(DVMT)+\beta_2 \ln(\text{Bike})+\sum_j \beta_j x_{ij}+\varepsilon_i)} \quad \text{Equation (12)}$$

In the case of the SASM method developed for estimating the number of total and severe vehicular crashes, both DVMT and length of road (variable "Road") were used as measures of exposure, to capture both the presence of vehicular users and the relationship between the road network mileage and DVMT on the census tract level. The SASM method used to estimate the expected number of total and severe pedestrian crashes (Equation 12) uses both DVMT and the number of generated pedestrian trips in the census tract as units of exposure. The SASM method used to estimate the expected number of total and severe bicyclist crashes (Figure 13) uses DVMT and the number of generated bicyclist trips to represent bicyclist users exposure to crashes in census tracts. The ASM methods based on other statistical modeling techniques (GLM, GAM, FBH) used the same framework to represent the exposure. The main assumption behind the exposure incorporated in the SASM models in this way was that if the exposure of one of the two conflicting modes was zero, it was expected that the number of crashes would be zero as well.

The NB models presented in the Equations 10-13 above do not account for the presence of spatial autocorrelation in the data, which may be a limitation to adequately representing the data generating process, particularly when data are spatially aggregated and the number of crashes in one area may depend or be similar to the number of crashes in the areas nearby (i.e., a spatial spillover effect). In cases where spatial autocorrelation is present, it may increase the variance of estimated parameters, while their standard errors may be underestimated by the NB model (Aguero-Valverde & Jovanis, 2006; Quddus, 2008). In such cases, the NB model can be modified through an additional term that is added to the model to represent spatial random effects in the data.

Detecting Spatial Autocorrelation

The NB model is estimated using the maximum likelihood approach, constructed on the basis of the assumption that the observations in the model are independent. This assumption does not hold when data are clustered (Anselin, 2013). Clusters appear in the case when spatial correlation is present in the dataset, where nearby entities are related more than the entities that are far apart (Greene, 2003).

It is previously acknowledged that due to shared spatial effects, crash data have the tendency for clustering (Aguero-Valverde & Jovanis, 2006). In addition, the way data are organized and aggregated, rarely follows the actual cluster boundaries (Anselin, 2013). In the case of the dataset built for the purpose of this research, census tracts are not very likely to match the spatial agglomeration of the crashes, contributing to the additional bias in the modeling process. Several measures of spatial autocorrelation may be utilized to indicate the existence of clusters in the dataset, including Moran's I, Getis-Ord's G, and Geary's C (Anselin, 2013). Due to its broad application and the convenience of interpretation, Moran's I was used in this research as the indicator of global and local auto-correlation.

Global Moran's I measures the general tendency to clustering based on location of an entity and the values of the selected entity's attributes. The Global Moran's Index value with z-score and p-value that indicate the significance of the index is calculated as follows (Anselin, 2013):

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad \text{Equation (13)}$$

Where:

n – total number of entities

z_i – deviation of an attribute from its mean

$w_{i,j}$ – spatial weight between features i and j

$$S_o = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}$$

$$z_I = \frac{I - E[I]}{\sqrt{V[I]}} \qquad \text{Equation (14)}$$

Where:

$E[I] = -1/(n-1)$

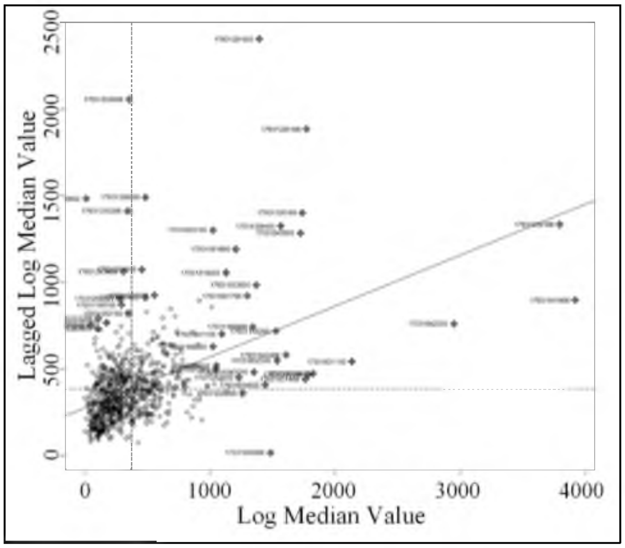
$V[I] = E[I^2] - E[I]^2$

The Global Moran's I is interpreted in terms of its null hypothesis which states that the analyzed attribute is randomly distributed among the entities of interest. One of three alternative assumptions about the data may be made when Moran's I test is applied to detect spatial autocorrelation: normality, randomization, or no assumptions (Acevedo, 2013). If the data are a part of a known larger trend, where the values of the variable in each region are drawn from the same normal distribution, and the mean and the variance are the same for all regions, the normality assumption may be used. If the data are close to normally distributed, but the trend is unknown, it can be assumed that all permutations of the values of the variable are equally likely, and the randomization assumption may be used. When the previous two assumptions cannot be made about the data, Monte Carlo simulation of Moran's I may be used (Acevedo, 2013). While previous studies of crash data used Moran's I to detect and measure spatial autocorrelation, it is rarely indicated under which assumptions the test was conducted (Moeinaddini et al., 2014; Yiannakoulias et al., 2012).

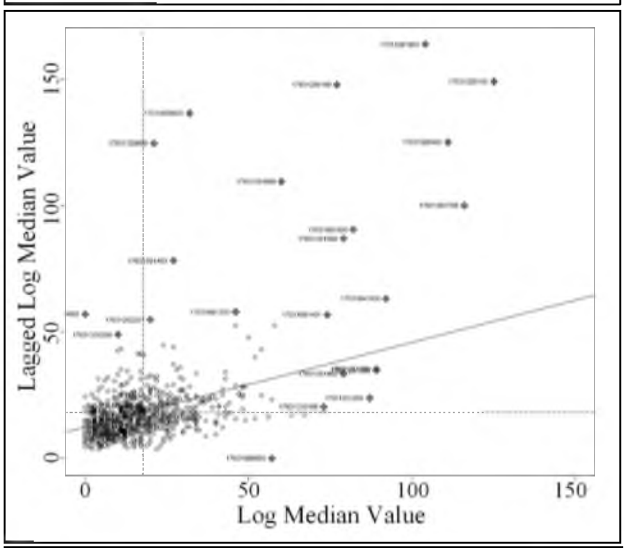
In this research, prior to conducting the Moran test, neighborhood functions between census tracts were created using boundary methods. Spatial weights were then assigned by using the inverse distance method. Global spatial autocorrelation was detected by using a Monte Carlo method, where data are rearranged several hundred times by re-assigning the values of the variable of interest (vehicular, pedestrian, and bicyclist crashes) to different spatial units and obtaining several hundred random spatial distributions of that variable. Moran's I is then calculated for each of these arrangements, and these simulated values are used to construct a simulated sample distribution. Then the observed value of Moran's I obtained from the original data arrangement is compared to this distribution obtained from random sampling, and if it exceeds 95% of simulated values, it is very likely that the observed distribution is significantly autocorrelated. In this case, the null hypothesis of spatial randomness is rejected.

This test is not two-sided, due to the fact that ranking is used, so either positive or negative autocorrelation should be assumed. In this case, the Monte Carlo method was applied to the data with the assumption of positive autocorrelation, the most common scenario (Acevedo, 2013). As the Monte Carlo test is distribution-free, crash-related variables on the census tract level did not need to be transformed. The tests were run with 1000 simulations and the plotted results are provided in Figure 18 and Figure 19. Although the values of the Moran statistics are low and would seem to indicate no spatial pattern, the Z-value is high due to low variance and the p-value of the hypothesis test is low, indicating that spatial autocorrelation is very likely present in the data. Modeling methods explained in the following parts of the paper attempt to account for the presence of spatial autocorrelation in the data.

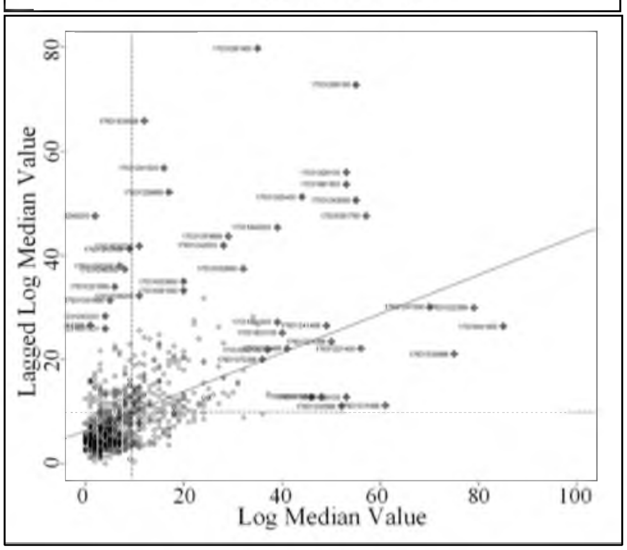
Since the global indicator of spatial correlation shows general tendency to clustering in the dataset, local Anselin Moran's Index was utilized to measure the degree of similarity between neighboring census tracts (Anselin, 2013). The calculations were based on several different neighborhood definitions for the local Moran's I calculations. The results of the local auto-correlation test should show potential presence of clusters of high values, low values, and spatial outliers for vehicular and nonmotorized crashes on



Vehicle-only Crashes
number of simulations + 1: 1000
statistic = 0.2948
observed rank = 1000
p-value = 0.001
alternative hypothesis: greater
(rejected null hypothesis)

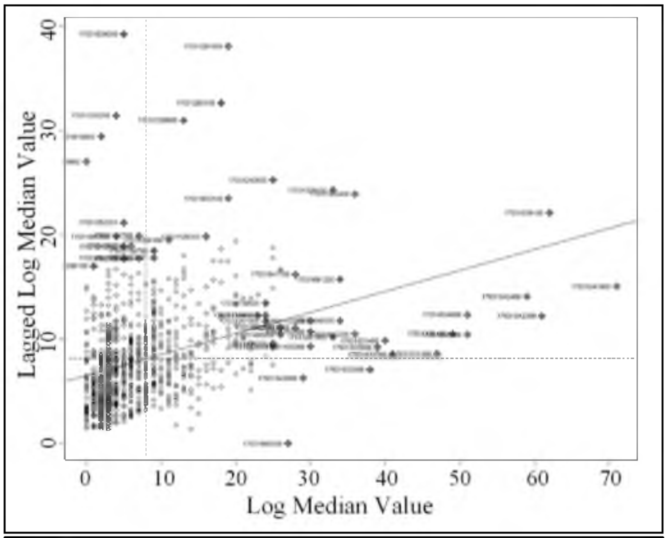


Pedestrian Crashes
number of simulations + 1: 1000
statistic = 0.3344,
observed rank = 1000,
p-value = 0.001
alternative hypothesis: greater
(rejected null hypothesis)

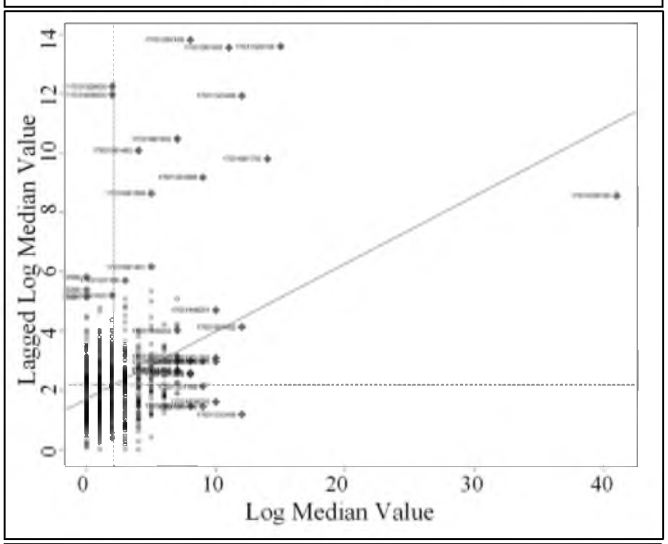


Bicyclist Crashes
number of simulations + 1: 1000
statistic = 0.3743,
observed rank = 1000,
p-value = 0.001
alternative hypothesis: greater
(rejected null hypothesis)

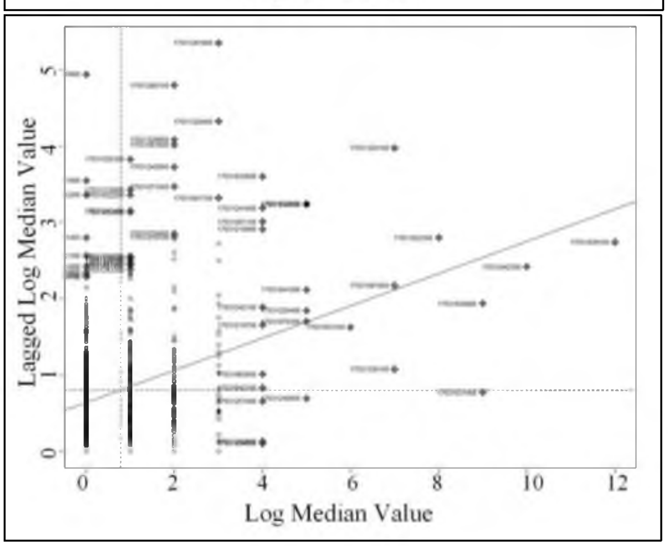
Figure 18 Monte Carlo Simulation of Moran's I for Total Multimodal Crashes



Vehicle-only KA Crashes
number of simulations + 1: 1000
statistic = 0.2011
observed rank = 1000
p-value = 0.001
alternative hypothesis: greater
(rejected null hypothesis)



Pedestrian KA Crashes
number of simulations + 1: 1000
statistic = 0.2283,
observed rank = 1000,
p-value = 0.001
alternative hypothesis: greater
(rejected null hypothesis)



Bicyclist KA Crashes
number of simulations + 1: 1000
statistic = 0.2177,
observed rank = 1000,
p-value = 0.001
alternative hypothesis: greater
(rejected null hypothesis)

Figure 19 Monte Carlo Simulation of Moran's I for Severe (KA) Crashes

the census tract level. Further methods were developed based on the traditional crash prediction techniques and these preliminary measurements of spatial dependence. The results of local Moran's Index are provided in Figure 20.

Generalized Linear Models

GLM are a flexible generalization of linear regression models that allow for response variables that have distribution other than normal. The previously described negative binomial model is considered to be a generalized linear model, and it may take some extended forms to accommodate random effects existing in spatially collected crash data. Two such forms, negative binomial with fixed effects and with random effects, are described in this section of the crash data analysis methodology.

While global Moran's I indicates the presence of spatial correlation in the data, local Moran's I identifies clusters of census tracts with similar (high or low) crash frequencies (Figure 20). These results indicate that crash models need to be developed to account for spatial correlation and acknowledge clustering in the dataset. Previous research also used local Moran's I results to spatially aggregate contiguous units of analysis in road safety, often for the purpose of identifying crash hot-spots (Huang et al., 2009; Miranda-Moreno et al., 2007).

After determining the presence of spatial correlation in the dataset using global Moran's I, the results of local Moran's I test were utilized to aggregate census tracts into higher level spatial categories that would approximately capture the identified clusters through the assignment of fixed and random effects to these groups within the NB model framework.

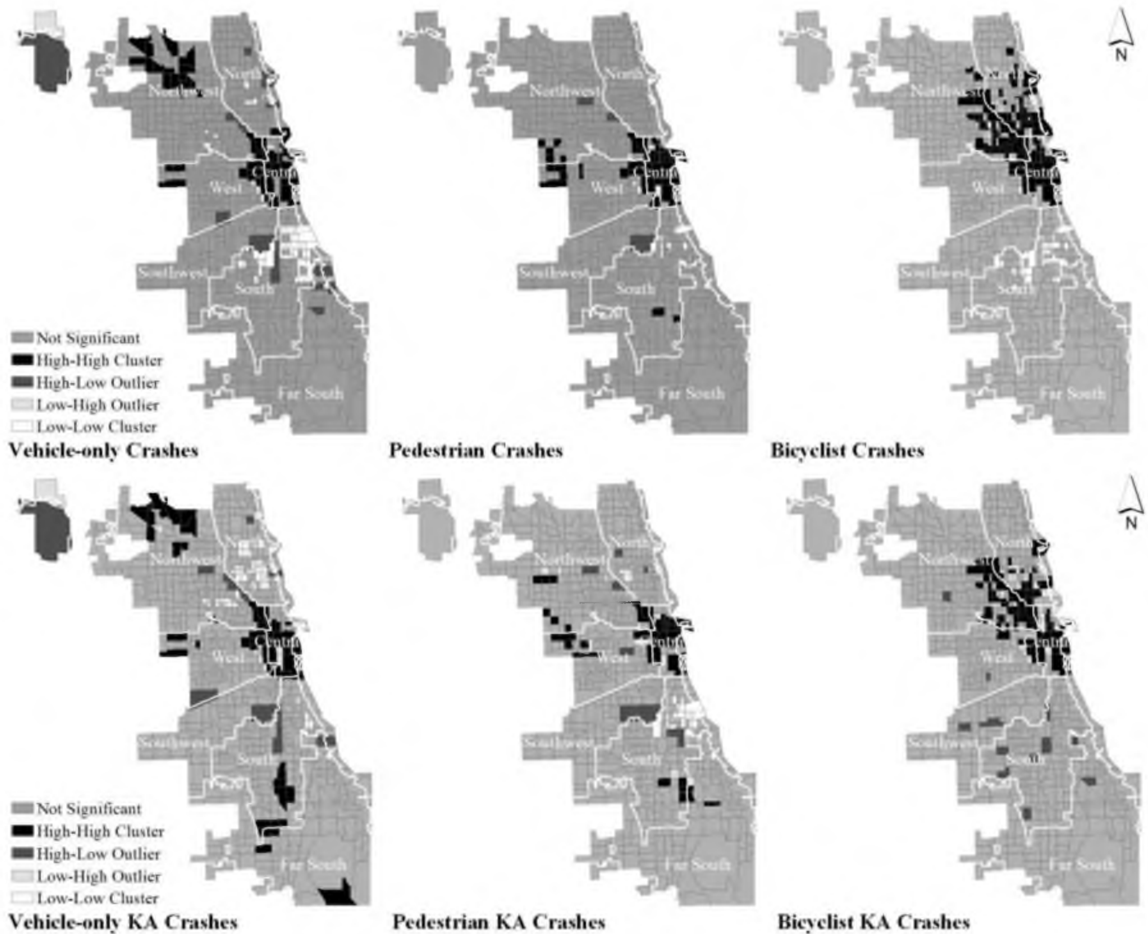


Figure 20 Local Moran's I Results

This is similar to building neighborhood structure in spatial auto-regression models for normal data and the approach has already been used in previous research, but considered only models with fixed effects (Wang et al., 2009). The NB model can account for spatial correlation if it is formulated in a way that includes an additional parameter that would represent the spatial dependence (Greene, 2003). This additional parameter for clustered data can be introduced through fixed or random effects panel models (Hilbe, 2007; Lord & Mannering, 2010). The fixed effects NB (FENB) model can be estimated as an unconditional or conditional model (Hilbe, 2007). The conditional FENB has the ability to accommodate a large number of panel units, but it has been questioned by some, as it does not control for all of its predictors and cannot be considered a "true fixed-effects model" (Allison, 2002). Some econometricians have gone as far as recommending that the unconditional FENB model be used rather than conditional (Greene, 2003). The unconditional FENB is specified by using indicator variables and can be represented as:

$$\theta_{ik} = e^{(\beta_0 + X_{ij}\beta_j + \beta_{j+1}\ln(Exp1_i) + \beta_{j+2}\ln(Exp2_i) + \delta_{ik})} \qquad \text{Equation (15)}$$

Where:

θ_{ik} – expected number of crashes for census tract i in category k

δ_k – fixed effect associated with census tract i nested in category k

The advantage of the FENB model in this context is that it can address situations where shared unobserved effects between the entities are correlated with independent variables (Allison, 2002; Lord & Mannering, 2010). The spatial FENB allows only the constant term to vary between the sub-categories of the data. Its limitation in this context is that the fixed effects model can only estimate the parameters associated with effects that vary over spatial units (e.g., census tracts) within a defined data cluster. Also, the standard errors of the parameters estimated by FENB can be larger (than RENB) if there is little variation in the predictor variables across the spatial units. The fixed effects model fully removes spatial dependence if the spatial data generating process corresponds to the categorical data structure (Anselin, 2013).

Based on the previously presented spatial correlation measures for the described dataset (Figure 20), local high and low clusters for the analyzed crashes tend to be approximately captured by the areal boundaries of planning districts of the City of Chicago. Categorizing census tracts into seven planning districts closely corresponds to identified crash clusters from the local Moran's I analysis. The distinction between the

Central district and the other planning districts in terms of crash concentration is noticeable. This potential categorical structure of the data with the existing planning districts as categories and the census tracts as observations led towards exploring the FENB model with indicator variables for planning districts as the one possible way to fit the data and account for spatial dependence.

Random effects NB models (RENB) are another option for trying to capture the spatial level heterogeneity in the dataset. The main assumption with the random effects model is that the unobserved shared effects among defined spatial entities are uncorrelated with the explanatory variables. If this is the case, the random effects estimator is consistent and estimated parameters will have smaller standard errors than the fixed effects model. The random parameter in RENB model typically follows Gaussian, inverse Gaussian, or preferably gamma distribution (Greene, 2003; Hilbe, 2007). The general form of the RENB model is similar to the form of FENB model (Hilbe, 2007):

$$\theta_{ik} = e^{(\beta_0 + X_{ij}\beta_j + \beta_{j+1}\ln(Exp1_i) + \beta_{j+2}\ln(Exp2_i))} e^{\eta_{ik}} \qquad \text{Equation (16)}$$

Where:

η_{ik} – random effects for observation i nested in category k

Generalized Additive Models

GAM represent another modeling technique that uses frequentist approach in estimating model parameters. Generalized additive models were introduced by (Hastie & Tibishirani, 1990), as an additive extension of the family of generalized linear models. These models were developed with linear predictors, just as generalized linear models, but with also including a sum of smoothing functions of explanatory variables. Since a smoothing function is a tool for summarizing the trend of a response measurement as a function of one or more explanatory variables, generalized additive models allow for a more flexible specification of the dependence of the response on the explanatory variables (Hastie & Tibishirani, 1990; Wood, 2006). Generalized additive models replace the linear form "$\beta_0 + \sum_i \beta_i \, x_i$" by the additive form "$\beta_0 + \sum_i f(\, x_i)$ " (Hastie & Tibishirani, 1990). Generalized linear models are estimated by computing the maximum likelihood estimates, as an iteratively reweighted least-squares procedure. This procedure is modified for the estimation of generalized additive models where the parameters are estimated by penalized likelihood maximization (Hastie & Tibishirani, 1990; Wood, 2006). The general additive model structure for the case of negative binomial distribution is as follows (Hastie & Tibishirani, 1990):

$$\theta_i = e^{(\beta_0 + \sum_j f_j(\, x_{ij}) + \varepsilon_i)} \qquad \text{Equation (17)}$$

Where:

θ_i - expected number of crashes for census tract "i"

β_0- intercept

f_j - smooth function quantifying the effect of the "j" explanatory variables characterizing census tract "i" on θ_i

x_{ij} - a set of "j" explanatory variables that characterize census tract "i" and influence θ_i

ε_i - disturbance term corresponding to census tract "i"

An additive model may have component functions with two or more dimensions (Hastie & Tibishirani, 1990). If a smoothing function is used across the locations on spatially aggregated data, generalized additive models may be used to represent spatial processes in the data and account for spatial variation. While two previous applications of additive models in crash studies developed smoothing functions related to explanatory variables such as traffic volumes and geometric design (Li, 2009; Xie, 2008), smoothing across the locations has only previously been used in epidemiology and ecological studies (Schmidt & Hurling, 2014; Wood, 2006). Ecology research uses generalized additive models to account for the effects of explanatory variables, as well as spatial autocorrelation by including a two-dimensional spatial trend function in the model (Wood, 2006). The general form of the model with a spatial trend function is shown in Equation 14 (Schmidt & Hurling, 2014; Wood, 2006):

$$log(\theta_i) = \beta_0 + \sum_j \beta_j\, x_{ij} + f_i(lat_i, lon_i) + \varepsilon \qquad \text{Equation (18)}$$

Where:

θ_i - expected number of crashes for census tract "i"

β_0- intercept

β_i - coefficients quantifying the effect of the "j" explanatory variables characterizing spatial unit "i" on θ_i

x_{ij} – a set of "j" explanatory variables that characterize census tract "i" and influence θ_i

ε_i - disturbance term corresponding to census tract "i"

$f_i(lat_i, lon_i)$ –two-dimensional smooth function for modeling spatial trends in census tract "i"

The essential part of parameter estimation in GAM is estimating a smooth function f_i by choosing an adequate basis to represent the smooth function as a linear model. In the case when a smooth function is assumed to be two-dimensional in order to account for spatial dependence as it is in the case of this research, the adequate basis is penalized thin plate regression spline, explained in detail in (Wood, 2006). The smoothing function f_i

used in this research is estimated by minimizing the following penalized least square function:

$$min \sum_{i} (y_i - f_i)^2 + \lambda J_{m,d}(f)$$ Equation (19)

Where:

y_i- observed number of crashes in census tract "i"

f_i- thin plate regression spline smoothing function for modeling spatial trends in census tract "i"

λ- smooth term resulting from GAM estimation

$J_{m,d}$(f)- penalty function measuring the roughness of the f estimate

The type of model setting represented in Equation 17 assumes that spatial dependence can be handled by including it in the systematic part of the model, similar to modeling a lag effect. The additive regression models were fitted with a two-dimensional smoothing function of the geographic location of each spatial unit of analysis, to capture the spatial autocorrelation and nonlinear effects which could not be captured by the observed explanatory variables (Schmidt & Hurling, 2014; Wood, 2006). Whether this approach is appropriate to model the existing spatial autocorrelation in the data depends on the complexity of spatial dependence. GAM with smoothing splines across the locations essentially models the trend in the autocorrelated data while other explanatory variables represent the deviation from this trend. The advantage of GAM models is that they allow for more complex trends than a simple trend surface. Modeling spatial dependence between observations in this manner reduces the possibility of residuals being autocorrelated and violating the assumptions of independence. In the cases of datasets where the error terms are stronger sources of autocorrelation, alternative methods should be applied to ensure that there the estimated coefficients and standard errors are not biased.

Bayesian Approach to Crash Modeling

Bayesian statistical inference offers an alternative to frequentist approach that uses a hypothesis testing framework and reports p-values to indicate the significance of estimated parameters. Bayesian methods have gained a lot of interest in the area of SASM over the previous decade, due to their ability to incorporate prior information in modeling process and parameter estimation. Bayesian approach includes modeling of both observed data and any unknowns as random variables, providing a comprehensive framework for combining prior knowledge with complex data models.

In the case of Bayesian models, in addition to specifying $f(y|\beta)$, for the set of observations $y = \{y_1, y_2, \ldots y_n\}$, for the vector of unknown parameters $\beta = \{\beta_1, \beta_2, \ldots \beta_n\}$, it is considered that β is a random quantity sampled from a prior distribution $\pi(\beta|\tau)$, where τ is the vector of hyper-parameters, controlling how β truly varies. When τ is known, the inference about β is based on the posterior distribution, given by the Bayes theorem:

$$p(\beta|y,\tau) = \frac{p(y,\beta|\tau)}{p(y|\tau)} = \frac{p(y,\beta|\tau)}{\int p(y,\beta|\tau)d\beta} = \frac{f(y|\beta)\pi(\beta|\tau)}{\int(y|\beta)\pi(\beta|\tau)d\beta} \qquad \text{Equation (20)}$$

Where:

p − conditional probability

f − likelihood function

π − external knowledge prior

The Bayesian inference based on the theorem given in Equation 19 is considered to provide advantages over the frequentist inference as it includes a knowledge-based foundation through the incorporated priors. Another advantage of Bayesian framework is that it allows modeling parameters β with random instead of fixed effects and allows the introduction of structures that capture spatial auto-correlation in the models, which is why Bayesian inference usage in statistical crash modeling significantly increased as the need to model crashes on the macroscopic level appeared.

Full Bayes Hierarchical Models

Based on the previously reviewed literature, spatial safety analysis was conducted by either applying the traditional models such as NB variations, and models with Bayesian inference. The advances in computing methods and the inability to estimate maximum likelihood function for data with less common distributions led to increased use of Bayesian estimating methods (Lord & Mannering, 2010). Bayesian approach allows the usage of sampling-based simulation methods to estimate more complex model forms, particularly when data exhibit spatio-temporal correlations (Huang & Abdel-Aty, 2010; Kim et al. 2007).

Previous studies found that the results of the safety analysis based on frequentist and Bayesian inference both agree or disagree (Aguero-Valverde & Jovanis, 2006; Quddus, 2008; Siddiqui et al., 2012; Wang & Kockelman, 2013). Certain authors recommend the exclusive application of Bayesian models, considering that they are flexible enough to account for both spatial effects and overdispersion (Huang & Abdel-Aty, 2010; Quddus, 2008;). Other authors found that frequentist and Bayesian models yield similar conclusions (Aguero-Valverde & Jovanis, 2006). Some authors consider that the complexity of Bayesian methods is a serious barrier to their application (Lord & Mannering, 2010).

Developing SASM under Bayesian framework has become more frequent over the past several years, as the computational capabilities increased to allow for more complex modeling processes (Lord & Mannering, 2010). Spatial autocorrelation issues may be resolved in models developed under Bayesian framework if spatial heterogeneity is accounted for through incorporation of Conditional Autoregressive (CAR) or Spatial Autoregressive (SAR) models. The majority of previous road safety studies use CAR model because of its suitability for the analysis of geographic regions (Wang & Kockelman, 2013). The combination of NB model and CAR model cannot be estimated by using maximum likelihood, and it has to be estimated by using Monte Carlo Markov Chain (MCMC) simulation (Park & Lord, 2007).

A Bayesian hierarchical model with Conditional Autoregressive (CAR) prior was used in this research, in order to compare the results obtained from previously explained modeling methods. This model is proposed by (Besag, 1975), and used by (Aguero-Valverde & Jovanis, 2006; Quddus, 2008). Acknowledging that more complex Bayesian models with more informative priors have been developed over the past several years (Wang et al., 2014), this paper uses the model with highly noninformative priors for parameter estimates, in order to provide a comparison between the estimates resulting from the Bayesian approach and models with frequentist inference explained in previous sections of this chapter.

In the Bayesian hierarchical model, the posterior distribution of all unknown parameters is proportional to the product of the likelihood and the prior distributions

(Aguero-Valverde & Jovanis, 2006; Quddus, 2008). The modeling approach assumes that crash counts have Poisson distribution:

$$y_i \sim Poisson(\theta_i) \quad \text{Equation (21)}$$

$$\log(\theta_i) = \beta_0 + \sum_i \beta x_i + v_i + u_i \quad \text{Equation (22)}$$

Where:

y_i-observed number of crashes in entity i

θ_i- expected mean of total crash frequency for entity i

β_0- intercept, assumed uniform distribution

β_i- coefficients, assumed normal prior ~N(0,1000)

x_i – explanatory variables influencing θ_i

v_i - spatially correlated random effect for entity i

u_i – unobserved heterogeneity among entities

Spatial dependence among entities, in this case census tracts, is incorporated through the CAR prior (Besag, 1975), which follows normal distribution with mean and variance $N(S_i, \tau_i)$:

$$S_i = \frac{\sum_j v_i w_{ij}}{\sum_j w_{ij}}; \ \tau_i{}^2 = \frac{\tau_v{}^2}{\sum_j w_{ij}} \quad \text{Equation (23)}$$

The term w_{ij} is 1 if entities "I" and "j" are adjacent, and 0 otherwise, while τ_v controls the variance of spatial correlation, and has the assumed prior Gamma distribution $\tau_v \sim Ga(0.5, 0.0005)$. The unobserved heterogeneity among entities is assumed to follow a normal distribution, $u_i \sim N(0, \tau_u{}^2)$; where τ_u is the parameter that controls Poisson extra-variation with a prior Gamma distribution $\tau_u \sim Ga(0.5, 0.0005)$, as previously used in (Aguero-Valverde & Jovanis, 2006; Quddus, 2008). The Bayesian hierarchical model was estimated using a Markov Chain Monte Carlo method (MCMC), with 10,000 iterations where the first 2,000 iterations were removed as burn-ins.

Preliminary and Final Model Specifications

The SASM methods explained in this chapter were applied towards the estimation of the expected number of crashes for six identified response variables: total vehicular crashes, severe vehicular crashes, total pedestrian crashes, severe pedestrian crashes, total bicyclist crashes, and severe bicyclist crashes. As the dataset built for the purpose of this research includes roughly 100 variables, including all independent variables in preliminary model specifications was not feasible. Instead of including all defined variables in the preliminary models, the SASM process started with including different sets of variables. This way, preliminary models were developed including variables that showed higher significance level across various sets of model specifications, consistent sign and magnitude, and appeared in the previous research studies that used SASM methodology.

Preliminary statistical models were developed by running NB models only, rather than running all types of models described in the previous chapter. The reasoning behind the modeling process initiated this way is that given the modeling methods features, NB models were most likely to overestimate the significance of variables included in specifications. It is typical to use this approach and apply less complex SASM models first in order to explore many possible specifications. After using negative binomial models to obtain preliminary specifications, final model specifications were obtained for all modeling methods and all outcome variables. The variable selection process that led to obtaining the final model specifications was carried out by looking at the *p*-values and the significance of each variable, by relying on the previous research done and the reviewed literature, and by considering logical relationships that were expected to be found between the independent and dependent variables. In addition, once the model specification became close to final, several different SASM methods were applied to the same specification to obtain the most consistent set of variables.

Diagnostics and Final Model Recommendations

After obtaining final model specifications for all six response variables, based on the process described in the previous section, results from all five SASM methods applied in this research were evaluated in order to recommend the final model for each of the six response variables. The combination of model-specific parameters, goodness of fit measures, and overall comparison of estimated parameters for the explanatory variables was used to recommend the final six SASM models. Model-specific parameters that were used as the preliminary indicators of performance for each SASM method applied in this research included the following:

- Alpha: The over-dispersion parameter in the NB models accounting for the fact that crash data variance is greater than the mean
- Pseudo R2: Pseudo r-squared is calculated as $\{1 - \frac{LL(model)}{LL(null)}\}$
- LL: The value of the log likelihood function of the final model
- Ln(r), Ln(s): Beta distribution parameters, where $(1/1 + alpha)$ follows Beta (r, s) distribution
- Smooth terms: Two-dimensional smooth function parameters based on penalized thin-plate regression splines. Coefficient estimates of smooth terms provided with

standard errors and p-values indicate statistical significance of smooth functions included to account for spatial autocorrelation

- Deviance explained: The percentage of deviance explained, based on the sum of squares of the deviance residuals, as the model deviance, and the sum of squares of the deviance residuals when the covariate effects are set to zero, as the null deviance
- Adj. R2: Adjusted r-squared as the proportion of variance explained in GAM models
- REML: The value of restricted (or penalized) maximum likelihood function in GAM models
- Tau2: Spatially correlated random effects in FBH models
- Sigma2: The variance of unobserved heterogeneity in the data in FBH models
- %accept: The probability of acceptance for the parameters in FBH models.

In addition, more general measures of model goodness of fit were calculated for all SASM methods applied in this research. These measures were calculated for all five SASM methods applied to estimate the expected number of crashes for six defined response variables. These diagnostics measures included the following:

- Akaike Information Criterion (AIC) is a measure of information lost using a specific model to represent the data generating process. Lower AIC values indicate better model goodness of fit. It is calculated as follows:

$$AIC = 2Pd - 2LL \qquad \text{Equation (24)}$$

Where:

P- the number of estimated model parameters

LL-log likelihood function

- Bayesian Information Criterion (BIC) is based on the likelihood function and used to avoid the "overfitting" the model by penalizing the number of parameters in the model. Lower BIC values indicate better model goodness of fit, and BIC is closely related to AIC. BIC is calculated as following:

$$BIC = -2LL + Pd \cdot \ln(n) \qquad \text{Equation (25)}$$

Where:

P- the number of estimated model parameters

LL- log likelihood function

n- the number of observations

- Deviance Information Criterion (DIC): Bayesian generalization of AIC and BIC for hierarchical models where structured random effects are present. When a model contains only fixed effects, DIC value of the model is close to AIC value. Lower DIC values indicate better model goodness of fit. DIC is defined as:

$$DIC = D(\hat{\theta}) + 2Pd \qquad \text{Equation (26)}$$

Where:

$D(\hat{\theta})$- the deviance of $\hat{\theta}$ as an expectation of θ

Pd- the number of effective model parameters

Once the final model specification was obtained, the model-specific parameters were used to assess the overall model goodness of fit. Then AIC and BIC values were used to compare frequentist models among themselves, and finally, DIC values were used to evaluate how close Bayesian models are to the "best" frequentist models, and whether there is a strong presence of structured random effects. The comparison between

Bayesian and frequentist models cannot be directly made, but the estimated coefficient values and standard errors were used to determine whether frequentist models can serve as a valid alternative in SASM process. The results of the applied SASM methods are presented in the following chapter.

CHAPTER 4

STATISTICAL AREAL SAFETY MODELING RESULTS

This chapter presents the results of the SASM analysis methods. The results are presented by crash type, for each of the six crash types which were the focus of the analysis, and include the estimates obtained using all SASM methods described in the previous chapter. Preliminary and final model specifications were obtained using the approach for carrying out the variable selection described in the previous chapter. While preliminary model specifications are shown only for negative binomial models, final model specifications are shown for all crash types and all applied SASM methods including NB models, FENB and RENB models, GAM, and FBH models. The presented models include the method-specific goodness of fit indicators and the diagnostics used to evaluate all applied SASM methods for different crash types. The final models for each crash type are recommended based on the comparison of the final model specification estimated from different SASM methods. The end of this chapter is dedicated to the results extracted to demonstrate the effects of multimodal trips and multimodal accessibility on the multimodal crash outcomes estimated from the final model selection. The interpretation of the results presented in this chapter is provided in the following Discussion chapter.

Preliminary Model Specifications

Six dependent variables were modeled in the described SASM process, including the expected number of total vehicular crashes, severe vehicular crashes, total pedestrian crashes, severe pedestrian crashes, total bicyclist crashes, and severe bicyclist crashes. Tables 8 and 9 show the preliminary model specifications, based on negative binomial models. The preliminary models provided in Tables 8 and 9 were further used to obtain final model specifications for estimating each response variable. The coefficients estimated in preliminary models provided indications about the sets of variables that potentially may be a part of specifications that would adequately represent the data generating process.

Table 8 Preliminary Specification of NB Model Used to Obtain Final Model Specifications for Total Vehicular, Pedestrian, and Bicyclist Crashes

Model	Vehicle-only crash model			Pedestrian crash model			Bicyclist crash model		
Variable	Coef.	Std. Err.	Pr(>|z|)	Coef.	Std. Err.	Pr(>|z|)	Coef.	Std. Err.	Pr(>|z|)
Population density (per mile2)	0.0000	0.0000	0.000	0.0000	0.0000	0.000	0.0000	0.0000	0.000
Unemployed Population (%)	-0.0023	0.0019	0.229	0.0114	0.0030	0.000	-0.0280	0.0033	0.000
ln(Road miles)	0.9654	0.0666	0.000	1.1561	0.1043	0.000	0.7373	0.1175	0.000
ln(DVMT)	0.2863	0.0213	0.000	-0.0167	0.0337	0.620	0.1696	0.0367	0.000
Intersection density	0.0010	0.0003	0.000	0.0012	0.0004	0.005	0.0024	0.0004	0.000
Signalized intersections (%)	1.3023	0.1348	0.000	1.7251	0.2063	0.000	0.9257	0.2161	0.000
L Train line (miles)	-0.0529	0.0509	0.299	-0.1840	0.0781	0.019	-0.0230	0.0844	0.785
L Train stops	-0.0051	0.0539	0.925	0.0069	0.0790	0.931	-0.1477	0.0888	0.096
Bus routes (miles)	-0.0049	0.0042	0.243	-0.0074	0.0060	0.216	-0.0352	0.0060	0.000
No. of Bus stops	-0.0010	0.0042	0.808	0.0001	0.0063	0.993	0.0036	0.0066	0.588
Bike lanes (miles)	-0.0151	0.0276	0.585	-0.0622	0.0421	0.140	0.1508	0.0440	0.001
No. of Bike racks	0.0033	0.0021	0.126	0.0135	0.0032	0.000	0.0299	0.0035	0.000
Sidewalk area (ft2)	-0.1757	0.0441	0.000	-0.3383	0.0650	0.000	-0.3280	0.0724	0.000
Transit trips to work (%)	0.0062	0.0013	0.000	0.0096	0.0020	0.000	0.0143	0.0022	0.000
Walk trips to work (%)	-0.0034	0.0047	0.474	0.0012	0.0066	0.857	-0.0049	0.0071	0.487
Trips to work by other means (%)	0.0181	0.0055	0.001	0.0197	0.0084	0.020	0.0399	0.0089	0.000
Land use diversity	-0.0235	0.0188	0.210	-0.0494	0.0286	0.084	-0.0111	0.0306	0.716
Land use entropy	0.0874	0.1569	0.577	0.1216	0.2384	0.610	-0.2312	0.2509	0.357
Weighted transit accessibility	0.0014	0.0006	0.029	0.0027	0.0009	0.004	0.0010	0.0010	0.309
Weighted bicyclist accessibility	0.0000	0.0000	0.184	0.0000	0.0000	0.654	0.0000	0.0000	0.841
15min walk destinations	-0.0016	0.0006	0.005	-0.0037	0.0009	0.000	-0.0048	0.0009	0.000
Weighted pedestrian accessibility	0.0047	0.0014	0.001	0.0104	0.0021	0.000	0.0143	0.0022	0.000
Complete streets network (%)	0.3483	0.1305	0.008	0.7620	0.1943	0.000	0.8141	0.1990	0.000
Intercept	0.7934	0.2198	0.000	0.1151	0.3442	0.738	-1.7066	0.3759	0.000
/lnalpha	-1.8760	0.0506		-1.2739	0.0642		-1.3634	0.0788	
alpha	0.1532	0.0078		0.2797	0.0180		0.2558	0.0202	
Pseudo R2	0.1050			0.0989			0.1478		

Table 9 Preliminary Specification of NB Model Used to Obtain Final Model Specifications for Vehicular, Pedestrian, and Bicyclist Severe Crashes

Model	Vehicle-only KA crash model			Pedestrian KA crash model			Bicyclist KA crash model		
Variable	Coef.	Std. Err.	Pr(>|z|)	Coef.	Std. Err.	Pr(>|z|)	Coef.	Std. Err.	Pr(>|z|)
Population density (per mile2)	0.0000	0.0000	0.032	0.0000	0.0000	0.000	0.0000	0.0000	0.000
Unemployed Population (%)	0.0086	0.0026	0.001	0.0060	0.0041	0.139	-0.0308	0.0068	0.000
ln(Road miles)	1.0223	0.0983	0.000	1.0724	0.1562	0.000	1.0203	0.2340	0.000
ln(DVMT)	0.2948	0.0296	0.000	-0.0431	0.0478	0.367	0.1199	0.0731	0.101
Intersection density	0.0000	0.0004	0.958	0.0009	0.0006	0.138	0.0014	0.0008	0.085
Signalized intersections (%)	1.2033	0.1871	0.000	1.5276	0.2625	0.000	0.9621	0.3975	0.015
L Train line (miles)	-0.0131	0.0613	0.830	-0.0727	0.0999	0.466	0.0159	0.1393	0.909
L Train stops	-0.0852	0.0693	0.219	0.0119	0.1073	0.912	-0.1264	0.1706	0.459
Bus routes (miles)	0.0053	0.0051	0.296	-0.0080	0.0070	0.252	-0.0280	0.0093	0.003
No. of Bus stops	-0.0019	0.0050	0.706	0.0080	0.0078	0.306	-0.0158	0.0114	0.165
Bike lanes (miles)	0.0087	0.0333	0.794	-0.0896	0.0547	0.102	0.2078	0.0742	0.005
No. of Bike racks	-0.0020	0.0026	0.432	0.0113	0.0038	0.003	0.0214	0.0050	0.000
Sidewalk area (ft2)	-0.1140	0.0563	0.043	-0.2771	0.0938	0.003	-0.4341	0.1402	0.002
Transit trips to work (%)	0.0069	0.0019	0.000	0.0121	0.0028	0.000	0.0162	0.0043	0.000
Walk trips to work (%)	-0.0048	0.0060	0.428	0.0041	0.0081	0.609	0.0102	0.0106	0.336
Trips to work by other means (%)	0.0330	0.0079	0.000	0.0318	0.0117	0.007	0.0563	0.0164	0.001
Land use diversity	-0.0276	0.0275	0.314	-0.0826	0.0420	0.049	-0.0336	0.0641	0.600
Land use entropy	0.4237	0.2134	0.047	-0.0109	0.3347	0.974	0.6870	0.4879	0.159
Weighted transit accessibility	0.0011	0.0008	0.160	0.0018	0.0012	0.127	0.0031	0.0016	0.058
Weighted bicyclist accessibility	0.0000	0.0000	0.393	0.0000	0.0000	0.426	0.0000	0.0000	0.994
15min walk destinations	-0.0010	0.0008	0.192	-0.0041	0.0011	0.000	-0.0058	0.0016	0.000
Weighted pedestrian accessibility	0.0020	0.0019	0.278	0.0114	0.0027	0.000	0.0160	0.0037	0.000
Complete streets network (%)	0.1822	0.1689	0.281	0.5680	0.2275	0.013	0.4983	0.3211	0.121
Intercept	-3.4050	0.3091	0.000	-1.2176	0.4852	0.012	-4.1474	0.7466	0.000
/lnalpha	-1.9756	0.1111		-1.6097	0.1852		-1.7175	0.3985	
alpha	0.1387	0.0154		0.2000	0.0370		0.1795	0.0715	
Pseudo R2	0.1705			0.1015			0.1441		

Final Model Specifications

The final SASM model specifications, obtained through a statistical modeling process that started with the preliminary specifications, are provided in Tables 10 through 15. The results in this section are presented for each response variable and each SASM method applied. As described in the previous chapter, starting with the negative binomial models, leading to more complex models with frequentist inference, and Bayesian models. This chapter provides a total of thirty estimated models and each of the final

Table 10 Total Vehicular Crash Models

Vehicular Crashes	**Negative Binomial Model**			**NB with Fixed Effects**			**NB with Random Effects**			**Generalized Additive Model**			**Bayes Hierarchical Models**		
Variables	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Median	2.50%	97.50%
Population Density	0.0103	0.0014	0.000	0.0082	0.0012	0.000	0.0085	0.0010	0.000	0.0086	0.0009	0.000	0.0089	0.0070	0.0102
ln (Road Mileage)	0.8888	0.0646	0.000	1.0091	0.0639	0.000	0.8661	0.0555	0.000	0.9912	0.0600	0.000	1.0028	0.8699	1.1121
ln (DVMT)	0.2864	0.0202	0.000	0.2164	0.0213	0.000	0.2438	0.0190	0.000	0.2607	0.0199	0.000	0.2719	0.2449	0.2893
Intersection Density	0.0013	0.0003	0.000	0.0013	0.0003	0.000	0.0017	0.0002	0.000	0.0011	0.0003	0.000	0.0014	0.0010	0.0020
Signalized Intersections (%)	1.4529	0.1283	0.000	1.6126	0.1244	0.000	1.3423	0.1006	0.000	1.5351	0.1202	0.000	1.6309	1.4934	1.7969
Bus Stops	0.0089	0.0023	0.000	0.0107	0.0022	0.000	0.0110	0.0014	0.000	0.0071	0.0023	0.002	0.0067	0.0035	0.0082
Sidewalk Area	-0.2095	0.0434	0.000	-0.2532	0.0422	0.000	-0.2192	0.0285	0.000	-0.2282	0.0421	0.000	-0.1907	-0.2428	-0.0948
Region 1	-	-	-	0.2735	0.0358	0.000	-	-	-	-	-	-	-	-	-
Region 2	-	-	-	0.1507	0.0426	0.000	-	-	-	-	-	-	-	-	-
Region 3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Intercept	0.9567	0.1785	0.000	1.3622	0.1777	0.000	-10.4702	0.1706	0.000	1.1410	0.1737	0.000	0.8836	0.5548	1.0463
	alpha			alpha			*ln(r)*				*Smooth terms*			*tau2*	
	0.1652	0.0083		0.1652	0.0083		4.71	0.75		7.7200	8.1730	0.000	0.2489	0.1611	0.3651
Model-specific indicators	*Pseudo R2*			*Pseudo R2*			*ln(s)*			*Deviance explained*		*Adj. R2*		*sigma2*	
	0.0994			0.1044			8.57	0.75		76.30%		0.801	0.0870	0.0676	0.1093
	LL = 4944			*LL = 4916*			*LL = 4934*			*REML = 4923*			*% accept: 58.4*		

Table 11 Severe Vehicular Crash Models

Severe Vehicular Crashes	Negative Binomial Model			NB with Fixed Effects			NB with Random Effects			Generalized Additive Model			Bayes Hierarchical Models		
Variables	Coeff	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff	Std. Err.	P>|z|	Median	2.50%	97.50%
ln (Road Mileage)	0.9408	0.0857	0.000	0.9685	0.0906	0.000	0.8103	0.0740	0.000	0.9600	0.0925	0.000	0.8601	0.6944	1.0587
ln (DVMT)	0.2557	0.0279	0.000	0.2450	0.0300	0.000	0.2857	0.0263	0.000	0.2641	0.0309	0.000	0.3118	0.2579	0.3678
Signalized Intersections (%)	1.4242	0.1706	0.000	1.4986	0.1940	0.000	1.2806	0.1361	0.000	1.3066	0.1707	0.000	1.4624	1.0971	1.8179
Bus Stops	0.0080	0.0029	0.005	0.0082	0.0029	0.005	0.0089	0.0021	0.000	0.0054	0.0030	0.000	0.0063	0.0002	0.0130
Sidewalk Area	-0.1938	0.0521	0.000	-0.2024	0.0532	0.000	-0.1437	0.0400	0.000	-0.1536	0.0546	0.074	-0.0994	-0.2108	-0.0018
L Train Stops	-0.1047	0.0603	0.083	-0.0939	0.0611	0.124	-0.0774	0.0479	0.106	-0.0856	0.0614	0.005	-0.1119	-0.2397	0.0086
Land Use Entropy	0.4582	0.1697	0.007	0.4653	0.1758	0.008	0.4125	0.1523	0.007	0.3166	0.1798	0.163	0.2211	-0.2056	0.5740
Region 1	-	-	-	0.1112	0.1380	0.420	-	-	-	-	-	-	-	-	-
Region 2	-	-	-	0.1093	0.1431	0.445	-	-	-	-	-	-	-	-	-
Region 3	-	-	-	0.0608	0.1420	0.669	-	-	-	-	-	-	-	-	-
Intercept	-2.5372	0.2400	0.000	-2.5709	0.2921	0.000	-10.8579	0.2314	0.000	-2.5875	0.2541	0.078	-3.0329	-3.5355	-2.5401
	alpha			*alpha*			*ln(r)*			*Smooth terms*			*tau2*		
	-1.8230	0.1034		-1.8257	0.1034		4.7112	0.7502		6.0100	7.0520	0.001	0.2401	0.1285	0.4406
Model-specific indicators	*Pseudo R2*			*Pseudo R2*			*ln(s)*			*Deviance explained*		*Adj. R2*	*sigma2*		
	0.158			0.158			8.5667	0.7545		63.20%		0.721	0.0829	0.0410	0.1253
	LL = 2107			*LL = 2106*			*LL = 2102*			*REML = 2109*			*% accept: 61.1*		

Table 12 Total Pedestrian Crash Models

Pedestrian Crashes	**Negative Binomial Model**			**NB with Fixed Effects**			**NB with Random Effects**			**Generalized Additive Model**			**Bayes Hierarchical Models**		
Variables	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Median	2.50%	97.50%
ln (DVMT)	0.0375	0.0280	0.180	0.0549	0.0288	0.056	0.0506	0.0255	0.047	0.0493	0.0277	0.075	0.1027	0.0496	0.1529
ln (Pedestrian Trips)	0.2428	0.0322	0.000	0.2622	0.0338	0.000	0.2717	0.0285	0.000	0.2949	0.0363	0.000	0.3595	0.2559	0.4227
Weighted Ped. Accessibility	0.0122	0.0022	0.000	0.0128	0.0022	0.000	0.0100	0.0017	0.000	0.0114	0.0021	0.000	0.0072	0.0026	0.0104
Average Daily Transit Accessibility	0.0045	0.0006	0.000	0.0044	0.0006	0.000	0.0041	0.0004	0.000	0.0045	0.0006	0.000	0.0032	0.0021	0.0044
Destinations within 15-min. Walk	-0.0045	0.0009	0.000	-0.0046	0.0009	0.000	-0.0038	0.0007	0.000	-0.0038	0.0009	0.000	-0.0024	-0.0037	-0.0007
Percentage of Arterials	0.1449	0.0401	0.000	0.1381	0.0401	0.001	0.0300	0.0377	0.426	0.1271	0.0421	0.003	0.0842	-0.0179	0.1749
Intersection Density	0.0025	0.0005	0.000	0.0026	0.0006	0.000	0.0030	0.0005	0.000	0.0027	0.0005	0.000	0.0027	0.0015	0.0037
Signalized Intersections (%)	1.0850	0.2065	0.000	1.0344	0.2073	0.000	0.8743	0.1507	0.000	1.1283	0.1909	0.000	0.8037	0.5020	1.2965
Street Connectivity	-0.0789	0.0196	0.000	-0.0817	0.0196	0.000	-0.0679	0.0182	0.000	-0.0834	0.0189	0.000	-0.0630	-0.1099	-0.0283
Sidewalk Area	0.0159	0.0475	0.738	-0.0143	0.0486	0.768	0.0809	0.0371	0.029	-0.0585	0.0504	0.246	0.1108	-0.0419	0.2562
Network Completeness	0.5050	0.1913	0.008	0.4419	0.1916	0.021	0.1542	0.1094	0.159	0.5031	0.1741	0.004	0.3914	0.0531	0.6796
Region 1	-	-	-	-0.1334	0.0558	0.017	-	-	-	-	-	-	-	-	-
Region 2	-	-	-	-0.1198	0.0681	0.078	-	-	-	-	-	-	-	-	-
Region 3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Intercept	0.8739	0.2725	0.001	0.7602	0.2764	0.006	-9.0285	0.2510	0.000	0.6620	0.2694	0.014	-0.3054	-0.8550	0.0515
	alpha			*alpha*			*ln(r)*			*Smooth terms*			*tau2*		
	0.3396	0.0208		0.3359	0.0207		5.5197	1.0626		1.003	1.006	0.0011	0.6186	0.3736	0.9164
Model-specific indicators	*Pseudo R2*			*Pseudo R2*			*ln(s)*			*Deviance explained*		*Adj. R2*	*sigma2*		
	0.07780			0.0788			7.216016	1.05945		43.70%		0.5600	0.1417	0.0935	0.1926
	LL = 2857			*LL = 2854*			*LL = 2854*			*REML = 2895*			*% accept: 57.2*		

Table 13 Severe Pedestrian Crash Models

Severe Pedestrian Crashes	Negative Binomial Model			NB with Fixed Effects			NB with Random Effects			Generalized Additive Model			Bayes Hierarchical Models		
Variables	Coeff	Std. Err.	P>|z|	Coeff	Std. Err.	P>|z|	Coeff	Std. Err.	P>|z|	Coeff	Std. Err.	P>|z|	Median	2.50%	97.50%
ln (DVMT)	0.1782	0.0345	0.000	0.1764	0.0342	0.000	0.1880	0.0323	0.000	0.16855	0.03511	0.000	0.2072	0.1316	0.2847
ln (Pedestrian Trips)	0.2960	0.0412	0.000	0.3229	0.0418	0.000	0.3434	0.0413	0.000	0.34914	0.04410	0.000	0.4016	0.2962	0.5291
Weighted Ped. Accessibility	0.0135	0.0028	0.000	0.0143	0.0028	0.000	0.0137	0.0024	0.000	0.01302	0.00277	0.000	0.0093	0.0032	0.0174
Destinations within 15-min. Walk	-0.0051	0.0012	0.000	-0.0052	0.0012	0.000	-0.0049	0.0010	0.000	-0.00448	0.00118	0.000	-0.0028	-0.0064	-0.0002
Signalized Intersections (%)	0.8555	0.2391	0.000	0.7808	0.2379	0.001	0.5668	0.1941	0.004	1.01953	0.22968	0.000	0.8184	0.2447	1.3658
Region 1	-	-	-	-0.2357	0.0679	0.001	-	-	-	-	-	-	-	-	-
Region 2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Region 3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Intercept	-2.3461	0.3337	0.000	-2.3208	0.3305	0	-10.3244	0.3408	0.000	-2.46641	0.33982	0.000	-3.1371	-3.9877	-2.4300
	alpha			*alpha*			*ln(r)*			*Smooth terms*			*tau2*		
	0.3500	0.0464		0.3333	0.0454		5.0468	0.9542		1.7340	1.9980	0.000	0.4814	0.2762	0.8445
Model-specific indicators	*Pseudo R2*			*Pseudo R2*			*ln(s)*			*Deviance explained*		*Adj. R2*	*sigma2*		
	0.0584			0.0622			4.8233	0.9413		20.80%		0.281	0.1689	0.0843	0.2556
	LL = 1467			*LL = 1461*			*LL = 1463*			*REML = 1479*			*% accept: 61.8*		

Table 14 Total Bicycle Crash Models

Bicyclist Crashes	**Negative Binomial Model**			**NB with Fixed Effects**			**NB with Random Effects**			**Generalized Additive Model**			**Bayes Hierarchical Models**		
Variables	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Coeff.	Std. Err.	P>|z|	Median	2.50%	97.50%
ln (DVMT)	0.2191	0.0307	0.000	0.1784	0.0276	0.000	0.1589	0.0258	0.000	0.2183	0.0278	0.000	0.2280	0.1611	0.2900
ln (Bicyclist Trips)	0.7478	0.0518	0.000	0.4926	0.0482	0.000	0.3996	0.0339	0.000	0.4933	0.0449	0.000	0.5202	0.4116	0.6028
Weighted Bicyclist Accessibility	0.0001	0.0000	0.016	0.0001	0.0000	0.003	0.0001	0.0000	0.000	0.0001	0.0000	0.006	0.0001	0.0000	0.0001
Intersection Density	0.0036	0.0005	0.000	0.0028	0.0004	0.000	0.0025	0.0003	0.000	0.0022	0.0004	0.000	0.0021	0.0011	0.0029
L Train Line (miles)	-0.2727	0.0846	0.001	-0.1727	0.0764	0.024	-0.1064	0.0605	0.079	-0.1412	0.0743	0.057	-0.1738	-0.3055	-0.0239
Bike Lanes (miles)	0.2651	0.0449	0.000	0.3054	0.0395	0.000	0.2584	0.0266	0.000	0.2650	0.0365	0.000	0.2762	0.2037	0.3530
Central Business District	-0.7518	0.1790	0.000	0.2520	0.1772	0.155	-0.5095	0.3455	0.140	-0.4601	0.1656	0.005	-0.3113	-0.9519	0.2209
Region 1	-	-	-	0.7803	0.0609	0.000	-	-	-	-	-	-	-	-	-
Region 2	-	-	-	0.2430	0.0755	0.001	-	-	-	-	-	-	-	-	-
Region 3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Intercept	-1.3359	0.3110	0.000	-1.1895	0.2779	0.000	-9.3542	0.2702	0.000	-1.0690	0.2814	0.000	-1.2903	-1.9243	-0.6562
	alpha			*alpha*			*ln(r)*			*Smooth terms*			*tau2*		
	0.3856	0.0261		0.2845	0.0214		2.1111	0.8326		7.351	7.955	0.000	0.4061	0.2139	0.7298
Model-specific indicators	*Pseudo R2*			*Pseudo R2*			*ln(s)*			*Deviance explained*		*Adj. R2*	*sigma2*		
	0.1080			0.1386			3.0624	0.8194		62.20%		0.578	0.1635	0.1048	0.2171
	LL = 2359			*LL = 2278*			*LL = 2313*			*REML = 2297*			*% accept: 59.5*		

Table 15 Severe Bicycle Crash Models

Severe Bicyclist Crashes	**Negative Binomial Model**			**NB with Fixed Effects**			**NB with Random Effects**			**Generalized Additive Model**			**Bayes Hierarchical Models**		
Variables	Coeff	Std. Err.	P>|z|	Coeff	Std. Err.	P>|z|	Coeff	Std. Err.	P>|z|	Coeff	Std. Err.	P>|z|	Median	2.50%	97.50%
ln (DVMT)	0.1911	0.0543	0.000	0.1601	0.0538	0.003	0.1561	0.0529	0.003	0.2199	0.0552	0.000	0.2338	0.1231	0.3416
ln (Bicyclist Trips)	0.5153	0.0644	0.000	0.3442	0.0825	0.000	0.3417	0.0698	0.000	0.2684	0.0639	0.000	0.3286	0.1551	0.4776
Weighted Bicyclist Accessibility	0.0001	0.0000	0.009	0.0001	0.0000	0.012	0.0001	0.0000	0.006	0.0001	0.0000	0.046	0.0001	0.0000	0.0001
Bike Lanes (miles)	0.2505	0.0665	0.000	0.3108	0.0625	0.000	0.2706	0.0497	0.000	0.2932	0.0605	0.000	0.2753	0.1684	0.3795
Region 1	-	-	-	0.1404	0.2649	0.596	-	-	-	-	-	-	-	-	-
Region 2	-	-	-	-0.3268	0.2904	0.260	-	-	-	-	-	-	-	-	-
Region 3	-	-	-	-0.8164	0.3103	0.009	-	-	-	-	-	-	-	-	-
Intercept	-2.9175	0.5316	0.000	-2.3427	0.6101	0.000	-9.0266	0.5722	0.000	-3.1670	0.5374	0.000	-3.4315	-4.5549	-2.3477
	alpha			*alpha*			*ln(r)*			*Smooth terms*			*tau2*		
	0.4295	0.0934		0.2855	0.0792		3.7293	0.8281		6.5230	7.4470	0.000	0.5992	0.3100	1.2958
Model-specific indicators	*Pseudo R2*			*Pseudo R2*			*ln(s)*			*Deviance explained*		*Adj. R2*	*sigma2*		
	0.0926			0.1222			2.2835	0.7723		31.70%		0.35	0.0021	0.0003	0.0159
	LL = 888			*LL = 859*			*LL = 869*			*REML = 874*			*% accept: 61.7%*		

modeling specifications is provided with the model-specific indicators of goodness of fit that were used in the process of model comparison described in the following chapter.

The final model specification results for total vehicular crashes provided in Table 10 includes the following variables: population density, total miles of road, DVMT, intersection density, percent of signalized intersections, bus stops, and sidewalk area. Table 11 provides the final modeling specification results for the frequency of severe vehicular crashes including road mileage, DVMT, percent of signalized intersections, bus stops, sidewalk area, L train stops, and land use entropy. The estimated statistical models for the expected number of total pedestrian crashes in census tracts are provided in Table 12 and the following variables were associated with the expected number of pedestrian crashes: DVMT, the number of pedestrian trips within the census tract, weighted pedestrian accessibility, the number of destinations accessible within 15-minute walking time, average daily transit accessibility, percentage of arterials, intersection density, percent of signalized intersections, street connectivity, sidewalk area, and the percent of network with complete streets.

The final model specifications for the expected number of severe pedestrian crashes in census tracts are provided in Table 13 and include DVMT, the number of pedestrian trips within the census tract, weighted pedestrian accessibility, the number of destinations accessible within 15-minute walking time, and the percent of signalized intersections.

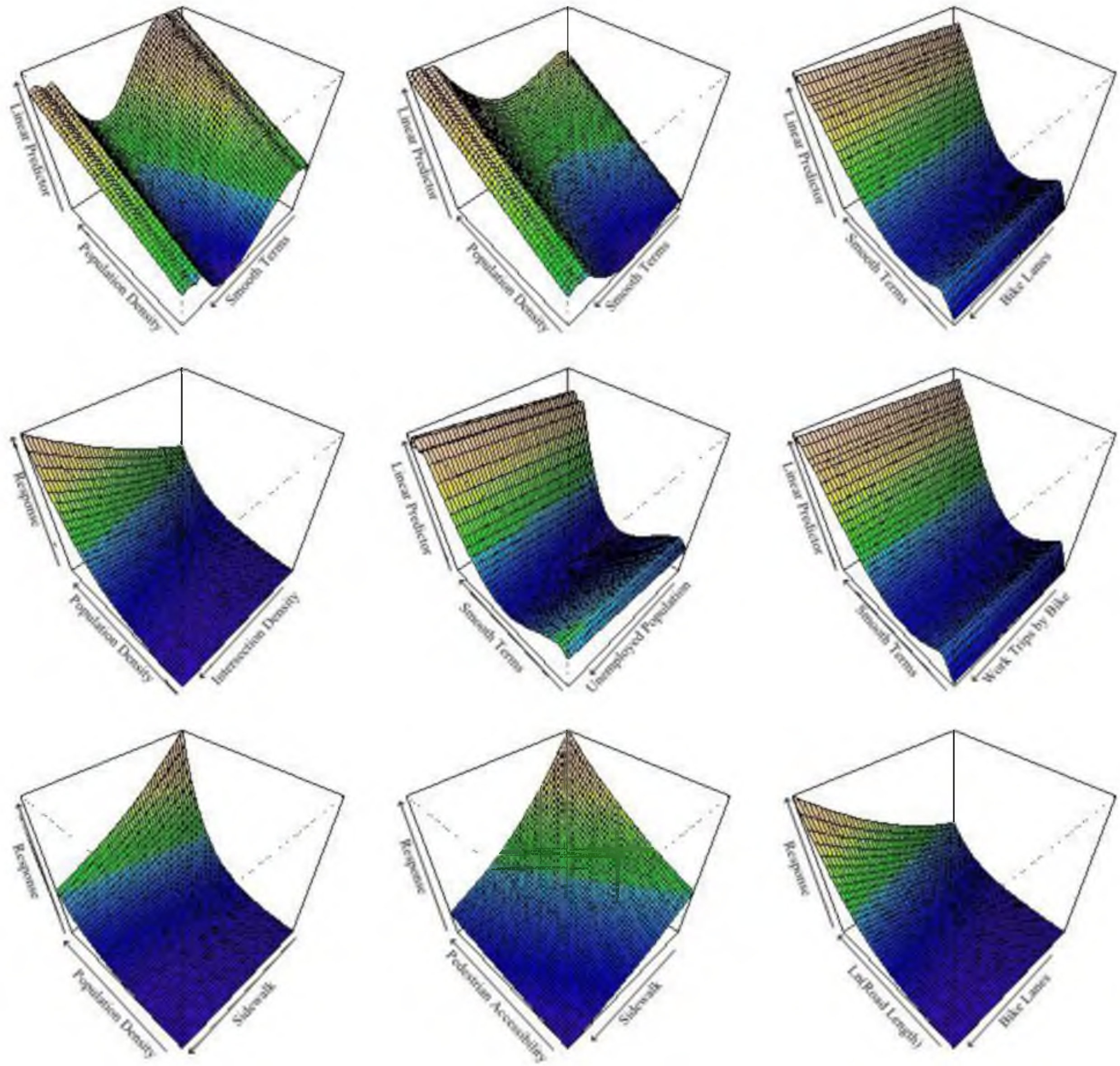
Table 14 provides the estimated final model specification for the total bicyclist crashes in census tracts, including the following variables that were associated with the expected number of bicyclist crashes: DVMT, the number of bike trips within the census tract, weighted bicyclist accessibility, intersection density, bus stops, bike lanes mileage, (Central Business District), and the presence of L Train lines. The final model specifications for the expected number of severe bicyclist crashes in census tracts are provided in Table 15 and include the following variables: DVMT, the number of bike trips within the census tract, weighted bicyclist accessibility, and bike lanes mileage. The visualization of the effects of selected variables from the final model specifications on crash outcomes for each crash type is provided using GAM models. These effects are presented in Figures 21 and 22.

Diagnostics and Final Model Recommendations

The diagnostics measures for all models presented in the previous section of this chapter are provided in Table 16. These measures were used to partially determine what model form is "the best" model given the final specification for each crash type. Tables 17 through 22 present the recommended "best" model for each crash type analyzed in this research. The recommendation of final model specification by crash type was based on model diagnostics, the overall comparison of estimated parameters and their standard errors, the ability of the models to capture spatial effects in the data, as well as the potential of the model to be considered for future applications to some new datasets from different urban environments. The expanded discussion of how the final model selection for each crash type was conducted is provided in the following chapter.

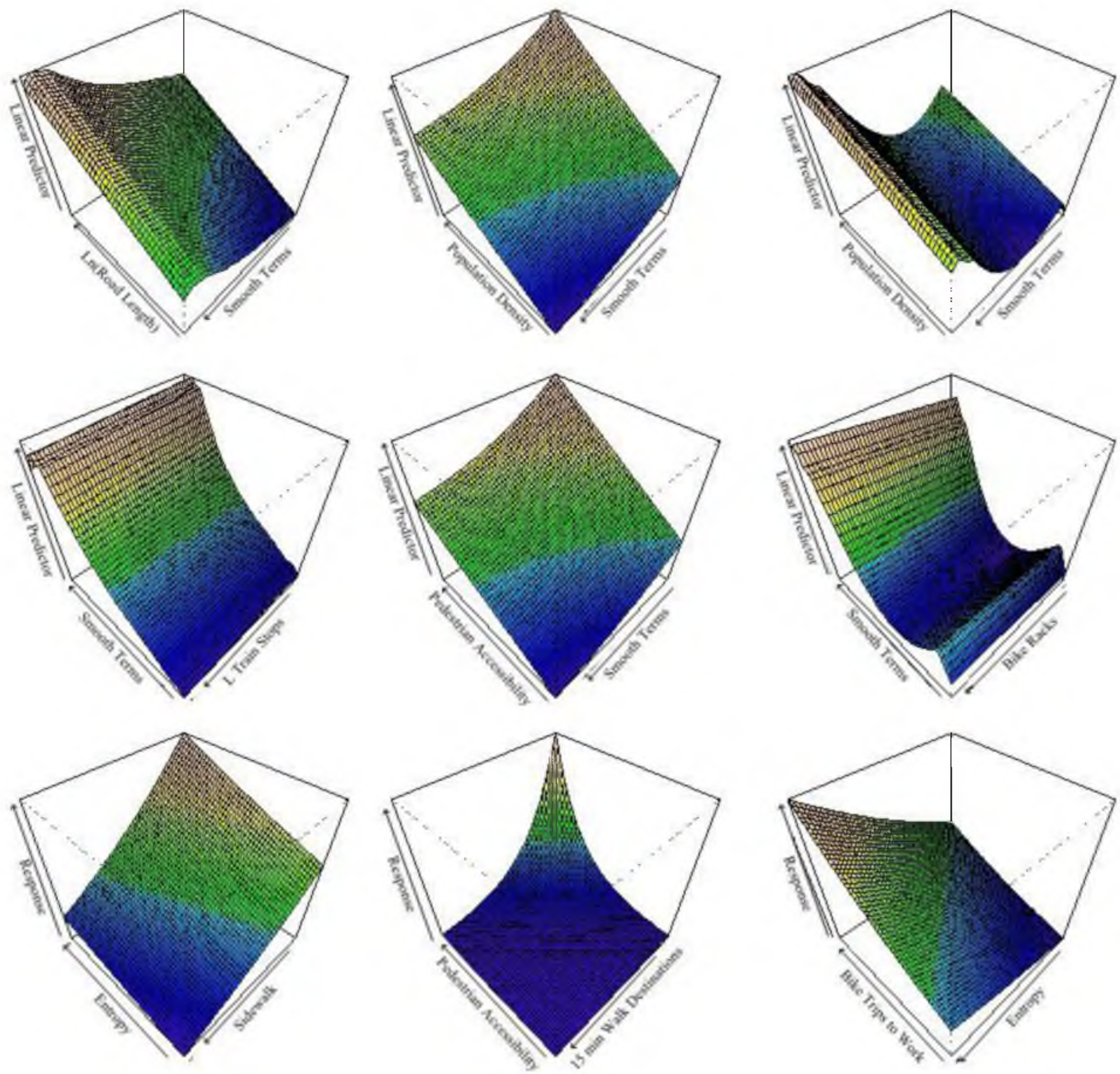
Safety Effects of Multimodal Exposure and Accessibility

The variables that were included in the final model specifications for each crash type are discussed in detail in the following chapter. In addition, the last section of this chapter presents the effects of the variables that represent multimodal exposure and accessibility on each of the crash types analyzed in this research.



a) Vehicle-only crashes b) Pedestrian crashes c) Bicyclist crashes

Figure 21 Visualization of GAM for Some of the Statistically Significant Explanatory Variables in Total Crash Models



a) Vehicle-only KA crashes b) Pedestrian KA crashes c) Bicyclist KA crashes

Figure 22 Visualization of GAM for Some of the Statistically Significant Explanatory Variables in Severe Crash Models

Table 16 Diagnostics for NB, FENB, RENB, GAM, and FBH Models

Areal Safety Statistical Model	AIC				BIC				DIC
	NB	FENB	RENB	GAM	NB	FENB	RENB	GAM	FBH
Vehicular Crashes	9908	9856	9888	9806	9950	9907	9935	9885	7516
Severe Vehicular Crashes	4232	4236	4225	4191	4274	4293	4272	4266	3966
Pedestrian Crashes	5740	5738	5737	5733	5801	5808	5803	5799	4925
Severe Pedestrian Crashes	2950	2940	2942	2936	2982	2977	2980	2978	2798
Bicyclist Crashes	4737	4579	4647	4535	4779	4630	4694	4613	4157
Severe Bicyclist Crashes	1788	1737	1754	1716	1817	1779	1786	1778	1704

Table 17 Recommended Model for Total Vehicle-only Crash Estimation

Vehicular Crashes	**Generalized Additive Model**		
Variables	Coeff.	Std. Err.	P>|z|
Population Density	0.0086	0.0009	0.000
ln (Road Mileage)	0.9912	0.0600	0.000
ln (DVMT)	0.2607	0.0199	0.000
Intersection Density	0.0011	0.0003	0.000
Signalized Intersections (%)	1.5351	0.1202	0.000
Bus Stops	0.0071	0.0023	0.002
Sidewalk Area	-0.2282	0.0421	0.000
Intercept	1.1410	0.1737	0.000
Smooth terms	7.7200	8.1730	0.000
Deviance explained	76.30%	*Adj. R2*	0.801
	REML = 4923		

Table 18 Recommended Model for Vehicle-only KA Crash Estimation

Severe Vehicular Crashes	**Generalized Additive Model**		
Variables	Coeff.	Std. Err.	P>|z|
ln (Road Mileage)	0.9600	0.0925	0.000
ln (DVMT)	0.2641	0.0309	0.000
Signalized Intersections (%)	1.3066	0.1707	0.000
Bus Stops	0.0054	0.0030	0.000
Sidewalk Area	-0.1536	0.0546	0.074
L Train Stops	-0.0856	0.0614	0.005
Intercept	-2.5875	0.2541	0.078
Smooth terms	6.0100	7.0520	0.001
Deviance explained	63.20%	*Adj. R2*	0.721
	REML = 2109		

Table 19 Recommended Model for Total Pedestrian Crash Estimation

Pedestrian Crashes	**Generalized Additive Model**		
Variables	Coeff.	Std. Err.	P>|z|
ln (DVMT)	0.0493	0.0277	0.075
ln (Pedestrian Trips)	0.2949	0.0363	0.000
Weighted Ped. Accessibility	0.0114	0.0021	0.000
Average Daily Transit Accessibility	0.0045	0.0006	0.000
Destinations within 15-min. Walk	-0.0038	0.0009	0.000
Percentage of Arterials	0.1271	0.0421	0.003
Intersection Density	0.0027	0.0005	0.000
Signalized Intersections (%)	1.1283	0.1909	0.000
Street Connectivity	-0.0834	0.0189	0.000
Network Completeness	0.5031	0.1741	0.004
Intercept	0.6620	0.2694	0.014
Smooth terms	1.003	1.006	0.0011
Deviance explained	43.70%	*Adj. R2*	0.5600
	REML = 2895		

Table 20 Recommended Model for Pedestrian KA Crash Estimation

Severe Pedestrian Crashes	**Bayes Hierarchical Models**		
Variables	Median	2.50%	97.50%
ln (DVMT)	0.2072	0.1316	0.2847
ln (Pedestrian Trips)	0.4016	0.2962	0.5291
Weighted Ped. Accessibility	0.0093	0.0032	0.0174
Destinations within 15-min. Walk	-0.0028	-0.0064	-0.0002
Signalized Intersections (%)	0.8184	0.2447	1.3658
Intercept	-3.1371	-3.9877	-2.4300
tau2	0.4814	0.2762	0.8445
sigma2	0.1689	0.0843	0.2556
	% accept: 61.8		

Table 21 Recommended Model for Total Bicyclist Crash Estimation

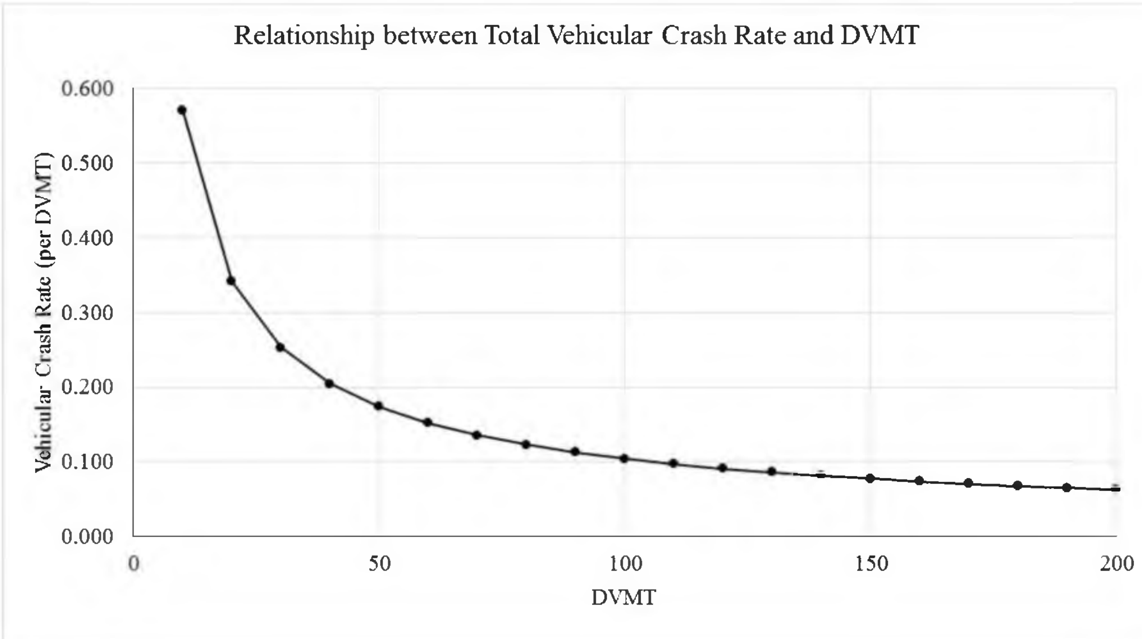
Bicyclist Crashes	**Generalized Additive Model**		
Variables	Coeff.	Std. Err.	P>|z|
ln (DVMT)	0.2183	0.0278	0.000
ln (Bicyclist Trips)	0.4933	0.0449	0.000
Weighted Bicyclist Accessibility	0.0000	0.0000	0.006
Intersection Density	0.0022	0.0004	0.000
L Train Line (miles)	-0.1412	0.0743	0.057
Bike Lanes (miles)	0.2650	0.0365	0.000
Central Business District	-0.4601	0.1656	0.005
Intercept	-1.0690	0.2814	0.000
Smooth terms	7.351	7.955	0.000
Deviance explained	62.20%	*Adj. R2*	0.578
	REML = 2297		

Table 22 Recommended Model for Bicyclist KA Crash Estimation

Severe Bicyclist Crashes	**Bayes Hierarchical Models**		
Variables	Median	2.50%	97.50%
ln (DVMT)	0.2338	0.1231	0.3416
ln (Bicyclist Trips)	0.3286	0.1551	0.4776
Weighted Bicyclist Accessibility	0.0000	0.0000	0.0001
Bike Lanes (miles)	0.2753	0.1684	0.3795
Intercept	-3.4315	-4.5549	-2.3477
tau2	0.5992	0.3100	1.2958
sigma2	0.0021	0.0003	0.0159
	% accept: 61.7%		

Figure 23 presents the relationship between DVMT and the estimated vehicular crash rate for total and severe vehicular crashes, in the case when all other variables for these particular models are kept constant. Figure 24 presents the relationship between the exposure variables considered in the pedestrian crash models, including the DVMT and the estimated generated pedestrian trips. The effects of the variables that resulted from the multimodal accessibility analysis and were found to be associated with total and severe pedestrian crashes are provided in Figures 25 and 26. Figure 26 presents the relationship between the exposure variables in the bicyclist crash models that include DVMT and estimated generated bicyclist trips, and total and severe bicyclist crash outcome. Figure 27 presents the effects of bicyclist accessibility on total and severe bicyclist crashes.

These results presented in Figures 23 through 28 are extracted to support the further interpretation of the results provided in the finally recommended models that are provided in Tables 17 through 22. The estimated coefficient values and signs in the final model recommendations mostly show that the increase in exposure or accessibility is associated with the increase in crashes for different modes, but a more detailed representation of results shows nonlinear relationships between these variables and crash outcomes. The interpretation of the effects presented in Figures 23 through 27 is provided in the following Discussion chapter.



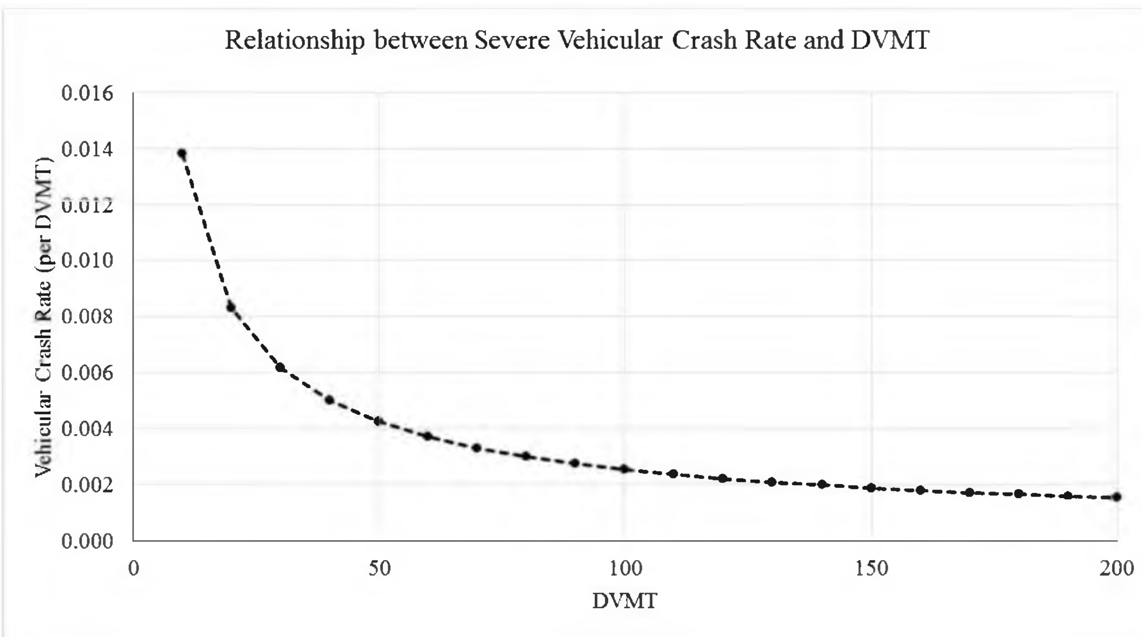
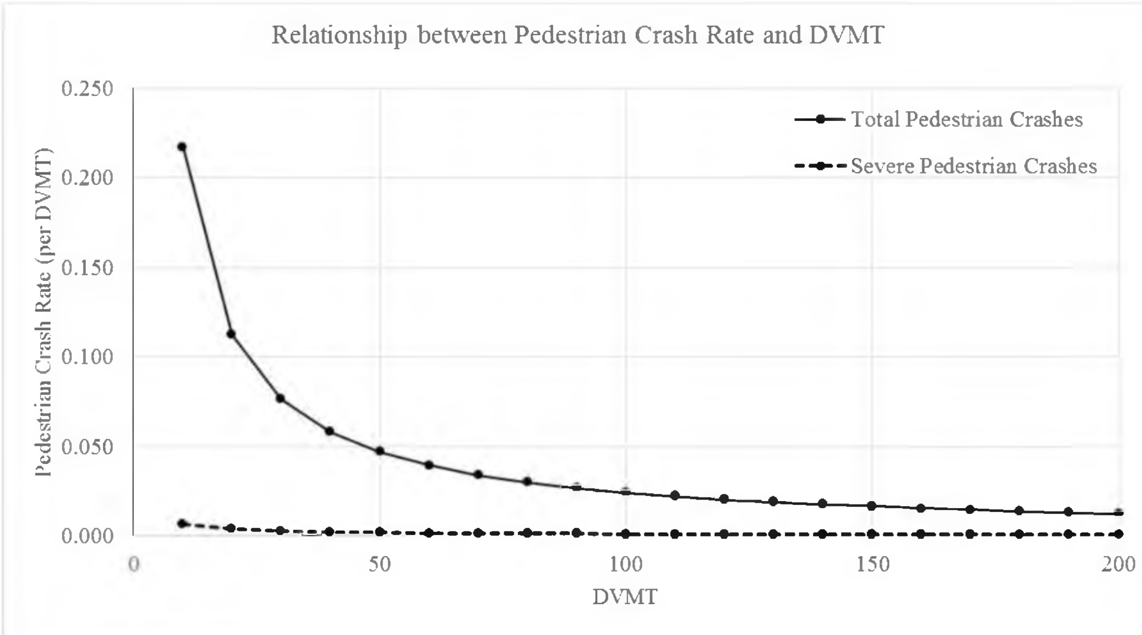


Figure 23 The "Safety in Numbers" Effect for Private Vehicle Users



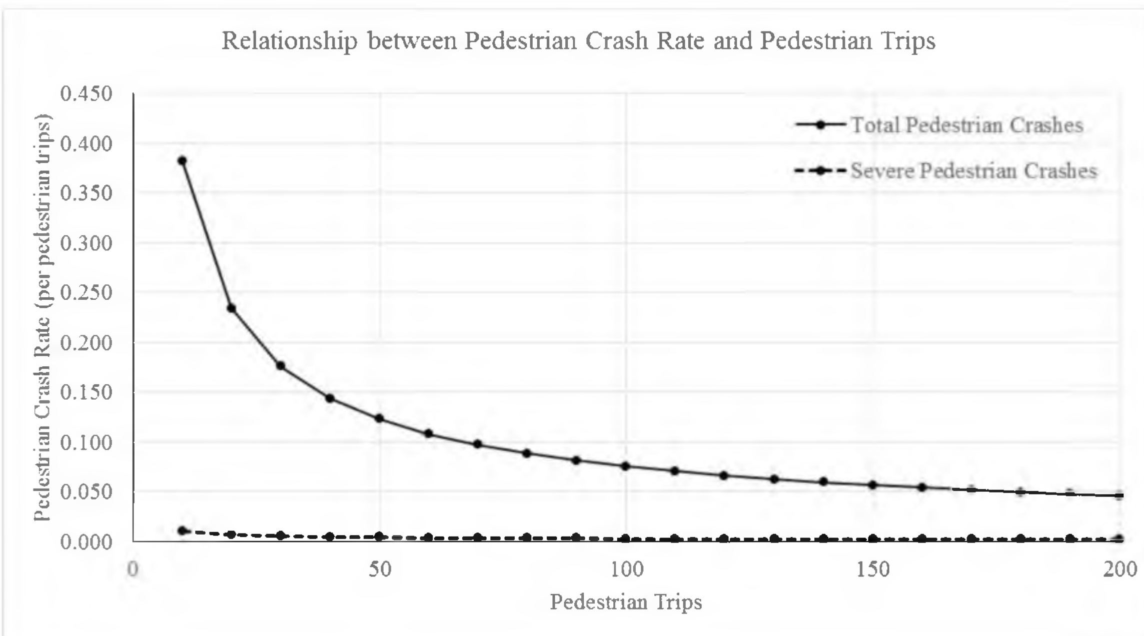


Figure 24 The "Safety in Numbers" Effect for Pedestrian Users

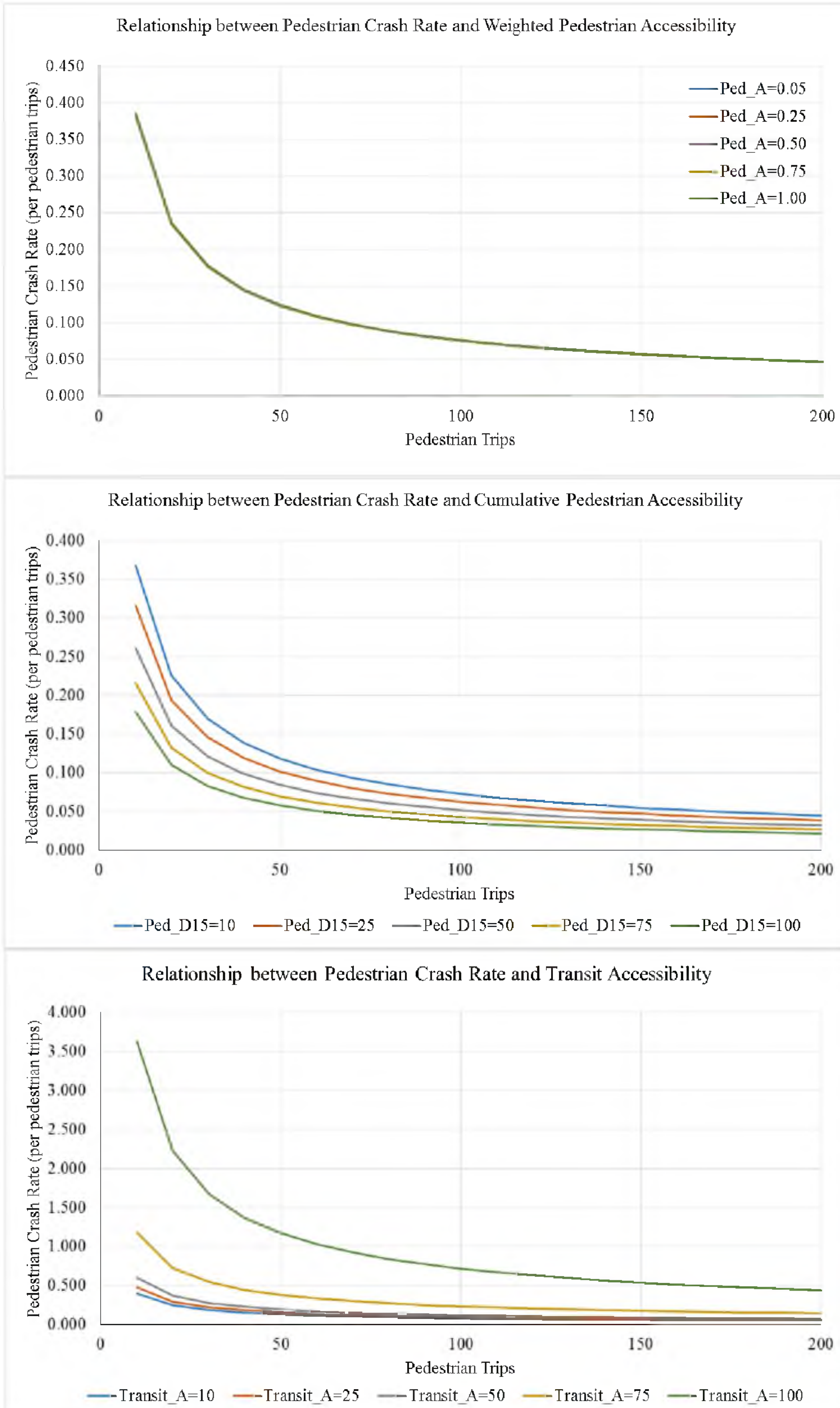
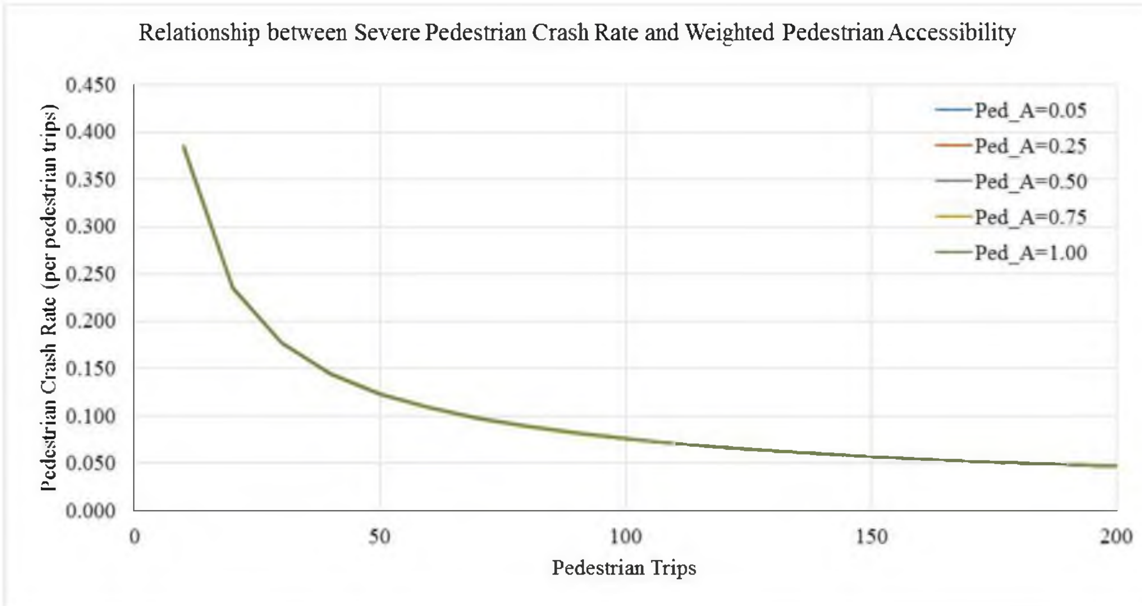


Figure 25 Relationship Between Total Pedestrian Crashes and Accessibility Variables



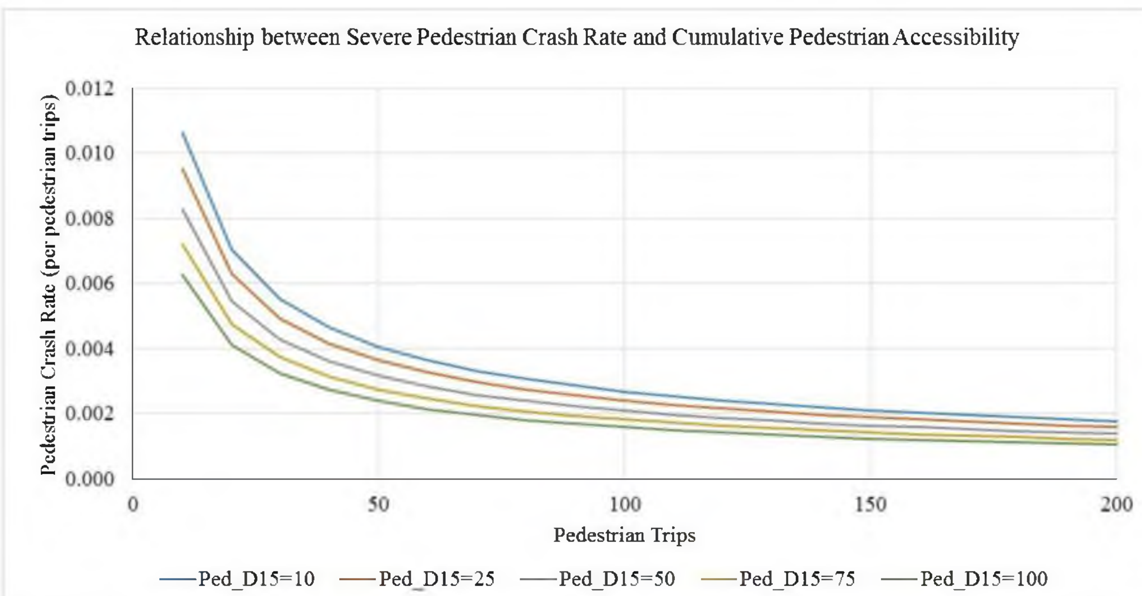
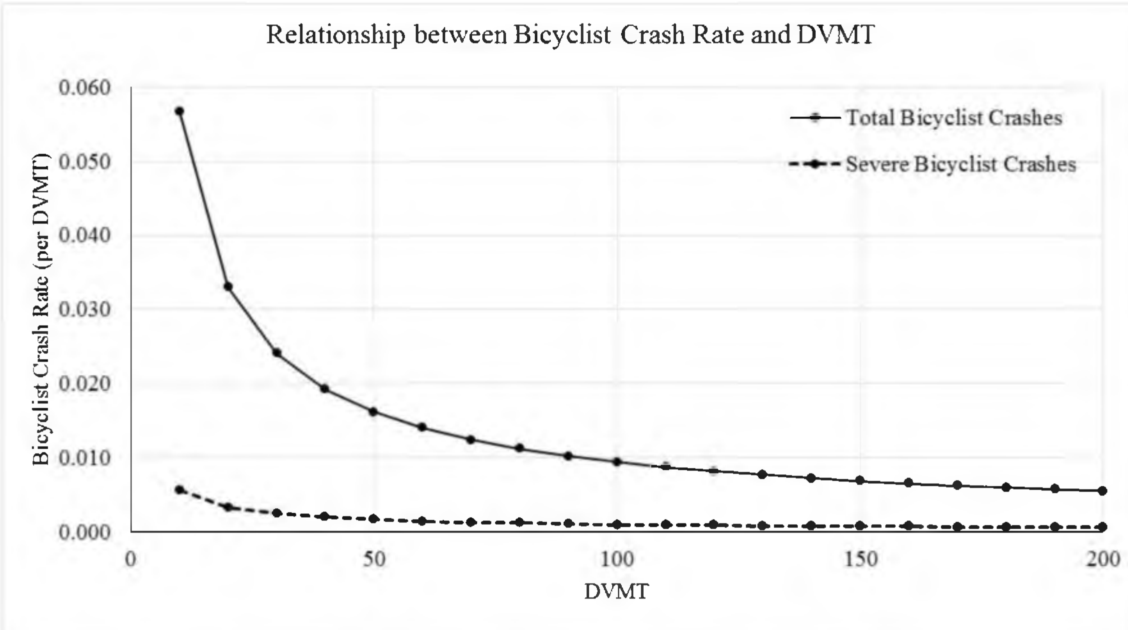


Figure 26 Relationship Between Severe Pedestrian Crashes and Accessibility Variables



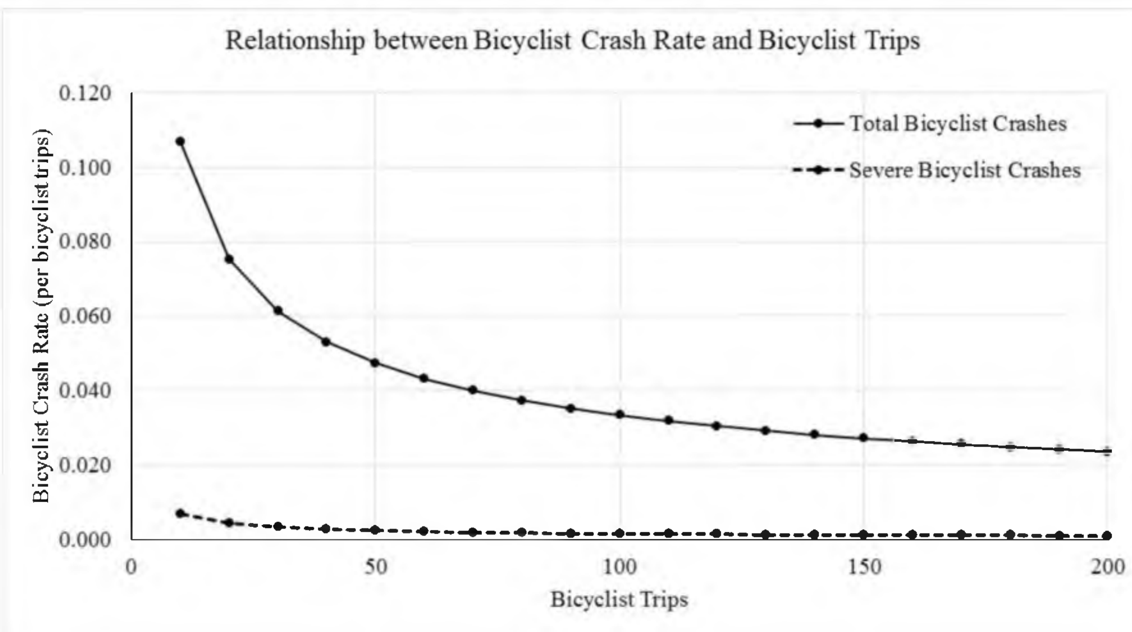


Figure 27 The "Safety in Numbers" Effect for Bicyclist Users

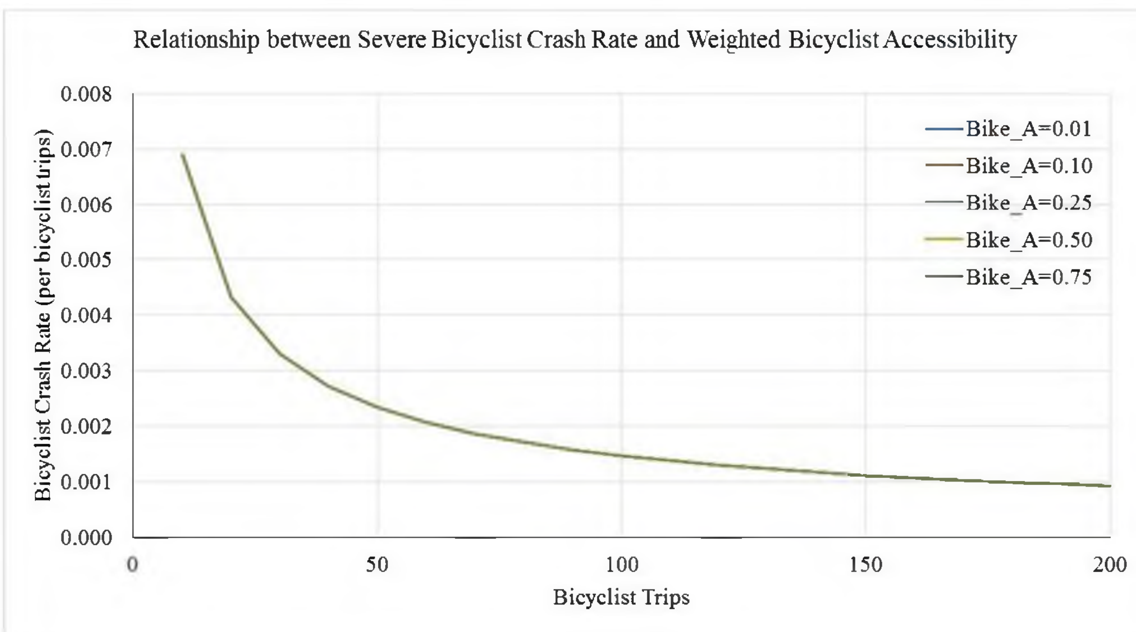


Figure 28 Relationship Between Bicyclist Crashes and Accessibility Variables

CHAPTER 5

DISCUSSION OF STATISTICAL AREAL SAFETY MODELING RESULTS

This chapter presents the discussion of the SASM modeling results that are provided in the previous chapter. For each crash type, this chapter discusses all the variables that were associated with the expected number of crashes. Models are interpreted starting with the preliminary modeling specifications, to the final modeling specifications that were interpreted in detail. The SASM diagnostics provided in the previous chapter and the estimated final model specifications were used to explain how the final model recommendation was made. The end of this chapter provides the interpretation of the "Safety in Numbers" effect and the potential role of using accessibility measures to model multimodal safety outcomes.

Preliminary Model Specifications

Initial SASM analysis was based solely on the negative binomial models for all six crash types that were analyzed in this research. The preliminary models for each crash type were run iteratively using different groups of variables provided in the Data chapter, as the number of variables did not allow the inclusion of all variables into a single model, particularly considering that the dataset consisted of roughly 100 variables for 801 observations/census tracts.

In order to obtain the preliminary set of potentially relevant variables that were further considered for the final model specifications, the variable selection was carried out using the approach described in the Methodology chapter. The groups of variables that proved to be potential candidates for the final model specifications for all crash types included variables related to demographics, exposure, accessibility, intersections and traffic control, multimodal infrastructure, land use, street connectivity, and network completeness. Variables that were excluded after the preliminary modeling process included economic characteristics, commuter trips to work by mode, and the majority of variables representing functional classification of the street network.

Final Model Specifications

Tables 10 through 15 present the final model specifications for each response variable by SASM method applied. This section provides a detailed discussion of the effects of each variable included in final model specifications by crash type.

Total Vehicular Crashes

The statistical modeling results for total vehicular crashes are provided in Table 10, for all modeling approaches applied to the dataset. The final model specification for vehicle crash frequency includes population density, total miles of road, DVMT, intersection density, percent of signalized intersections, bus stops, and sidewalk area.

The results indicate that the expected crash frequency increases as population density increases, and similar findings have been reported in the literature (Castro et al., 2013; Flask & Schneider, 2013; Noland & Quddus, 2004). Other socio-economic variables did not show significant effects on the expected frequency of vehicular crashes. This could be due to the level of mobility of vehicular traffic, as vehicular trips can be generated through the census tract areas regardless of economic status of the population. The natural logarithm of road mileage and DVMT were used as the exposure variables to estimate the expected number of vehicular crashes on the census tract level. Although DVMT is calculated from the ADT values related to each link in census tract multiplied by the length of corresponding links, thus incorporating road segments length into this measure, total road mileage is still included in vehicular crash models. Under the assumption that the dataset includes two census tracts with the same DVMT, one of these census tracts could have a denser road network and higher road mileage with lower volumes of traffic, while the other census tract could have fewer roads but higher traffic volumes resulting with the same DVMT value. It is expected that these two hypothetical census tract areas would have different number of vehicular crashes, even though their DVMT value is the same, due to differences in the road network structure, and traffic flow intensity and its distribution across the network. This is why road mileage variable is included as an additional exposure variable in vehicular crash models.

As expected, increases in total length of roads in miles and daily vehicle miles traveled were associated with an increase in expected crash frequency at the 99 % confidence level. Comparing the two measures of exposure, and their effect on the expected number of crashes, the length of roads contributes to the increase in the expected number of vehicular crashes more than the value of DVMT. If road mileage on the census tract level was doubled, according to the estimated models for total vehicle-only crashes, the expected number of crashes is expected to almost double. The impact of DVMT cannot be interpreted in the same manner, as the estimated model shows that if DVMT on a census tract level doubles, crashes are expected to increase by less than 20 %.

Intersection-related variables, such as intersection density and the percentage of signalized intersections, were associated with expected crash frequency on census tract level, where increases in these variables were associated with increases in crashes. Intersections are considered to be major points of conflict, which could be the reason for the positive sign of the coefficients estimated for these variables. Previous studies have found some similar relationships between network and intersection densities and crash frequencies (Moeinaddini, 2014; Siddiqui, 2012). The estimated coefficients show that the increase in the share of signalized intersections contributes to associated increase in the expected number of crashes up to fifteen times more than the same change in the overall number of intersections per mile squared. The presence of traffic signals may be increasing certain types of crashes (e.g., rear-end crashes), which may be the reason for the positive parameter sign and significance of this variable in the models.

The presence of L Train lines in Chicago is usually associated with environments where multimodal transportation is encouraged, with more people walking, biking, or taking transit. Particularly, the areas around L Train stops in downtown are designed to discourage higher vehicle speeds, and perhaps even reduce the number of people driving. During the preliminary modeling process, the presence of L Train lines was statistically significant variable in the models, with the negative sign of the coefficient. The significance of the variable and the magnitude of the estimated coefficients, however, varied between different statistical models, so the variable was not included in the final model specification.

Presence of bus stops was associated with an increase in expected vehicle crash frequency. There are usually the areas where vehicles may be forced to change their speeds, which could lead to higher number of conflicts, and higher crash frequency. The increase in the number of bus stops by 1 % is estimated to contribute to 0.3 % increase in the expected number of vehicular crashes.

The total area of sidewalk was associated with decrease in vehicular crash frequency, where the addition of 500 feet squared of sidewalk could reduce the expected number of crashes by up to 2 %. This impact, however, is not as strong as the estimated impact of some previously discussed variables that are associated with the increase in crashes. Previous studies mostly relate this variable to nonmotorized crash frequency (Wang & Kockelman, 2013). In urban environments, presence of sidewalk and other features related to walkability may be a characteristic of areas where people drive less, or drive more cautiously, thus leading to lower number of vehicular crashes.

Severe Vehicular Crashes

Table 11 provides the results of the estimated statistical models for the frequency of severe vehicular crashes. The variables that are found to be associated with the expected number of severe vehicular crashes include road mileage, DVMT, percent of signalized intersections, bus stops, sidewalk area, L train stops, and land use entropy.

To account for the difference between census tracts with the same DVMT values, but different road network mileage, both road mileage and DVMT were used as the exposure variables in the estimated models for severe vehicular crashes. Similar to total vehicular crashes, the estimated model results show that it can be expected that the number of crashes follows the rate of change of road segment lengths, while the increase in traffic volumes is not followed by the proportional increase in crashes.

The results from the estimated severe vehicular crash models also show that if the share of signalized intersections in census tracts is increased by 1 %, the expected increase in severe vehicular crashes would be 1.39%. The presence of traffic signals contributes to increase in both total and severe vehicular crashes. The effect of this variable on crash frequency and severity implies that some additional research that would consider crash types (e.g., rear-end, angle crashes) would be beneficial when it comes to exploring urban safety. The impact of the presence of signals on the increase of frequency and severity of intersection related crashes is already proven in previous research and recognized in intersection crash predictive methods.

Presence of sidewalk was associated with the decrease in severe vehicular crashes. The estimated results show that the addition of 500 feet squared of sidewalk would result in 1.29% reduction in severe vehicular crashes. The results from the estimated models for total vehicular and sever vehicular crashes indicate that sidewalk could be considered as a safety countermeasure in urban environments. The limitation that should be considered here is that very few cities would have the available data on sidewalk area coverage, so some approximations should be considered in order to use the model in different locations.

Just as in the case of the models developed for total vehicular crashes, the number of bus stops within the census tract was associated with the increase, while the number of L Train stops was associated with the reduction in the severe vehicular crashes. One percent increase in the number of bus stops is expected to lead to less than 0.2 % increase in severe vehicular crashes. The expected reduction of severe vehicular crashes with the addition of L Train stops (1 % increase in numbers) is lower than 0.1 %. The opposite signs of the effects of L Train facilities which are grade separated, and bus stops which are mostly alongside the lanes shared by both private vehicles and buses, indicate the potential benefits from investing in prioritizing transit and separating it from the rest of the traffic flow whenever possible.

The increase in land use mix expressed as entropy measure on a scale from zero (single land use) to one (all land uses) showed association with the increase of the number of severe crashes. This association is not very strong, as 1 % increase in entropy would result to 0.35% increase in the expected number of severe vehicular crashes. The influence of mixed land use on the expected number of crashes is explored in some previous studies, mostly related to pedestrian crashes. The possible explanation for the effect of land use mix on the increase on severe vehicular crashes is the diversity of land use mix characteristics that exists among census tracts in Chicago, ranging from predominantly single-use to very high land use mix areas, where the majority of trips, particularly work commute trips, are directed towards destinations in high land use mix parts of the city such as downtown. This variable is eventually excluded from the final model recommendation for the severe vehicular crashes due to inconsistent values of the estimated coefficients as well as lack of logical explanation for the interpretation of the relationship. However, the potential impact of entropy could be important to consider in order to distinguish between different aspects of urban environment, rather than just adopting the same effects on safety outcome for urban roads and networks in general, or simply categorizing area-wide effects as urban and suburban.

Total Pedestrian Crashes

The estimated statistical models for the expected number of total pedestrian crashes in census tracts are provided in Table 12. The variables that were associated with the expected number of pedestrian crashes include DVMT, the number of pedestrian trips within the census tract, weighted pedestrian accessibility, the number of destinations accessible within 15-minute walking time, average daily transit accessibility, percentage of arterials, intersection density, percent of signalized intersections, street connectivity, sidewalk area, and the percent of network with complete streets.

The expected pedestrian crash outcome depends on both DVMT and the number of pedestrian trips. Based on the results provided in Table 12, 1 % increase in the expected pedestrian crashes would result from 5 % increase in pedestrian trips, if all other variables remain unchanged. The same increase of 1 % in pedestrian crashes is also expected to occur if the value of DVMT increases by 15 %. This gives the impression that the presence of pedestrians contributes to the increase in pedestrian crashes. The estimated coefficients for the exposure variables, however, indicate that the expected number of crashes does not increase proportionally with the increase in vehicular or pedestrian trips, and this effect will be discussed in the last section of this chapter.

The accessibility indicators were used in the estimated statistical models as the additional variables that could indicate pedestrian activity within and between the census tracts. The accessibility indicators that were found to have statistically significant impact on the pedestrian crash outcome primarily refer to the ability of pedestrians whose trips origins are within census tracts to reach destinations by walking or transit. Pedestrian crashes are expected to increase as the pedestrian accessibility increases as a function of the number of accessible destinations and travel time to destinations. This relationship between the number of the accessible destinations and the travel time for pedestrians depends on the land use patterns and the street network structure. The increase in weighted accessibility could occur due to the increase in the number of opportunities within the given travel time, or due to the decrease in the travel time needed to reach the opportunities. The total number of destinations that pedestrians are able to reach within the 15-minute walk is associated with decrease in pedestrian crashes. These two variables have different signs, indicating that the concentration of opportunities in such a way that it decreases the length of pedestrian travel time could lead to pedestrian crash reduction. The reasoning behind this could be that shorter pedestrian trips to destinations, and developing land use patterns and transportation structuring networks in a way that enables pedestrians to reach the opportunities within shorter amount of time, could influence the reduction of their exposure to conflicts and as a result of that the reduction of crashes. As the number of pedestrian destinations outside of the 15-minute threshold increases, their weight will decrease but the overall accessibility can still gradually increase, and influence the creation of longer pedestrian trips and thus more opportunity to be exposed to crashes. One percent increase in the average daily transit accessibility is estimated to lead to 0.9% increase in the expected number of pedestrian crashes. The statistical significance of accessibility indicators in the estimated pedestrian crash models implies that these indicators could serve to provide additional information about pedestrian exposure to crashes in urban environments, particularly when estimating the expected number of crashes on a larger scale.

Variables that represent functional classification, street network connectedness, conflict points, and intersection traffic control are associated with the increase in pedestrian crashes. If the presence of arterials on the street network were to increase by 1 %, it is expected that the frequency of pedestrian crashes would increase by 0.1 %. If the intersection density was increased in the similar way, it is estimated that it would have a slightly stronger effect on pedestrian crashes that are expected to increase by 0.2 %. Intersection density represents the number of intersections per mile squared of census tract area, while street connectivity is a better indicator of street network connectedness as is it obtained by dividing the number of nodes by the actual miles of road in the census tract. Street connectivity is associated with the reduction of pedestrian crashes, implying that two census tracts with the same intersection density may differ in terms of the expected number of pedestrian crashes if one of them has higher number of four-leg intersections, as according to the results census tracts with more three-leg intersections are expected to have lower pedestrian crash frequency. The presence of signalized intersections is associated with the expected number of pedestrian crashes, and appears to be the major driver of pedestrian crash occurrence among the variables in the pedestrian crash model. According to the estimated model, pedestrian crashes are expected to increase by 1.16 % in census tracts with the 1 % increase in signalized intersections. The estimated impact of signalized intersections on pedestrian crashes is expected as signalized intersections can be identified as the network locations with the major potential for vehicle-pedestrian conflicts. Similar effects of the presence of signalized intersections on pedestrian crashes were reported in previous research (Ukkusuri et al., 2012).

The key for determining the final model specification for estimating pedestrian crash outcome was to select the adequate measures of exposure to capture the opportunities for pedestrian crashes to occur within census tracts. The product of DVMT and the number of pedestrian trips within census tract estimated from the CMAP trip generation model served as the main indicator of pedestrian exposure to crashes. It was assumed that if either of these two variables (DVMT or the number of pedestrian trips) is equal to zero, no pedestrian crashes would be expected. Additional measures that would serve as a proxy for exposure were considered during the statistical modeling process, including the total road mileage and sidewalk area. In the case where roadway mileage was included in the models, sidewalk area was treated as a form of pedestrian safety countermeasure and the statistical modeling results would show sidewalk as associated with crash reduction. In the case where roadway mileage was excluded from the models, sidewalk served as the approximation for roadway facilities with pedestrian presence, and was associated with the increase in pedestrian crashes. A better, more complete measure that indicates pedestrian presence on roadway facilities, particularly in the context of the potential conflicts between multimodal users, was the indicator of network completeness, expressed as the percentage of network that serves all four modes. The estimated model results show that if the percentage of street network that serves all four modes is increased by 1 %, the expected increase in pedestrian crashes would be 0.39 %. Statistical models that serve to estimate pedestrian crash outcome, particularly on the areal level, should include some indicators related to pedestrian infrastructure that would complement the measures of exposure. Whether simply road mileage, or sidewalk area, or in this case, an indicator of the presence of complete streets in the network is used, will depend primarily on the data availability and the complexity of multimodal networks.

Some other variables were also considered and included in the preliminary model specifications for pedestrian crashes, such as the population density and the percentage of unemployment in census tracts. Both of these variables were associated with the increase in the expected number of pedestrian crashes. The presence of L Train lines and stops was associated with the reduction of pedestrian crashes during the statistical modeling process, while bus routes appeared to be associated with the increase in pedestrian crashes. Some of these findings were expected. For example, it is more likely that people would walk in lower-income neighborhoods, which may be the reason why the percentage of unemployment showed some association with the increase in pedestrian crashes. The areas around L Train lines are usually highly walkable areas, where vehicular speeds tend to be lower despite the fact that trains are grade-separated. This explains the negative coefficient sign which indicated the association of the presence of L Train lines with a decrease in pedestrian crashes. Increases in the number of bus routes were also associated with increases in the expected number of pedestrian crashes, as pedestrian protection islands and similar measures are not too frequent along the bus routes, especially in higher density and mixed land use areas. These several variables were not included in the final model specification for total pedestrian crashes, as they did not remain statistically significant through the statistical modeling process, and some of them were unique to the City of Chicago and would be difficult to implement if similar models were to be developed for other urban environments.

Severe Pedestrian Crashes

The estimated statistical models for the expected number of severe pedestrian crashes in census tracts are provided in Table 13. The variables that were associated with the expected number of severe pedestrian crashes include DVMT, the number of pedestrian trips within the census tract, weighted pedestrian accessibility, the number of destinations accessible within 15-minute walking time, and the percent of signalized intersections.

For the relevant measures of exposure for severe pedestrian crashes, the same approach was used as in the case of estimating total pedestrian crashes. The estimated DVMT and the number of pedestrian trips were used as the measures of exposure. Statistical models for severe pedestrian crashes are setup in such a way that if one of these two variables (either DVMT or the number of pedestrian trips) in a particular census tract is zero, it is assumed that no pedestrian crashes are expected to occur in that census tract. According to the results presented in Table 13, if DVMT within the census tract increases by 1 %, the expected increase in severe pedestrian crashes is estimated to be 0.2 %. The same 1 % increase in the number of generated pedestrian trips on the census tract level is expected to contribute to 0.39 % increase in severe pedestrian crashes. While the increase in pedestrian trips seems to have a stronger influence on the expected severe pedestrian crash outcome then the increase in DVMT, the expected increase in severe pedestrian crashes is not proportional to the increase in DVMT and pedestrian trips.

While weighted pedestrian accessibility shows association with the increase in severe pedestrian crashes, the number of destinations accessible within 15-minute walking time are associated with crash reduction. The 1 % increase in overall pedestrian accessibility may be contributing to up to 0.5 % of increase in severe pedestrian crashes. The estimated effects of the 15-minute cumulative pedestrian accessibility measure are less strong, as the number of destinations accessible by walking needs to be more than doubled in order to expect measurable crash reduction. Cumulative measures are capturing spatial distribution of activity points and pedestrian network robustness, while weighted accessibility is more representative of the travel efficiency expressed through travel time. These results indicate that while pedestrians are safer in environments where there are more opportunities to reach diverse destinations, more efficient trips are not always expected to be safer.

Just as in the case of total pedestrian crash model, the major driver of severe pedestrian crashes seems to be the percent of signalized intersections within the census tract. According to the results from the Table 13, if the number of signalized intersections within census tracts was increased by 1 %, severe pedestrian crashes would increase by 0.8 %. These results indicate that signalized intersections are associated with higher concentrations of total and severe pedestrian crashes, which could be an implication for future city-wide pedestrian safety investments.

Some other variables that showed association with the increase in severe pedestrian crashes included population density, intersection density, the number of bus stops, the number of bike racks, transit work trips, and land use diversity. Census tract sidewalk area showed association with the reduction of severe pedestrian crashes during the statistical modeling process included. The majority of these variables were similar to those included in the model specification for total pedestrian crash estimation. This is expected, as variables such as the intersection density or the number of bus stops relate to the number of conflicts to which pedestrians are exposed. An additional explanation could be that if a pedestrian is in a crash, it is more likely that the pedestrian will be severely injured when compared to, for example, vehicle occupants. These variables varied in terms of their effect on severe pedestrian crashes as well as statistical significance in the models, and were excluded from the final model specification.

Total Bicyclist Crashes

The estimated statistical models for the expected number of bicyclist crashes in census tracts are provided in Table 14. The variables that were associated with the expected number of bicyclist crashes include the estimated DVMT, the number of bike trips within the census tract, weighted bicyclist accessibility, intersection density, bus stops, bike lanes mileage, CBD, and the presence of L Train lines.

The estimated DVMT and the number of generated bike trips were used as the primary measures of exposure. The estimated coefficients for volumes of vehicles and bicyclist trips in census tracts show nonlinear relationship with the bicyclist crash outcome. Similar to pedestrian crashes, the expected number of bicyclist crashes is increasing at a significantly lower rate when compared to the increase in vehicular and bicyclist volume rates. It is estimated that it would take a 6 % increase in DVMT, or the alternative 3 % increase in the number of biking trips, to expect a 1 % increase in bicyclist crashes.

Bike lanes mileage, the weighted bicyclist accessibility, and the intersection density were used as the approximate measures of the opportunities for conflicts between bicyclists and vehicles. While in the case of vehicular crashes where doubling the road length would be expected to result in almost double number of crashes, the same conclusion cannot be drawn for the bicyclist crashes and bike lanes where doubling the mileage of bike lanes is not expected to be followed by the same increase in bicyclist crashes (bicyclist crashes are expected to increase by 24% rather than double). This is probably due to the fact that biking may also be present on the road segments that do not include bike lanes.

Weighted bicyclist accessibility is the indicator of the potential biking activities in the city, and is included in the model as a statistically significant variable. The estimated impact on crash outcome, however, is very small, as 1 % increase in bicyclist accessibility is estimated to result in 0.02% increase in bicyclist crashes. This effect is much less significant than the effect that pedestrian and transit accessibility indicators were estimated to have on pedestrian crashes. The overall destination accessibility is always higher for bicyclists than for pedestrians, and pedestrian mode is more sensitive to the way street network is integrated with land use patterns, which may be the cause of the estimated results. In addition, bicyclists are not always expected to use only biking infrastructure, while pedestrians movements are usually expected to be closely related to pedestrian facilities which influence the accessibility indicators and could potentially influence the exposure to crashes.

Intersection density proved to be statistically significant variable in the total bicyclist crashes model specification. While the presence of traffic signals was the major driver of vehicular and pedestrian crashes, the density of intersections appears to be more relevant for the expected number of bicyclist crashes. Pedestrians are mostly exposed to crashes at particular points along the roadway segments (pedestrian or mid-block crossings), where the exposure increases with the volumes of vehicles that are higher at signalized intersections. Bicyclists are more exposed to crashes than pedestrians in terms of spatial opportunities for conflicts, as the conflicts may occur anywhere along the roadway segments, which may be the reason why the type of intersection traffic control is less significant. The effect of intersection traffic control on bicyclist crashes on a smaller scale should be further explored.

The CBD area, presence of bus stops, and the presence of L Train facilities served as additional area-wide effects that proved to have significant influence on the expected number of bicyclist crashes. The downtown area in Chicago tends to be more oriented towards nonmotorized modes, with better defined biking facilities network. However, additional analysis is needed to determine if different types of biking facilities (e.g., protected bike lanes), tend to lead to reduction of biking crashes. Biking trips do have higher concentrations in the downtown area, and given the estimated coefficient that indicates that bicyclist crashes are less likely to occur in CBD area, this could confirm the nonlinear relationship between the number of people biking and bicyclist crash outcome.

The estimated model results (Table 14) show that 1 % increase in bicyclist crashes is expected to occur if the number of bus stops in census tracts is increased by 2 %. The bus stops routes in Chicago rarely have dedicated lanes, and the bus stops are typical speed-changing areas due to bus traffic lane-changing and interfering with vehicular traffic. These types of interactions may be causing conflicts with bicyclists as well, especially because bike racks are usually located near the bus stations. Bike racks have appeared as a statistically significant variable during the statistical modeling process, but were excluded from the final model specification as they did not show stable effect through the iterative modeling process, and they showed smaller effect when compared to other variables included in total bicyclist crashes specification. This probably occurred due to the fact that the presence of bike racks is captured through other variables such as bike lanes or CBD. This, however, could be a promising variable to explore, particularly when exploring bicyclist crashes on a larger scale in the future.

The L Train facilities showed association with bicyclist crash reduction. The addition of 1 mile of train facilities is estimated to result in 13 % reduction in bicycle crashes. It is important to acknowledge here that the crash reduction may not be the result of the presence of train facilities, but the environment that is created due to the particular design of train line and station facilities, particularly in Chicago. In this case, having the elevated rail structures is very often followed by lower driving speed, more walking and biking, which could be the reason of association of L Train presence with the bicyclist crash reduction.

Among other variables, socio-economic variables do not appear to have statistically significant effects on crashes involving bicyclists. The effects of entropy and land uses were also explored, and did not show stable association with bicyclist crash outcome.

Severe Bicyclist Crashes

The estimated statistical models for the expected number of severe bicyclist crashes in census tracts are provided in Table 15. The variables that were associated with the expected number of severe bicyclist crashes include the estimated DVMT, the number of bike trips within the census tract, weighted bicyclist accessibility, and bike lanes mileage.

All variables that were statistically significant in the estimated severe bicyclist crash model were already included in the total bicyclist crashes model specification. The same exposure variables, the estimated DVMT and bicycle trips within the census tracts, were used to estimate the expected number of severe bicyclist crashes. These variables are estimated to have a nonlinear relationship with the expected number of severe bicyclist crashes, where a percent increase in bicycle trips or DVMT is followed by 0.2% to 0.25% increase in bicyclist crashes.

Bicyclist accessibility is included in the estimated model for severe bicyclist crashes, as a statistically significant variable. However, the effect is very small, similar to the effect present in the case of total bicyclist crashes. Unlike the pedestrian crashes, bicyclist crashes are less dependent on accessibility-related variables. As the ability to reach destinations by bike is much higher than the ability to reach destinations by walking, bicyclist accessibility (cumulative or weighted) did not show statistically significant impact on bicyclist crash frequency or severity.

Another predictor that was found to have a significant effect on the severe bicyclist crashes is the total length of bike lanes within census tracts. Severe bicyclist crashes are expected to increase in census tracts that have higher mileage of bike lanes, but not at the same rate at which the bike lane length increases.

Some other variables, including the sidewalk area and the land use entropy, showed some impact on the severe bicyclist crashes, but the direction of impact did not seem logical (e.g., increase in sidewalk area was associated with the increase in bicyclist crashes), and these variables were not included in the final model specification.

Diagnostics and Final Model Recommendations

The final model recommendation for each crash type depended on the comparison of final model specifications estimated by using the applied SASM methods, the model-specific goodness of fit indicators provided in Tables 10 through 15, and the model diagnostics provided in Table 16.

Based on the results provided in Tables 10 through 15, the SASM approaches applied in this research were fairly consistent in terms of the variables that were influential and statistically significant in each crash model. Negative binomial models, although not able to capture spatial spillover effects, provided a strong indication about the variables that should be considered when modeling various types of crashes in urban multimodal environments. However, using only negative binomial models, without running other statistical models, would not lead to adequate final model specifications, as the application of different SASM methods helped to eliminate the variables with inconsistent signs and estimated coefficient values. Running different types of models with same sets of variables is what helped to determine first the final model specification, and then the best model recommended for the estimation of each crash type in the analysis.

As the data were spatially collected, accounting for spatial auto-correlation and generally spatial relationships between census tracts was an important part of SASM process. The first step to account for spatial effects in the data by simply assuming that larger spatial entities such as Planning Districts and Regions can capture spatial dependence between census tracts. This approach was modeled by incorporating fixed and then random effects into negative binomial models. Regions proved to be statistically significant in negative binomial models with fixed effects for all crash types. Looking at the model diagnostics presented in Table 16, models with fixed effects also outperformed negative binomial models with random effects, but further steps needed to be taken to ensure that the impact of certain variables is not overestimated due to spatial autocorrelation present in crash data for all users. This is why generalized additive models with smooth functions across the locations were used, as an alternative frequentist approach that has the ability to fit spatially collected data. When compared to negative binomial models, GAM showed that the smooth terms included in the model to represent spatial trends in the data were significant at the 99% confidence level for total and severe vehicular, pedestrian, and bicyclist crashes. The inclusion of smooth functions to account for spatial autocorrelation resulted in slightly higher standard errors and lower statistical significance levels for some variables in the models. For example, the presence of bus stops appears to be less significant in terms of its effects on vehicular crashes when modeled with spatial trend functions in GAM approach compared to other frequentist methods. Similar trends occur with land use entropy in severe vehicular crash models, with L Train lines in total bike crash models, and weighted bicyclist accessibility in severe bike crash models. The percent of deviance explained by the models is the highest for the total vehicular crash models (76.30%), and slightly lower for total bicyclist (62.20%) and total pedestrian crash models (43.70%). While the model for severe vehicular crashes has relatively high percent of deviance explained by using the generalized additive models (63.20%), the scores are significantly lower for severe bicyclist crashes (31.70%), and severe pedestrian crashes (20.80%).

The clear advantage of FBH models presented in Tables 10 through 15, over frequentist modeling approaches, is the estimation of two sets of random effects: one resulting from spatial correlation, and the other from unobserved heterogeneity among census tracts. The set of statistically significant variables is almost the same for Bayesian models when compared to negative binomial and GAM. The variables that are marginally significant in negative binomial models are not significant in the Bayesian hierarchical models, similar to GAM results. The variance due to spatial correlation estimated in Bayesian models is low but different from zero, confirming the findings from the GAM approach that spatial correlation is statistically significant.

Table 16 shows the model diagnostics for vehicle, pedestrian, and bicyclist crash models. The values of AIC and BIC were used for frequentist approaches, while DIC was used for FBH models. The DIC and BIC values provided in Table 16 were the lowest for GAM models among all frequentist models, indicating that GAM models are a more efficient approach than other explored frequentist SASM methods to represent the data generating process for different crash types. When comparing the AIC and BIC values for the methods based on frequentist statistical inference, GAM outperform linear forms of negative binomial model, including the models with fixed and random effects. While direct comparison of the statistical models based on frequentist and Bayesian approach cannot be made, the models can be compared in terms of the coefficients and the overall efficiency of executing the modeling process. It is well known that the major disadvantage of FBH modeling process is that it may be more time consuming and challenging in terms of the coefficient interpretation, as it provides the results in the form of a distribution rather than p-values and confidence intervals.

The results of the obtained models show very similar coefficient values for GAM and FBH models, with a relatively high percent of deviance explained by the GAM in the case of the models used to estimate total crash frequency for different modes of transportation. Similar conclusion can be made about the GAM models used to estimate severe vehicular crashes. The percentage of deviance explained and the similarity in the coefficients resulting from GAM and FBH estimation led to the selection of GAM approach as the recommended approach for vehicular (total and severe), total pedestrian, and total bicyclist crash estimation. In the case of these four crash types, the spatial auto-correlation is lower than in the case of severe nonmotorized crashes, and there are not too many census tracts with zero crash outcomes, meaning that the application of FBH would not significantly contribute in terms of treating these data issues. This is why GAM approach, which also outperforms other frequentist approaches in terms of diagnostics values and estimated coefficient standard errors, is selected as a valid SASM alternative to estimate these crash types.

In the case of severe pedestrian and severe bicyclist crashes, spatial auto-correlation is slightly higher than for the other analyzed crash types. The number of census tracts with zero crash outcomes is also higher for these two crash types. The FBH models have been known to handle the excessive number of zero observations in crash datasets, as the approach is based on MCMC simulation which allows more flexibility in terms of sampling values from the posterior distribution without actually declaring zero-state as a fixed state for any of the observations. This is why in the case of severe pedestrian and bicyclist crashes, FBH models were recommended as the most suitable.

Safety Effects of Multimodal Exposure and Accessibility

In addition to interpreting the variables that were included in the final model recommendations for each crash type, the variables related to multimodal exposure and accessibility were extracted and their effects on multimodal safety outcomes were separately presented in Figures 23 through 28. The estimated models for total and severe vehicular, pedestrian, and bicyclist crashes show that the increase in crashes for all crash types is associated with the increase in the majority of variables representing multimodal infrastructure, exposure, or accessibility. This section of the Discussion chapter is intended to clarify these relationships by taking a more detailed look into the effects of exposure and accessibility on multimodal safety outcomes.

Figures 23, 24, and 26 show the relationships between the exposure variables and associated crash rates for total and severe crashes. As previously explained, non-motorized crashes were estimated using the combinations of exposure measures for private vehicles (DVMT) and the adequate nonmotorized mode (pedestrian trips or bicyclist trips). The relationships between crash rates for all crash types and the related exposure measures are nonlinear. The estimated coefficients for the exposure variables in all estimated models have a value lower than one. This means that while the crashes are expected to increase as the exposure increases, the increase in crash rate is expected to be much lower than the rate at which the exposure increases, and this can be concluded for crash outcomes for all crash types. This effect where crashes increase at a lower rate (rate that is not proportional to exposure rate) than the exposure is known in the literature as the “Safety in Numbers” effect (Elvik, 2015; Hauer, 1982).

As the exposure increases for private vehicle users, total vehicular crashes are expected to increase at a much higher rate than the severe vehicular crashes, which can be observed from the Figure 23. Similar conclusions can be drawn for pedestrian and bicyclist crashes (Figures 23 and 26), as it is expected that with the increase in exposure (both vehicular and nonmotorized), less severe crashes are likely to increase at a higher rate than the severe crashes.

The estimated crash rates based on the models for severe vehicular and severe pedestrian crashes show that for the same rate of change in the estimated DVMT, while all other variables (including the pedestrian user exposure) remain constant, the expected rate of severe vehicular crashes is only two times higher than the expected rate of severe pedestrian crashes. As the vehicular mode share is usually more than double when compared to pedestrian mode share, these estimates are related to another expected outcome which is the result of user vulnerability: if a nonmotorized user is involved in a crash, the crash is more likely to be severe for nonmotorized user than for a vehicle occupant. Severe pedestrian crashes are more sensitive to change in pedestrian exposure than to change in vehicular exposure, while according to the estimated models, severe bicyclist crashes almost equally depend on bicyclist and vehicular exposure.

Figures 25, 26, and 28 show the relationships between the variables that represent multimodal accessibility and total and severe pedestrian and bicyclist crashes. Based on the estimated crash models for pedestrians and bicyclists (Tables 17 through 22), pedestrian crash outcome is more dependent on the accessibility variables than bicyclist crash outcome. Both pedestrian and transit accessibility were found to be associated with pedestrian crashes, while bicyclist crashes were found to be related only to indicators of bicyclist accessibility.

In terms of the size of the effect of accessibility on total pedestrian crashes, Figure 25 shows that pedestrian crash frequency is more sensitive to changes in cumulative pedestrian accessibility, as well as transit accessibility than weighted pedestrian accessibility that includes the component of travel time in its impedance function. Similarly, severe pedestrian crash outcome is more sensitive to cumulative than weighted pedestrian accessibility. As cumulative accessibility increases both total and severe pedestrian crashes are expected to decrease, indicating that census tracts with higher concentrations of potential pedestrian destinations are expected to have lower pedestrian crash frequency and severity.

The extracted SASM results from Figure 25 allow the estimation of the expected pedestrian crash rate based on the number of pedestrian trips and level of accessibility in the census tract. For example, if a census tract generates fifty pedestrian trips, and the cumulative pedestrian accessibility is ten destinations accessible within a 15-minute walk, the expected crash rate for that census tract would be 0.120. If the cumulative accessibility increases up to one hundred destinations accessible within a 15-minute walk time, crash rate is expected to be reduced by half. Transit accessibility can be interpreted in the similar manner, but it has the opposite effect when compared to cumulative pedestrian accessibility (e.g., increase in transit accessibility is associated with increase in crashes). Figure 25 shows that the same census tract that generates fifty pedestrian trips, but has transit accessibility as high as being able to reach the average of one hundred stop times within a 15-minute budget time, is expected to have crash rate of 1.200. Figure 26 can be used to derive conclusions about severe pedestrian crashes, based on the different accessibility and exposure levels.

Figure 28 shows the estimated relationships between total and severe bicyclist crashes and weighted bicyclist accessibility that includes bicyclist travel time as the impedance factor. As in the case of weighted pedestrian accessibility, changes in weighted bicyclist accessibility are statistically significant but not associated with major changes in bicyclist crash outcomes for both total and severe bicyclist crashes.

While some of the findings from the pedestrian and bicyclist crash models interpreted in this chapter appear, at first glance, counterintuitive and possibly controversial (e.g., presence of bike infrastructure associated with increases in bike crashes), it is important to recognize that these types of variables are currently acting as surrogates for true exposure data. The models themselves are still useful for estimating the expected number of crashes at a spatial level for use in road safety management, but are still not quite to the stage where "cause-effect" relationships can be drawn using the estimated parameters for all of the right-hand-side variables.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

The main objective of this research was to explore the factors that are associated with safety outcomes in urban multimodal transportation systems, and develop SASM methods that can be used to estimate safety effects of investing in multimodal infrastructure and accessibility improvements. Cities are interested in improving accessibility for multimodal users in order to build healthier, more affordable and more sustainable transportation systems, while not compromising safety, particularly for more vulnerable nonmotorized users. This dissertation developed methods that can be used to measure city-wide multimodal transportation improvements and predict how those improvements could influence safety on the areal level. Data from Chicago aggregated on the census tract level were used to develop a comprehensive dataset that allowed to examine system-wide effects that may influence urban multimodal safety including socio-economic characteristics, land use characteristics, transportation infrastructure, exposure, and accessibility. This chapter presents the summary of research findings, describes major research contributions and limitations, and provides recommendations for the future research development.

Research Contributions

As cities across the U.S. attempt to "retrofit the suburbia" in an effort to improve accessibility for all modes of transportation, and thus move towards more sustainable transportation and environment in general, transportation safety remains the primary concern. An additional challenge is the fact that our cities are already built in certain ways, and new sets of policy and measures will need to account for this barrier and "make the most" of what already exists. The lack of data, measures, and methods that can serve to evaluate multimodal urban safety is evident.

The idea behind the methodological approach developed in this research was to explore some options that will allow practitioners and researchers to "plan for safety", rather than waiting for realization of system-wide transportation plans and then dealing with segment and intersection-level safety issues. The way we integrate transportation and land use, as well as the way we design our street networks and allow the users to access both transportation and their final destinations, will affect their amount of travel and opportunities for conflict in traffic, generally defined as exposure. While it is desirable that the exposure of transit and nonmotorized modes increases, we should be looking for ways to achieve this without increasing the number of crashes.

The analysis on the census tract level allowed for the inclusion of other factors that impact traveler behavior, and are already proven to impact transportation safety, such as socio-economic and land use variables. The described methods and findings of this research will help practitioners as they are planning for system-wide transportation investments, during the decision-making processes that debate between enhanced street connectivity or street widening, complete streets or balanced/complete networks (where not all streets need to meet the needs of all users, but network should allow everyone to reach their destinations), and building multimodal facilities within optimal distances from activity destinations.

The data collection was conducted to acknowledge the complexity of multimodal transportation systems. The existing guidelines on safety evaluation methodology simply differentiate between urban and rural environments, and use limited amount of factors to estimate nonmotorized crashes. The research that acknowledges the diversity of factors that influence urban multimodal safety is still the emerging field, and this research is an important contribution as the developed dataset includes high level of detail on urban multimodal transportation features, and merges several groups of factors that could influence safety. The developed dataset integrates data obtained from various transportation agencies, acknowledges the importance of open transportation data by using open data sources, and includes additional variables calculated to represent multimodal accessibility. The dataset demonstrates the application of open transportation data platforms combined with other data sources, which makes the case for further expansion of Open Data initiatives in order to advance transportation decision making in the cities.

In addition to the traditional activity-based exposure measures or “summary” exposure measures that capture the number of trips for each mode, this research includes the variables representing multimodal infrastructure and connectivity, network completeness, and multimodal accessibility. These variables that capture characteristics of multimodality also represent travel opportunities, distances, and potential conflicts, serving as proxies for exposure of multimodal users to crashes. The particular contribution of this research is the acknowledgement that accessibility, with emphasis on destination accessibility, is not the same for different modes of transportation (e.g., pedestrians cannot reach the same number of destinations as transit users), which is rarely recognized in the existing literature. This inclusion of “multimodal” accessibility on a higher level is achieved through the developed frameworks that were focused specifically on pedestrians, bicyclists, and transit, while other measures related to network design served as more general accessibility indicators. The developed measures of accessibility and network completeness can also serve as indicators of success of multimodal transportation systems in terms of accommodating the needs of all transportation users on urban street networks.

The improved access to multimodal transportation options may lead to increase in crash frequency and severity, due to increased exposure and users’ vulnerability, but there are also findings that improved accessibility changes traveler behavior in a way that it makes it “safer” and may also lead to improved safety. This research adds to the existing literature, by further clarifying the nature of the relationship between accessibility and safety. Two different components of accessibility, cumulative and weighted measures, have different direction of impact on crash outcomes. While denser street networks and land use developments may lead to pedestrian crash reduction, pedestrian crashes may increase as travel time to destinations decreases, indicating that highly walkable environments should be equipped with adequate countermeasures to prevent or reduce conflicts between vehicles and pedestrians.

Particular attention should be paid to the way multimodal facilities such as bus stops, bike racks, and bike lanes are installed, as these facilities tend to be associated with the increased number of crashes for multimodal users. While complete streets are desirable in livable cities, the strategy of allocating complete streets should be re-established, as the obtained results show that networks that carefully prioritize different modes are safer than networks that enforce all modes to be served on a single facility. Intersections, particularly signalized, remain the key points on the street network contributing to crashes that involve all users.

SASM is also an emerging field in transportation safety statistical modeling. With the recent advances in computational capabilities, the application of more complex statistical methods is becoming more common. This is particularly the case for spatially aggregated data which may exhibit a variety of issues such as spatial correlation and the dependence of estimated models on the selected units of analysis. The amount of research that applies Bayesian methods and frequentist methods based on additive models to resolve the issues in spatially aggregated crash data is still limited, especially in the context of urban multimodal transportation, which makes this study valuable for researchers from methodological perspective. GAM with smooth functions used to account for spatial trends were used in other research disciplines, and very few crash studies (Li et al., 2009; Xie & Zhang, 2008) use these models while not focusing on areal crash modeling. Previous crash studies which include areal analysis rarely consider bicyclist crashes, and this is another contribution of this research. As more complex statistical methods are becoming available, the applicability of classical statistical inference is still an option to be considered, as it is less computationally demanding, so the application of the main two methods in safety statistical modeling, frequentist and Bayesian, contributes in terms of the recommendation for the applicability of each approach.

The implications of the “Safety in Numbers” effect that is demonstrated through the relationships between multimodal exposure and crashes are three fold. First, the increase in multimodal exposure is expected to be associated with increase in crashes up to a certain point, when crash rate becomes almost constant even though the exposure increases. Second, while crashes (for all users) are expected to increase at a lower rate than the rate of exposure increase, the increase in multimodal exposure is even less likely to contribute to the increase in severe crashes for all users. Third, nonmotorized users are more sensitive to changes in nonmotorized exposure measures than to changes in vehicular exposure, in terms of the expected number of crashes.

The results obtained from different SASM methods also provide implications for urban road safety statistical modeling in terms of variables that should be included when modeling crashes on both macroscopic and microscopic levels. The amount of data available in urban environments is rapidly increasing, and this could improve the way the expected number of crashes is estimated. The results also show how each city can be unique in terms of the factors that may contribute to safety outcomes, particularly expected crash reductions. In the case of Chicago, the overall size of sidewalk areas and the presence of train facilities seemed to be associated with crash frequency reductions for various modes of transportation. The dataset used in this research accounted for various aspects of a true multimodal transportation system, and showed how different contributing factors may interact in multimodal environments to either increase or reduce crash frequency. This further provides implications for decision making related to future safety investments (e.g., designing streets to accommodate both buses and pedestrians).

What distinguishes this research from the existing literature is the level of detail in the developed dataset which should bring together a variety of factors that have the potential to influence urban multimodal safety with a particular emphasis on Open data, measures of availability and accessibility of multimodal transportation options that could serve as indicators of multimodal transportation system quality and performance, and methods used to establish the relationship between multimodal transportation features and safety for a variety of users. The application of two main statistical approaches in road safety statistical modeling in the context of urban multimodal transportation showed that GAM as the alternative frequentist approach has the ability to account for a variety of issues that researchers may encounter in spatially collected crash data, and recommend the most appropriate methods with regards to the ability to handle the system-wide effects in urban multimodal systems and barriers imposed due to computational complexity.

Research Limitations

The major limitation of this research is that the dataset is developed using the data from only one city, as the focus of the dissertation is primarily on the methods. This limits the application of the statistical models obtained from this study, and requires further data collection and research to test for transferability of the obtained results to other urban environments. As a part of the potential future research efforts, data should be collected from census tracts from the cities of different sizes, to check how the final models from the proposed study could be calibrated to other locations.

Another limitation of the presented research is the need to expand the regional analysis and establish what the implications would be for the segment-level studies in road safety. This could be achieved if the future research focuses on similar street segments from census tracts with various accessibility levels, in order to determine the effects of multimodal accessibility while controlling for the elements of street design and traffic conditions. Street segments with similar cross section design and traffic volumes from areas that are different in terms of network completeness and destinations accessibility might have different safety outcomes, and this should be a part of the potential future research efforts, after the proposed study is conducted.

The proposed dataset includes 8 years of crash data from the City of Chicago, disaggregated on the census tract level. This dataset could further be disaggregated on the annual level, and developed as a panel dataset. If more information is obtained on the temporal variation of independent variables, it would be beneficial to see how crash frequency and severity change over time. As temporal correlation could partially be overcome by aggregating the data over a longer period of time, the proposed study is focused on spatial correlation as a potentially more serious issue in the proposed dataset.

In terms of the statistical modeling methods, a multivariate approach to estimate crash outcomes for all users through a single model would be a logical step to improve the findings of this research. In addition, incorporating additive model form under Bayesian framework would be an innovative approach that has not been applied in previous road safety studies.

Future Research Needs

The success of a city, in terms of economic, environmental, and social development, highly depends on how well transportation serves the "needs, uses, and functions" of a city. The majority of "traffic problems" today are mostly prescribed to the invention and usage of automobiles and the convenience of travel they provide, neglecting the fact that the disintegration of city and transportation planning policies resulted in low accessibility auto-oriented cities that became quite common in the U.S. Automobiles and transportation in all its forms are simply a service that should be a response to users' needs and city needs in general. While it is commonly accepted that cities well served by their transportation systems do not put auto-mode above other transportation modes, it is also recognized that "we blame automobiles for too much" (Jacobs, 1961; Lynch, 1961). The importance of distributing the right-of-way, particularly on urban streets, more equally across different modes of transportation in order to provide better "access for all", as well as concerns about transportation safety for a variety of users, appeared at about the same time in transportation policy development.

This research was primarily focused on addressing the transportation safety issues in urban multimodal context. The results show how complex the relationship between multimodal features and transportation safety may be, particularly in major cities. There is, however, need to increase the focus on urban multimodal transportation safety research, and further explore how SASM can be used to improve city-wide decision making in terms of improving multimodal transportation options and preserving safety of multimodal transportation users.

Urban multimodal transportation systems are constantly changing and the potential of urban data is growing. Transportation decision making is becoming more and more data driven, as terabytes of data are collected on a daily basis. Transportation agencies today have the access to the amount of data that was never available before at a very low or no cost. Data are collected automatically and manually from the freeways, arterials, probe vehicles, and fused to provide more reliable information sources for a variety of decision makers. The "era of Big Data" is starting to have a large impact in urban environments, with predicted generation of over 4.1 terabytes of data per square kilometer of urban land per day by 2016 (Dobre, 2014). This influence is particularly visible in traffic and transportation field. Cities already design and develop data platforms based on automated data collection processes and built to handle large amounts of data from a wide range of sources for multiple applications (Rockafeller Foundation, 2014). Transportation research in general is starting to acknowledge the benefits of these innovative data resources, while transportation safety as a research area has yet to explore their potential.

The way we are measuring the performance of transportation systems is changing, and the inputs and methodologies for those measurements are advancing with the emerging technologies and needs for new transportation policies. The efforts towards building more sustainable transportation systems in urban context need to incorporate safety targets, in both long-range planning and short-range engineering projects. Data, measurements, and methods provided in this research demonstrate how to start exploiting the data sources potential, and expand the current methodologies in safety evaluation through SASM processes implemented in this study. This, however, is just a starting point in addressing the issues that exist with proper representation of multimodal exposure and quality performance measurement of multimodal systems. In order to further improve the existing transportation safety methodology and implementation, and bridge the gaps between research and practice, looking at transportation as a multimodal system integrated within its context and environment could be the key approach for future research contributions.

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