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Modeling Bicyclist Exposure to Risk and Crash Risk: Some Exploratory Studies

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16. Abstract (Limit: 250 words)

This report presents models for estimating bicyclist exposure to risk and crash risk. Direct demand models for estimating weekday PM peak-period bicyclist exposure to risk are estimated from a database of PM peak-period bicycle counts in Minneapolis and used to estimate exposure for the street network. Bicycle crashes in Minneapolis are described and crash risk is assessed. Probability models to assess crash risk at both intersections and along segments show that both bicyclist exposure and vehicular exposure are associated with the likelihood of a bicycle crash. Estimates of exposure at 184 roadway-trail crossings are used to apply warrants for traffic controls. The results show that warrants for traffic signals and pedestrian hybrid beacons are most likely to be met using weekend peak-hour traffic flows. Most locations that meet warrants already have controls, but site specific safety investigations may be warranted at 9% of all crossings. Count-based models of bicyclist exposure are estimated for Duluth using origin-destination centrality indices as explanatory variables. Although these indices correlate positively and significantly with bicyclist volumes, estimates of exposure do not correlate with bicycle crashes. Together, these analyses illustrate how measures of bicyclist exposure to risk can be used in assessments of safety and crash risk. The approaches can be used in planning-level studies where consistent measures of exposure or risk are needed. These results underscore the need to continue bicycle traffic monitoring and make available estimates of exposure for safety assessments.

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FINAL REPORT

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EXECUTIVE SUMMARY

Transportation planners and engineers need information about bicyclist exposure to risk and crash risk to build safe, efficient transportation systems. This report presents models for estimating bicyclist exposure to risk and illustrates how these measures can be used to assess crash risk and incorporated in planning level studies of the need for countermeasures to increase safety.

We present count-based demand models for estimating weekday PM peak-period bicyclist exposure to risk from a large database of PM peak-period bicycle counts in Minneapolis. We use these models to estimate bicyclist exposure for the entire street network in Minneapolis. Exposure is highest in the central business district, along arterials and collectors, in higher-density residential neighborhoods, and along multi-use trails and bicycle boulevards that link neighborhoods and recreational areas throughout the city. These demand models show the importance of traffic generators (e.g., job accessibility, population density), destinations (e.g., open space, retail area), aspects of the transportation network (i.e., off-street trails, on-street facilities), and weather parameters (i.e., temperature and precipitation) as correlates of exposure.

We describe bicycle crashes in Minneapolis and illustrate how exposure and crash data can be used to assess crash risk. We use probability models to assess crash risk at both intersections and along segments and show that both bicyclist exposure and vehicular exposure are associated with the likelihood of a bicycle crash. Factors associated with crashes at intersections include land-use mix, percentage of commercial land use, number of intersections within a 400-meter buffer, and presence of trails and trail crossings.

We present estimates of exposure at 184 roadway-trail crossings in Minneapolis and demonstrate how these estimates can be incorporated into safety assessments. Our exposure data show that non-motorized traffic volumes are highest on weekends and that warrants for traffic signals and pedestrian hybrid beacons are most likely to be met using weekend peak-hour traffic flows. Most locations that meet warrants for either traffic signals or pedestrian hybrid beacons already have controls, but 9% of all crossings warrant site-specific safety assessments.

We also present count-based models of bicyclist exposure for Duluth and test the correlation between measures of exposure and crashes. We introduce the use of origin-destination centrality indices as explanatory variables in the demand models and show that these measures correlate positively and significantly with bicyclist volume counts. In Duluth, however, the measures of bicyclist exposure do not correlate with bicycle crashes.

Together, these analyses illustrate how measures of bicyclist exposure to risk can be used in assessments of safety and crash risk. The approaches can be used in planning-level studies where consistent measures of exposure or risk are needed. More detailed site-specific data or estimates will be needed for studies to assess the need for countermeasures at particular locations. These results underscore the need for public and nonprofit organizations to continue efforts to initiate bicycle traffic monitoring and make available estimates of exposure.

CHAPTER 1: INTRODUCTION

Federal, state, and local policies support development of multimodal transportation systems that integrate facilities for vehicular, transit, bicycle, and pedestrian traffic. As development of multimodal systems proceeds, new issues of safety arise, especially as non-motorized modes of transportation – bicycling and walking – are integrated with motorized traffic modes. Protecting vulnerable road users is a priority for both transportation managers and the public. Research priorities established by the U.S. Department of Transportation in response to MAP-21 legislation include traffic operational safety and identify bicyclists and pedestrians as vulnerable road users. MnDOT and other state DOTs have developed countermeasures and interventions to increase safety of bicyclists and pedestrians, but the effectiveness of these interventions often cannot be assessed because of the lack of information. Specifically, analysts lack information about exposure to risk and crash risk. Crash and fatality rates cannot be determined in most places in the United States because state and local officials lack information about bicycle and pedestrian traffic volumes.

The objectives of this research project were to develop methodologies and tools for estimating bicyclist exposure to risk (i.e., bicyclist demand, or traffic volumes) and to illustrate, through case studies, how these measures can be used to assess crash risk and incorporated into planning level studies of the need for countermeasures to increase safety. The goal is to help state and local agencies protect high-risk road users on multimodal transportation systems.

Chapter 2 is a brief review of related literature about measures of exposure to risk for non-motorized traffic, approaches to bicycle traffic or demand modeling, and challenges in crash modeling. This review establishes that analysts lack data in most cases to develop site-specific measures of exposure to risk and crash risk and that new measures are needed. Chapter 3 presents bicycle demand models estimated from manual counts of bicyclists in Minneapolis and illustrates how these models can be used to estimate peak hour bicycle traffic volumes for the road and street network in Minneapolis. Chapter 4 summarizes bicycle crashes in Minneapolis and illustrates how the crash data can be used with the exposure data to model the likelihood of crashes. Chapter 5 illustrates how counts of traffic on multi-use trails can be used to apply guidelines for traffic signal warrants at trail-roadway intersections in Minneapolis. Chapter 6 presents models of exposure to risk and crash risk for Duluth, Minnesota. Chapter 7 summarizes briefly exploratory studies of bicycle and pedestrian traffic in Bemidji, Minnesota. Chapter 8 summarizes observations and presents conclusions.

Analysts agree that a data-driven approach is essential for increasing traffic safety and protecting vulnerable, high-risk users. Efforts to develop data-driven and evidence-based approaches to increasing bicyclist traffic safety have been hampered by the lack of data and tools for characterizing and assessing exposure to risk, crash risk, and the need for countermeasures. The research presented in this report shows that estimates of exposure to risk can be developed using count-based demand models and that crash risk is associated with exposure to risk. This research also shows that counts, or measures of exposure, are useful in planning-level studies of the need for countermeasures. The research presented here does not, however, explore site-specific factors (e.g., intersection geometry, time-of-day, weather) that contribute to specific crashes at specific locations. The approaches and tools presented herein remain limited because of the limitations of data on which they are based. Additional progress in monitoring and modeling non-motorized traffic, assessing crash risk, and using measures in safety assessments is needed to achieve the goal of protecting vulnerable road users.

CHAPTER 2: LITERATURE REVIEW

The literature on bicyclist and pedestrian safety is growing rapidly as researchers respond to the needs identified by policy-makers, engineers, and planners responsible for increasing safety and reducing crashes in multimodal systems. This review defines key terms and then focuses on measures of exposure to risk, modeling bicycle traffic demand, and modeling bicycle crashes.

A bicycle crash is defined as a reported collision between a bicycle and a motor vehicle, or between a bicycle and a pedestrian. Most analysts agree bicycle crashes are under-reported because many individuals who are involved in minor crashes fail to report them. In addition, the failure to merge police and health-based data systems also contributes to the under-reporting of crashes. The implication is that most estimates of crashes and crash frequency, including those reported in this report, are undercounts.

"Crash frequency" refers to the number of collisions at a certain location or within an area per some unit time. "Crash risk" refers to the likelihood that a crash will occur given exposure to risk. Researchers have often used crash frequency as a measure to evaluate the effectiveness of transportation infrastructure in improving cycling safety. However, not all roads are equally used by bicyclists, and bicycle traffic volumes change by time-of-day as well as by day-of-week and seasonally. Measures of crash frequency do not control for variation in bicycle traffic volumes. Thus, places with high crash frequencies may have low crash rates. That is, places with high crash rates could be relatively safe if these places are used intensively by bicyclists. Conversely, places with low crash frequency could have relatively high crash risk.

The shortcomings of the frequency-based approach to addressing crashes, and the importance of estimating crash risk, have underscored the need for valid measures of exposure to risk. At the most general level, exposure to risk is a "measure of the number of potential opportunities for a crash to occur" (Turner et al. 2017). In most places in the U.S., estimates of bicyclist exposure to risk do not exist. Hence, better methods for estimating exposure are needed.

Schepers et al. (2014, p. 331) argue that "Scientific literature lacks a model which combines exposure to risk, risk, and the relationship between them." They note that exposure to risk results from travel behaviors, which can be described as traffic volumes, modal splits, and patterns that vary over time and space. They also suggest that explicit links between exposure and crash risk are needed because of the non-linear relation between them. The next two sections of this review summarize literature related to exposure to risk and crash risk.

2.1 MEASURES OF BICYCLIST EXPOSURE TO RISK

Although many researchers are working to develop measures of exposure to risk and many specific measures have been proposed, "there is currently no commonly accepted or adopted measure of pedestrian and bicycle exposure to risk" (Molino et al. 2012, p. 145). Miranda-Moreno et al. (2011), for example, propose three measures of exposure: aggregated traffic flows, motor vehicle flows aggregated by movement type, and conflicts between motor vehicles and cyclists. Turner et al (2017) note that measures of exposure to risk vary depending on the purpose and scale of an analysis and the availability of data. They list 10 different measures (Turner et al. 2017):

- Pedestrian or bicyclist volume.
- Sum of entering flows (motorized and non-motorized) at intersection.
- Product of pedestrian or bicyclist volume (P or B) and motor vehicle volume (V), (P or B) × V.
- Square root of the above product, [(P or B) × V]1/2
- Estimated number of streets or travel lanes crossed.
- Estimated total travel distance, in person-miles of travel.
- Estimated total travel time, in person-hours of travel.
- Total number of pedestrian or bicyclist trips made (from travel survey).
- Overall census population.
- Proportion of census population who report regular walking or bicycling (from travel survey).

Some of these measures are location-specific (e.g., intersection), while others are area-wide measures. Area-wide measures such as population in a census tract or commuting population in a jurisdiction generally are considered relative crude indices because exposure cannot be matched directly with the location or characteristics of crashes. When population-based measures of exposure are used, crash risk may be estimated, for example, as the ratio of bicycling crashes to the population or the number of bicyclists in the area. This approach is often reported when the objective is to describe and compare cycling crashes at large geographic scales (e.g., between cities, regions or countries).

Location-specific measures such as bicycle traffic flow on a road or the number of bicyclists entering an intersection are desirable because they can be correlated with other factors such as vehicular traffic, road geometry, and facility characteristics, as well as number of crashes at the location. These types of measures generally are not available, however, especially for entire networks. Because of the importance of location-specific measures, transportation managers and researchers have worked on methods for estimating bicycle and pedestrian traffic volumes for more than 30 years. The costs of comprehensive monitoring programs, however, have limited implementation. More recently, with the increasing commercial availability of automated, continuous counters that provide valid and reliable measures of traffic volumes, federal, state, and local agencies have begun to develop and institutionalize monitoring programs. The Federal Highway Administration, for example, has included a chapter on non-motorized traffic monitoring in its *Traffic Monitoring Guide* (TMG; FHWA 2013). Many researchers have assessed the validity and reliability of traffic volume estimates from automated counters (Dharmaraju et al. (2001), Schneider et al. (2005), Bu et al. (2007), Greene-Roesel et al. (2008), Nordback and Janson (2010), Yang et al. (2010), Nordback et al. (2011)), and a new authoritative NCHRP assessment of automated monitoring technologies was recently published (Ryus et al., 2014; Ryus et al. 2016). Some state and local agencies now are working to implement bicycle traffic monitoring programs consistent with the framework outlined in the TMG.

Another measure of exposure to risk is bicycle miles traveled (BMT). When used the assess crashes, risk is estimated as the ratio of the number of crashes to distance cycled. Moritz (1997) compared the number of crashes per distance traveled for different types of bicycle facilities and found that the risk is lowest for bike lanes and marked bicycle routes. Molino et al. (2012) also used this measure to bicycle and pedestrian miles traveled on different types of shared facilities. The measure, which is analogous to vehicle miles traveled used as a measure of exposure in vehicular crash analysis, is very helpful in comparing risks among different types of bicycle infrastructure, and risks between groups of traveling different distances (Yiannakouliasa et al., 2012).

Given the costs and length of time required to implement comprehensive bicycle monitoring programs, researchers have begun to develop models to estimate exposure. Types of models for estimating bicycle traffic volumes are choice-based, regional transportation models and direct or facility demand models. The choice-based models follow the traditional four-step regional transportation demand model (i.e., trip generation through trip distribution and route assignment). These often have been completed for traffic analysis zones (TAZ), which are quite large. An outcome is that intra-zone trips, which may account for a large proportion of bicycle trips, are not modeled effectively. Direct or facility demand models do not consider the behavioral context of bicycle travel and simplify the modeling process by correlating bicycle traffic counts with road network, adjacent land use, and socio-demographic characteristics. Because of their tractability, facility demand model seem to be more common. Among others, Hudson et al. (2010), Haynes and Andrzejewski (2010), McDaniel et al. (2013), Lowry and Dixon (2012), Schneider et al. (2009), Hankey et al. (2012), Miranda-Moreno (2013), and Nordback (2013) have reported methodologies and tools to estimate bicycle and pedestrian traffic volumes that can be used as estimates of exposure. While their research represents significant progress, additional research is needed to provide tools that can be applied routinely by state and local officials, traffic engineers, and bicycle and pedestrian professionals to estimate traffic volumes and exposure to risk, especially in smaller communities.

2.2 MEASURES OF BICYCLE CRASH RISK

As noted, bicycle crash risk refers to the likelihood that a crash will occur given exposure to risk, and researchers have used variations of area-wide and facility-specific measures of exposure to estimate crash risk. Area-wide measures of crash risk are useful for comparing places or assessing trends, while location specific measures area more useful for planning interventions and or assessing the need for or effectiveness of countermeasures. For example, Brude and Larsson (2000) and Hels and Orozova-Bekkevold (2007) use the number of crashes per bicyclist (i.e., a traffic flow measure) to examine the safety impacts of roundabouts in Sweden and Denmark, respectively.

Despite use of different measures of exposure, some consistent outcomes have been reported. A number of studies have examined the relationship between vehicle and bicycle volumes and crash frequencies. Jacobsen (2003) found that safety for bicyclists and pedestrians may increase when numbers of bicyclists and pedestrians increase. Elvik (2009) summarized relevant studies and reported a non-linear relationship between both bicycle and vehicle volumes and crash frequencies. This non-linear relationship between bicycle volume and crashes is sometimes referred to as the “safety in numbers” effect: the likelihood an individual cyclist will experience a crash is hypothesized to decrease when the bicycle volumes increase. Elvik (2013) noted that both safety in numbers and “hazard in numbers” (i.e., when the in accidents is more than the proportionate increase in numbers) and demonstrated that the use of rates in assessing safety in numbers may results in spurious results that are statistical artficats of the modeling approach.

A number of crash studies have investigated the impacts of factors on bicycling crash outcomes (Table 2.1). Consistent with measures of exposure, these studies usually fall into one of two broad categories based on the unit of analysis. One type referred to as macro-level analyses are undertaken at broad geographic levels such as census tracts (9) or TAZs (Siddiqui et al., 2012; Wei & Lovegrove., 2013). The second type is at disaggregated level such as intersections or corridors (Siddiqui et al., 2012; Strauss et al., 2013). The dependent variable in bicycle crash models typically is some measure or index of crash frequency (e.g., Siddiqui et al., 2012), crash probability, or injury severity (e.g., Kim et al., 2007).

Table 2.1 Selected Studies on Cycling Crashes

Author	Analysis Units	Exposure to Risk	Dependent Variables	Explanatory Variables
Chen, 2015	TAZ	Daytime population density, retail density, and bicycle trip density to account for vehicular and bicyclist traffic exposures.	Number of crashes	Higher signalized intersection density is associated with more bicycle crashes. Furthermore, a positive association between the density of street parking signs and bicycle crash occurrences is also confirmed by this study; land-use mix, speed limit
Daniels et al., 2009	Roundabouts	No	Number of crashes	The presence and the types of cycle facilities, the number of lanes at the roundabout, the presence of lines or barriers between the roundabout and the cycle facility (in case of cycle lanes), the priority rules for bicyclists (in case of separate cycle paths), and the pavement color.
Gladhill K and Monsere., 2012	0.1 mi-grid	Volume to Capacity ratio on some roadways, VMT; Schools	Number of crashes	Business density, population, and transit stops
Jillian Strauss., 2013	Signalized intersections	Bicycling flows, vehicles flows	Number of crash	Presence of raised median; crosswalk length; presence of bus stops
Park et al., 2015	Street-segment		Number of crashes	Number of lanes, AADT per lane, median width, bike lane width, and lane width, population density
Scheper et al, 2011	Un-signalized priority intersection	Volumes of daily cyclist and motor vehicle volumes	Total number of crashes per intersection	Road Factor: Markings at bicycling crossing, speed-reducing measures, visibility, bike facility, types of intersections
Siddiqui et al, 2012	Traffic Analysis Zone (TAZ)	Population density, and total employment; TAZ level	Number of crashes at TAZ	road segment length with speed limits, popden, hotel, median income; employment den; edu; parking cost; workers,
Vandenbulcke et al., 2013	Per location	Potential bicycle traffic index(census tract level); vehicle traffic volume	Crash probability	on-road tram tracks, bridges without cycling facility, complex intersections, proximity to shopping centers or garages, and busy van and truck traffic.
Wei & Lovegrove, 2012	Community level	Total lane kilometers, and bicycle lane kilometers	Number of crashes	Volume; bus stops; increase arterial-local intersection
Zahabi, 2011	Individual crash level	NA	Crash probability	Intersection occurrence; speed limit; transit access, popden, mixuse, park presence school.

Bicycle crashes usually result from the interactions of multiple factors: including exposure (i.e., road users such as vehicles and bicyclists), infrastructure characteristics, the built environment, and weather and temporal factors (Schepers, P et al., 2014). Researchers often have focused on subsets of these factors when modeling crashes. Examples of exposure measures include vehicle volume (Scheper et al., 2011), bicycle volume (Strauss et al., 2013; Scheper et al., 2011; Miranda-Moreno et al., 2011) and large vehicle volume (Vandenbulcke & Thomas., 2014).

Characteristics of transportation networks and the built environment included as independent variables in models include road geometry, street functional class, roadway design, traffic controls, street features, and land use and socio-demographic variables. Results have shown that bicycle crashes are influenced by speed limits (Siddiqui et al., 2012), parking entrances (Miranda-Moreno., et al., 2011), street lighting (Kim et al., 2007), number and width of traffic lanes (Park & Lord., 2007), and presence and types of bicycle facilities (Chen et al., 2012; Wei & Lovegrove., 2012)

Most bicycle crashes occur at intersections because of the intensive, complex interactions between bicyclists and vehicles (Miranda-Moreno et al., 2011; Strauss et al., 2013). The presence of raised medians (Strauss et al., 2013), crosswalk length, presence of bus stops (Wei & Lovegrove., 2012), and presence of roundabouts (Daniel et al., 2009) haven been shown to be positively correlated with bicycle crashes. Vandenbulcke et al. (Vandenbulcke et al., 2014) developed a complexity index for intersections and found that complex intersections have a higher likelihood of bicycle crashes.

With respect to the impacts of land use, Siddiqui et al. (2011) found that population and employment densities were positively related to crash frequency. In a different study, proportion of commercial land use and an index of land-use mix were positively associated with bicycle crash frequency and cyclist injury severity (Narayanamoorthy, S., et al., 2013). In an aggregate level analyses (Siddique et al., 2011; Wei & Lovegrove., 2012) found that intersection density also has a positive association with bicycle crashes.

These studies have greatly increased understanding of factors that influence the probability of crashes, but many have been limited by data limitations, especially limitations related to measures of exposure to risk. Use of exposures measures computed for large areas at the macro level (e.g., for cities (Robinson 2005)) limits the specificity of conclusions. Many disaggregate studies have been limited to a few intersections or segments and not entire networks because of the lack of availability of counts (e.g., Jonsson's (2005) scope was limited to locations (i.e., intersections, segments where manual counts were available). Additional research to develop methods for quantifying exposure and determining its relation to crash risk is warranted. Among other needs, researchers and practitioners need additional tools to estimate bicycle and pedestrian traffic volumes.

CHAPTER 3: MODELS OF BICYCLIST EXPOSURE TO RISK IN MINNEAPOLIS

In most cities in the United States, an obstacle to characterization of bicyclist crash risk on urban street networks is the lack of exposure data for the network. Although jurisdictions are beginning to implement city-wide bicycle monitoring networks that can be used to characterize bicycling traffic volumes, most cities lack counts or models to estimate exposure to risk. This chapter presents bicycle demand models estimated from manual counts of bicyclists in Minneapolis, Minnesota and illustrates how these models can be used to estimate peak hour bicycle traffic volumes for the road and street network in Minneapolis. An objective is to characterize bicycle traffic flows on network segments. A limitation of the method illustrated here is that it does not generate data that can be used to infer turning movements at intersections.

Direct or facility demand models for estimating traffic volumes are conceptually relatively simple. As noted in the literature review, these models involve correlating bicycle traffic counts with factors such as road network features, the presence of bicycle facilities, adjacent land use, and neighborhood socio-demographics that are believed to influence bicycle traffic volumes. Regression analyses are used to estimate the strength of correlations. After the regression equations are estimated for segments where counts have been taken, the equations then are used to estimate, or predict, traffic volumes for segments where counts have not been taken. The approach is not novel, but cases in which sufficient counts are available for estimating robust models that can then be used to characterize entire networks are rare.

Chapter 3 begins with descriptions of the bicycle counts used to estimate the demand models (Section 3.1) and the general approach used in modeling (Section 3.2). Section 3.3 is a summary of the independent variables used in the demand models. Section 3.4 presents the final models; validation results are presented in Section 3.5. The bicycle demand model then is used to estimate bicycle traffic on the Minneapolis street network (Section 3.6). Section 3.7 is a brief a summary, including discussion of the limitations of the models. The models and results were presented previously at the 2016 Annual Meeting of the Transportation Research Board and subsequently published in *Transportation Research Record* (Hankey et al. 2016).

3.1 BICYCLE COUNTS IN MINNEAPOLIS

We used a count dataset that is part of an ongoing effort by the City of Minneapolis Department of Public Works (DPW) and Transit for Livable Communities (TLC) to assess biking and walking in Minneapolis. DPW and TLC have been collecting volunteer-based counts since year-2007 (City of Minneapolis, 2014) following procedures adapted from protocols recommended by the National Bicycle and Pedestrian Documentation Project. The DPW procedures focus on collection of p.m. peak hour segment counts taken on Tuesdays, Wednesdays, or Thursdays in the fall, but counts at other times sometimes are taken. The DPW and TLC chose count sites for a variety of reasons including (1) to gauge long-term trends in traffic levels, (2) assess corridors of interest (i.e., compare pre- and post- counts following facility installation), and (3) to assess exposure to risk for particular segments or intersections. For more information on DPW and TLC methods for collecting counts see the DPW (City of Minneapolis, 2013).

We filtered for counts that were PM peak-period (4-6pm), conducted in the month of September, and had sufficient supplementary information to include in the dataset (i.e., latitude and longitude, bicycle counts, and information on presence of a bicycle facility). This process resulted in a count database of 954 separate observations at 471 locations. Table 3.1 gives descriptive statistics of the count database by year. As shown in Figure 3.1, counts tend to be concentrated in the area of Downtown, off-street trails and streets with bicycle facilities.

Table 3.1 Descriptive Statistics of PM Peak Bicycle Traffic Counts in Minneapolis

Year	N	Bicycle volume		% off-street trail	% on-street facility	Mean temp (°C)	Mean precip (cm)
		Mean (median)	IQR				
2007	51	85 (57)	20-132	18%	14%	19	0.5
2008	78	134 (86)	48-194	22%	13%	21	0.0
2009	155	121 (68)	34-154	21%	8%	27	0.0
2010	84	93 (60)	16-127	29%	13%	20	0.2
2011	132	81 (34)	18-93	20%	22%	19	0.0
2012	142	117 (52)	26-138	20%	33%	29	0.0
2013	145	130 (66)	38-166	32%	26%	27	0.0
2014	167	97 (44)	22-110	18%	31%	22	0.2
Total	954	109 (58)	26-136	22%	22%	24	0.1

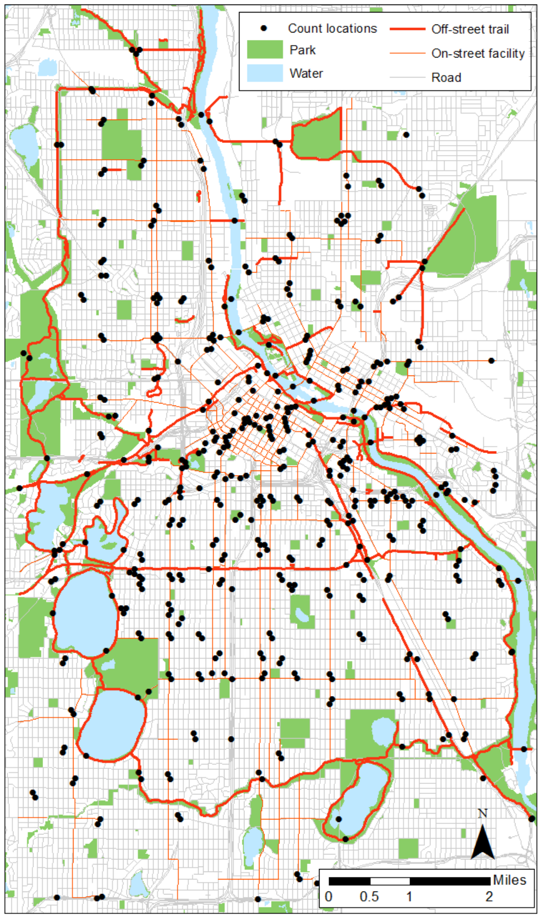


Figure 3.1 Count Locations in Minneapolis, MN

3.2 MODELING APPROACHES

A variety of approaches and methods are available for estimating facility or direct demand models. We use a log-linear, stepwise linear regression approach originally developed by Su et al. (2009) for urban air quality modeling. In this approach, independent variables are assembled at various buffer sizes and offered to the model for selection. Each variable is tested against the dependent variable (i.e., bicycling or pedestrian count) for strength of correlation. The independent variable most correlated with the dependent variable is selected, and the regression is run. Then, the independent variable most correlated with the model residuals is entered into the regression. This process repeats until either (1) the last entered variable is not significant in the model ($p > 0.05$) or (2) the Variance Inflation Factor (VIF) is greater than 5 (VIF is a check for multi-collinearity). Although negative binomial and Poisson models often are used to model count data, the log transformation of the counts helped to normalize their distribution. Because negative binomial models are more cumbersome to apply and our emphases are on practical applications, we chose not to pursue a step-wise, negative binomial approach.

A key advantage of this approach is that independent variables can be selected at different spatial scales; thus, we can assess whether certain aspects of the built environment have impacts at large or small spatial scales. Additionally, by including only variables that are statistically significant (and do not have issues with multi-collinearity), we develop more parsimonious models while maintaining predictive power. A disadvantage of the step-wise approach is that it is not necessarily theory-driven. That is, the approach can result in inclusion of variables that are counter-intuitive or inconsistent with theory, complicating interpretation for policy-makers and limiting potential for transferability.

To illustrate the implications of this aspect of the step-wise approach, we developed three sets of models (1) statistically optimal models (i.e., allowing for all variables to be selected in the model if they demonstrate sufficient correlation with the counts), (2) core models (i.e., we supervised variable selection to create reduced-form models that followed a priori assumptions consistent with theory) and (3) time-averaged models (where average counts were tabulated at locations with 3 or more counts over the sampling period).

3.3 CORRELATES OF BICYCLE TRAFFIC VOLUMES AND INDEPENDENT VARIABLE SELECTION

Based on results of previous studies in the literature, we assembled data for independent variables that have been shown to be correlated with bicycle traffic volumes (Table 3.2). Where potentially relevant, we calculated independent variables at varying spatial scales to allow them to be selected in the regression models at different scales. Specifically, we calculated network buffers around each count location (using Network Analyst in ArcGIS 10.1) at the following buffer sizes (in meters): 100, 200, 300, 400, 500, 750, 1000, 1250, 1500, 2000, 2500, 3000. These variables then were offered for selection into the facility-demand models using the stepwise linear regression process described.

We included spatial information on land use based on the current files available from the Metropolitan Council (the regional governing body in the Minneapolis-St. Paul urban area; 34) and the year-2010 US Census. We also included time-resolved variables. Weather parameters (daily high temperature and amount of precipitation) were assembled for the day of each count. We calculated year-specific buffer variables for off-street trails and on-street bicycle facilities to match the year of each count. The number of bicycle facilities (especially on-street) in Minneapolis has grown significantly during the past 8 years. To account for these changes we created separate shape-files of on-street and off-street facilities for each of the 8 years; we then calculated the on-street and off-street variables (within each buffer) using the year each count was collected. By constructing our facility variables in this way we were able to account for changes in bicycle facilities over time, thus potentially reflecting the changes in traffic volumes associated with the installation of a facility.

Table 3.2 Independent Variables included in Bicycle Demand Models

Variable	Variable Type	Statistically Optimal	Core	Reduced-form
All Roads	Buffer	X		
Principal Arterials	Buffer	X		
Major Roads	Buffer	X	X	
Local Roads	Buffer	X		
Off-street Trail	Buffer	X	X	X
Off-street dummy	Dummy	X		
On-street facility	Buffer	X	X	X
On-street dummy	Dummy	X		
Intersection density	Buffer	X		
Transit Stops	Buffer	X		

Transit Routes	Buffer	X		
Retail area	Buffer	X	X	X
Industrial area	Buffer	X	X	X
Open Space area	Buffer	X	X	X
Employment Density	Point	X	X	X
Job Accessibility	Time-based buffer*	X	X	X
Population Density	Buffer	X	X	X
House Density	Buffer	X		
HH Income	Buffer	X	X	
Precipitation	Continuous	X	X	X
Temperature	Continuous	X	X	X
Year	Level	X		
Allow variable at multiple buffer lengths?		Yes	No	No

*time-based buffer: Job accessibility within different time thresholds, job accessibility within 5 min, 10 min, 15 min, 20 min, 25 min, 30 min, 35 min, 40 min, 45 min, 50 min, 55 min and 60 min walking

3.4 BICYCLE TRAFFIC DEMAND MODELS

Table 3.3 presents the statistically optimal, core, and time-averaged bicycle demand models for estimated from the count database. Comparison of models illustrates tradeoffs in explanatory associated with different modeling choices.

3.4.1 Statistically Optimal Model

The statistically optimal model included the most independent variables. This demand model included the largest number of variables (n=20; nearly all available variables) and 3 variables were selected at multiple buffer lengths. Overall, the statistically optimal model had modest goodness-of-fit (adj-R2 for the bicycle model: 0.58).

Independent variables did not always follow a priori assumptions. For example, housing density decreased and principal arterials increased bicycling traffic. Furthermore, when variables were selected at multiple buffer lengths the direction of the coefficients sometimes contradicted each other (e.g., open space area increased bicycling traffic at 100 meters but decreased traffic at 3,000 meters). Our dummy variables for facility type (e.g., off-street dummy, on-street dummy) were included relative to the base case of no facility. Though these variables potentially could be negatively correlated with each other, both were included because they could have independent effects on volumes and met criteria for minimizing multicollinearity. Despite these issues, many variables did follow expectations for direction of effect. However, the large number of variables included in the models makes estimating traffic volumes at many locations a resource-intensive task.

Table 3.3 Three Bicycle Traffic Demand Models for Minneapolis[a,b]

Variables	Statistically optimal	Core	Time-averaged
All Roads			
Principal Arterials	7.4E-05 (750)		
Major Roads			

Local Roads	-5.9E-05 (750)		
Off-street Trail	9.2E-04 (200) 5.6E-05 (2000)	2.1E-03 (200)	7.4E-04 (400)
Off-street dummy	0.28		
On-street facility	1.5E-03 (100)	2.0E-03 (100)	
On-street dummy	0.37		
Intersection density	-0.05 (100) -7.8E-04 (3000)		
Transit Stops	-1.6E-03 (1250)		
Transit Routes			
Retail area	2.9E-05 (100)	2.3E-05	
Industrial area	1.4E-07 (3000)	-4.2E-07 (1250)	-2.8E-07 (2500)
Open Space area	2.6E-05 (100) -2.3E-07 (3000)	1.8E-05 (200)	2.5E-05 (100)
Employment Density	0.13		
Job Accessibility		4.9E-06	6.2E-06
Population Density	3.2E-04 (1250)	1.1E-04 (1250)	
House Density	-4.0E-05 (200)		
HH Income	1.5E-05 (2500)		
Precipitation	-0.3	-0.28	
Temperature		1.9E-02	
Year	-0.06		
Intercept	2.28	1.87	3.2
Adjusted R^2	0.58	0.46	0.47

[a] Model coefficients with buffer sizes (in meters) in parentheses. All dependent variables were log-transformed.
[b] All Accessibility measures were for the 60 minute time-based buffer.

3.4.2 Core Model

To build our core model we supervised variable selection to (1) ensure variables had directions of effect consistent with theory and (2) generate reduced-form facility demand models. The core model for bicycling traffic included variables that represent traffic generators (e.g., job accessibility, population density), destinations (e.g., open space, retail area), aspects of the transportation network (i.e., off-street trails, on-street facilities), and weather parameters (i.e., temperature and precipitation). Interestingly, industrial area was also included as a detractor to bicycling traffic. These results highlight the importance of the spatial location of origins and destinations, buildout of the bicycling network, and the importance of weather.

A unique aspect of our modeling approach is that variables can be selected at different spatial scales. Most of the variables in the core models were selected at relatively small spatial scales (i.e., 100-400 meters). Industrial area, population density, and job accessibility were selected at relatively larger spatial scales (5000 Kilometers;; 60 minute travel time for accessibility); this perhaps indicates that these variables have a more regional impact on bicycling traffic. For bicycles, trails were selected at 200 meters, suggesting that bicycling volumes are relatively large on most trails (i.e., the 200 meter variable acts essentially like a dummy variable).

3.4.3 Time-Averaged Model

The bicycle time-averaged model included fewer variables than the core models (4 variables). Each of the variables in the time-averaged model also was included in the core models. For the bicycle model, the spatial scale of each variable was similar to the core models (the industrial area variable increased in spatial scale to 2,500 meters). Overall, model goodness-of-fit (as measured by adj-R2) was similar between the core and time-averaged model (the statistically optimal models demonstrated slightly higher adj-R2), although this metric may be difficult to use as a basis for comparison since the sample sizes were much smaller for the time-averaged models.

Variables that remained significant in the time-averaged model were related to the location of origins and destinations (job accessibility, population density, retail area), aspects of the transportation network (transit stops, off-street trails), recreational areas (open space area), and traffic detractors (industrial area). The selection of the open space variable may indicate the importance of recreational areas for generating bicycle traffic. The significance of the industrial area variable may be because these areas do not serve as destinations for bicyclists or because bicyclists prefer to avoid these areas.

3.5 VADLIATION OF BICYCLE DEMAND MODELS

We performed two model validation exercises for the reduced-form (core and time-averaged) models. We assessed internal validation of model performance by plotting observed counts vs. the model estimates. In general, these plots showed relatively similar scatter around best fit lines (as indicated by the similar R^2 values among models). Scatterplots for each model are shown in Figure 3.2. We also explored how selection of count locations impacted model performance by performing a Monte Carlo-based random hold-out analysis. In this analysis we compared the “test” dataset (the randomly selected 10% hold-out) and the “build” dataset (the remaining 90% of the data) using R^2 as a performance metric. In theory, if a model is robust to count location selection the validation R^2 (based on the test dataset) should be similar to the model building dataset. Figure 3.2 also shows the distribution of model R^2 for the build and test datasets for the 100 iterations of the hold out analysis for each model. In general, the core model validation R^2 values were very similar to the model building R^2; this suggests that the core models are robust to random selection of count locations and should be fairly reliable for extrapolation. The time-averaged models displayed a wide range of validation R^2 values across the various random selections suggesting that the time-averaged models are not robust to count location selection. This indicates that extrapolation estimates from the time-averaged models should be used with caution. This result is perhaps attributable to the limited number of locations (n=84) that were available for modeling in the time-averaged models.

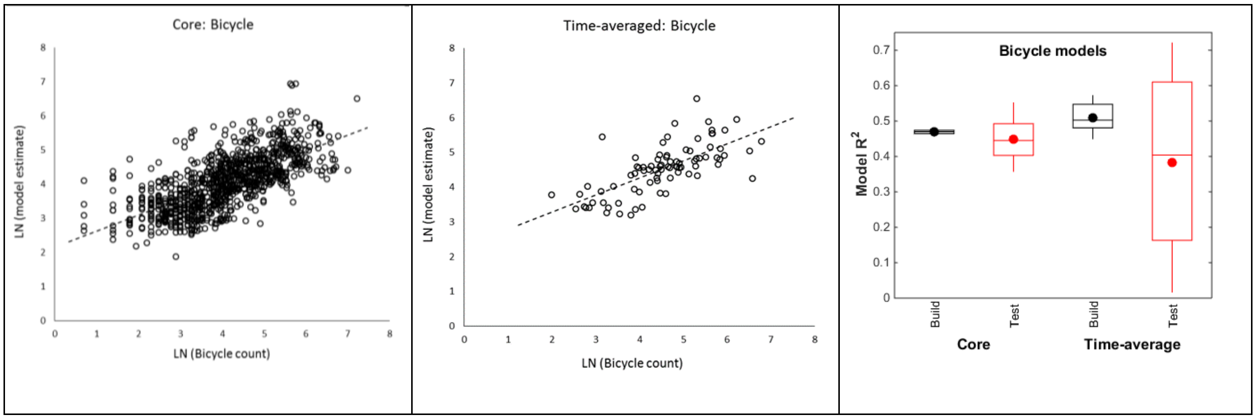


Figure 3.2 Summary of Model Validation Exercises: Scatterplots of Model Estimates vs. Observed Counts (two left panels); Results of Monte Carlo-based Random Hold-Out Analysis.

We tested for spatial autocorrelation among model residuals using Moran's I. Model residuals were distributed randomly for the time-averaged model (i.e., Moran's I was not statistically significant); however, the Moran's I index was significant ($p < 0.01$) and slightly positive for the core model (Moran's I index for bike: 0.15). These results suggest that there was slight spatial clustering of model residuals for the core model; future research should explore how developing count campaigns specifically for the purpose of spatial modeling can reduce the potential for spatial autocorrelation.

3.6 APPLYING THE MODELS: ESTIMATING BICYCLE TRAFFIC ON THE MINNEAPOLIS STREET SEGMENT

We next applied the core and time-averaged model and estimated peak-hour bicycle traffic volumes at the midpoint of each block for the entire transportation network (both streets and trails) in Minneapolis. This exercise resulted in 13,886 individual estimates of bicycle traffic (see Figure 3.3). The map reflects the relative importance of variables selected in each model. For example, peak-hour bicycle volumes clearly reflect the importance of off-street trails as well as activity generators such as population density and job accessibility. The fact that more variables were selected at larger buffer sizes in the time-averaged models is reflected in the spatial smoothing in the maps; likely, those estimates would be improved with better estimates of long-term averages of traffic (e.g., AADT) at more locations (i.e., better spatial density).

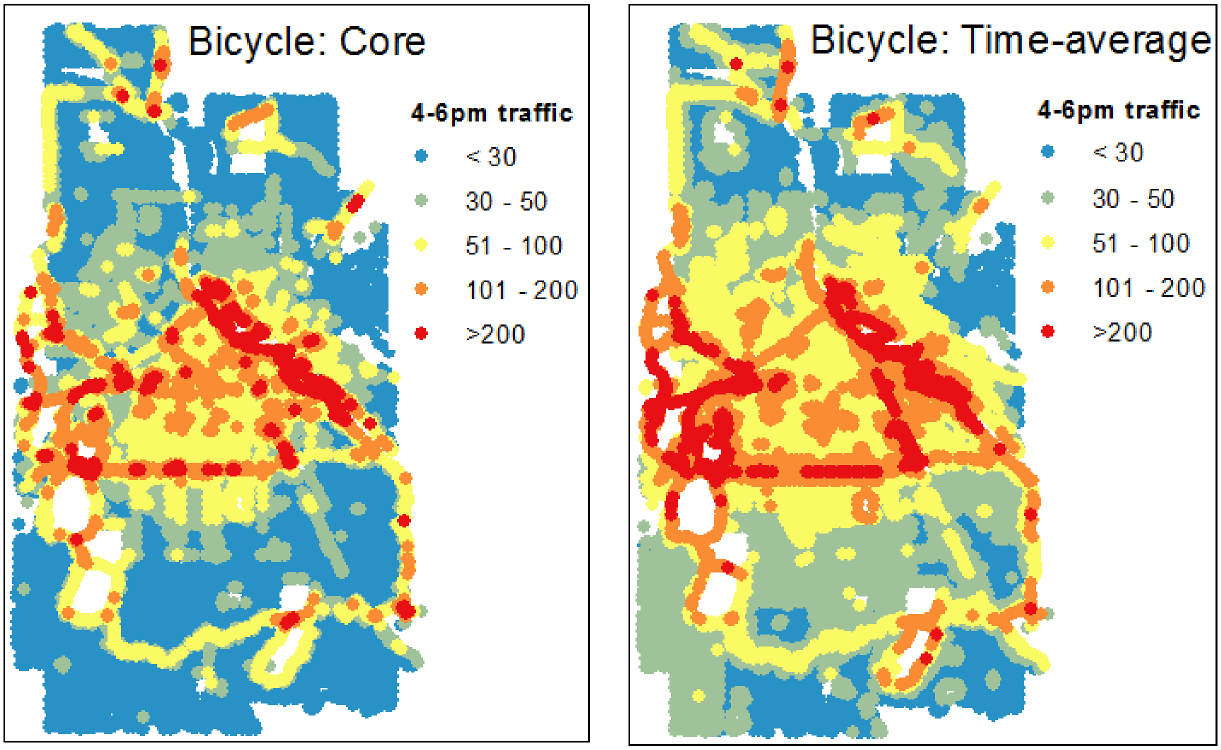


Figure 3.3 Spatial Estimates of Bicycle Traffic for the Core Model and Time-average Model

We developed three direct demand models of bicycle traffic using an 8-year sampling campaign of peak-period counts. Our dataset had good spatial coverage (471 locations or ~3 locations km-2) across the City of Minneapolis. Our dataset was limited by the fact that counts were collected only during peak-hours (4-6pm) on weekdays in the month of September. It is likely that patterns on weekends may be different. Our use of stepwise linear regression allowed for different spatial scales of predictor variables in the variable selection routine. Because of this approach, we were able to illustrate nuances of how the spatial scale of land use parameters impact traffic patterns. For example, we found that some variables (e.g., industrial area and population density) have the greatest impact at large spatial scales (i.e., >1 km), while other variables (e.g., bicycle facilities, retail area, open space) have impacts on smaller spatial scales (100-400 meters).

We compared statistically optimal models to reduced-form models (i.e., core and time-averaged) and explored how developing reduced-form models can be used to estimate traffic patterns across a city. The fully-specified models produced the best statistical fit, but model performance dropped only slightly in the reduced-form models. Furthermore, the reduced-form models were easier to interpret and included fewer variables, allowing for easier implementation in the field. In general, the time-averaged approach seemed to demonstrate more spatial smoothing than the models based on the full dataset.

We then applied the models to illustrate variation in bicycle traffic for the entire street network in Minneapolis. Specifically, we estimated block-level bicycle traffic volumes using the core and time-averaged models and mapped results. In the next chapter of this report, we demonstrate how these estimates of bicycle traffic can be used as estimates of exposure to risk and to assess crash risk.

CHAPTER 4: MODELS OF BICYCLIST CRASH RISK IN MINNEAPOLIS

Transportation planners and engineers need to understand the spatial magnitude and distribution of bicycle crash risk to develop comprehensive, systematic plans for reducing risk. However, the lack of exposure data in most cities has limited analyses of crash risk. In this chapter, we summarize bicycle crashes in Minneapolis and use the estimates of exposure to risk summarized in Chapter 3 to assess crash risk. Specifically, we develop estimate disaggregate models of crash risk. A challenge in modeling crash risk is that crashes are infrequent events. Although crashes may not have occurred at any given intersection or along any particular road segment, risk nonetheless exists. Our approach is a planning-level approach: we do not explore specific factors such as intersection turning movements or presence of traffic controls that may be associated with specific crashes at specific locations. The objective is more general: to identify an approach that can be used to characterize bicyclist risk across an urban road network.

Section 4.1 summarizes bicycle crash data in Minneapolis; crashes are separated into intersection-related and segment related crashes. We next use the exposure data (Chapter 3) to assess crash risk (Section 4.2) We use the crash data to develop a crash index for both intersections and street segments (Section 4.2.1). We then develop models of crash risk, using both exposure data and data for the built environment. (Section 4.2.2). We conclude this chapter with a discussion of the contributions and limitations of these models (Section 4.2.3). Some of these analyses and preliminary results were presented previously at the 2017 Annual Meeting of the Transportation Research Board (Wang et al. 2017).

4.1 BICYCLE CRASHES IN MINNEAPOLIS

We obtained crash data from Minnesota Department of Transportation (MnDOT). The crash dataset includes crashes from 2005 to 2014. The crash dataset includes 2,817 bicycle crashes (2,711 vehicle-related). We divided the original dataset into two parts, intersection-related and non-intersection related using a distance criterion of 10 meters. Engineers sometimes define intersection-related crashes using different criteria (e.g., 50 feet or where turn lanes begin). We used 10 meters, which is a fairly restrictive criterion, because this distance seemed to be consistent with other coding data in the MnDOT database. We identified and mapped specific intersections for each intersection-related crash and assigned non-intersection crashes to the nearest street segments.

Figure 4.1 is a map of the spatial distribution of these crashes. The distribution of crashes generally appears to be consistent with the distribution of bicycle traffic volumes (i.e., exposure) although few crashes appear to have occurred on urban trails with higher bicycle volumes. This outcome may be evidence that urban trails pose less risk than roads with or without bicycle facilities. However, reporting of crashes on trails may be understated because most locations on trails do not have specific addresses. High numbers of crashes occurred along several urban arterials in densely-populated neighborhoods (e.g., Franklin Ave., W. Lake Street, Hennepin Ave. and 4th St. Southeast).

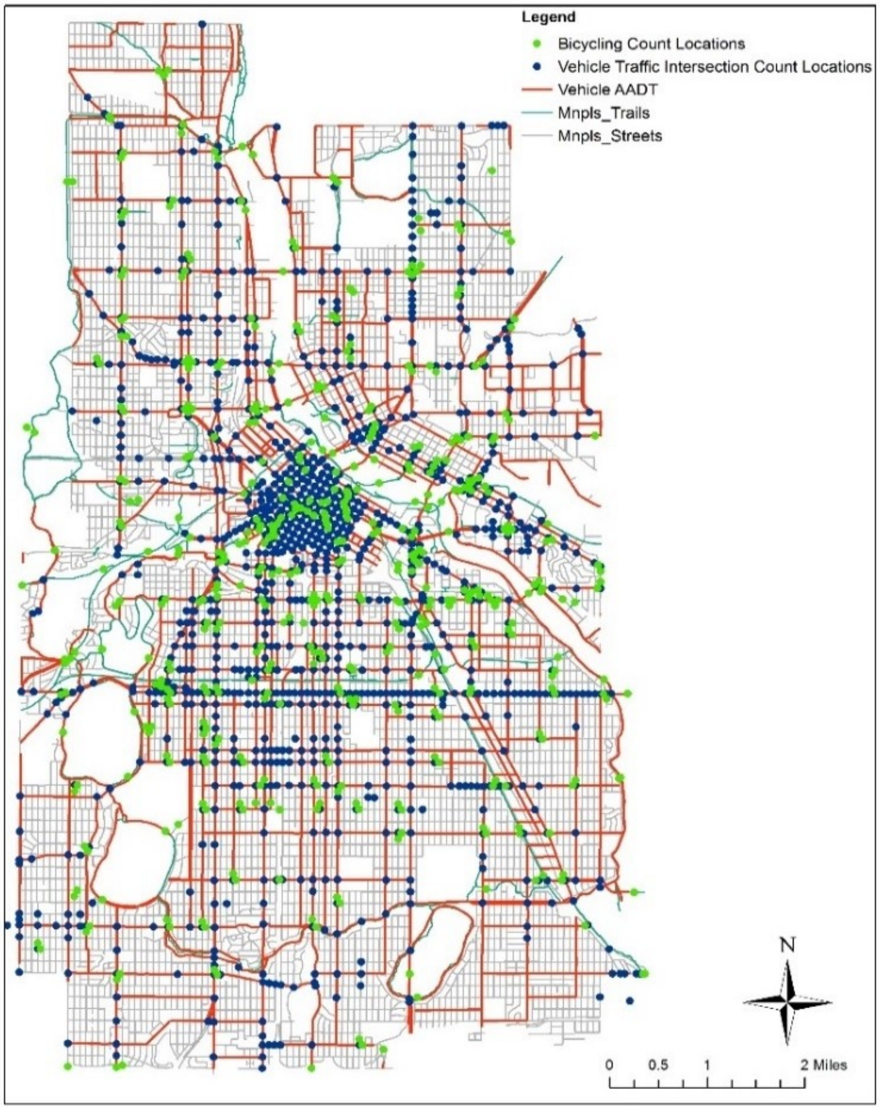


Figure 4.1 Bicycling and Vehicle Traffic in Minneapolis

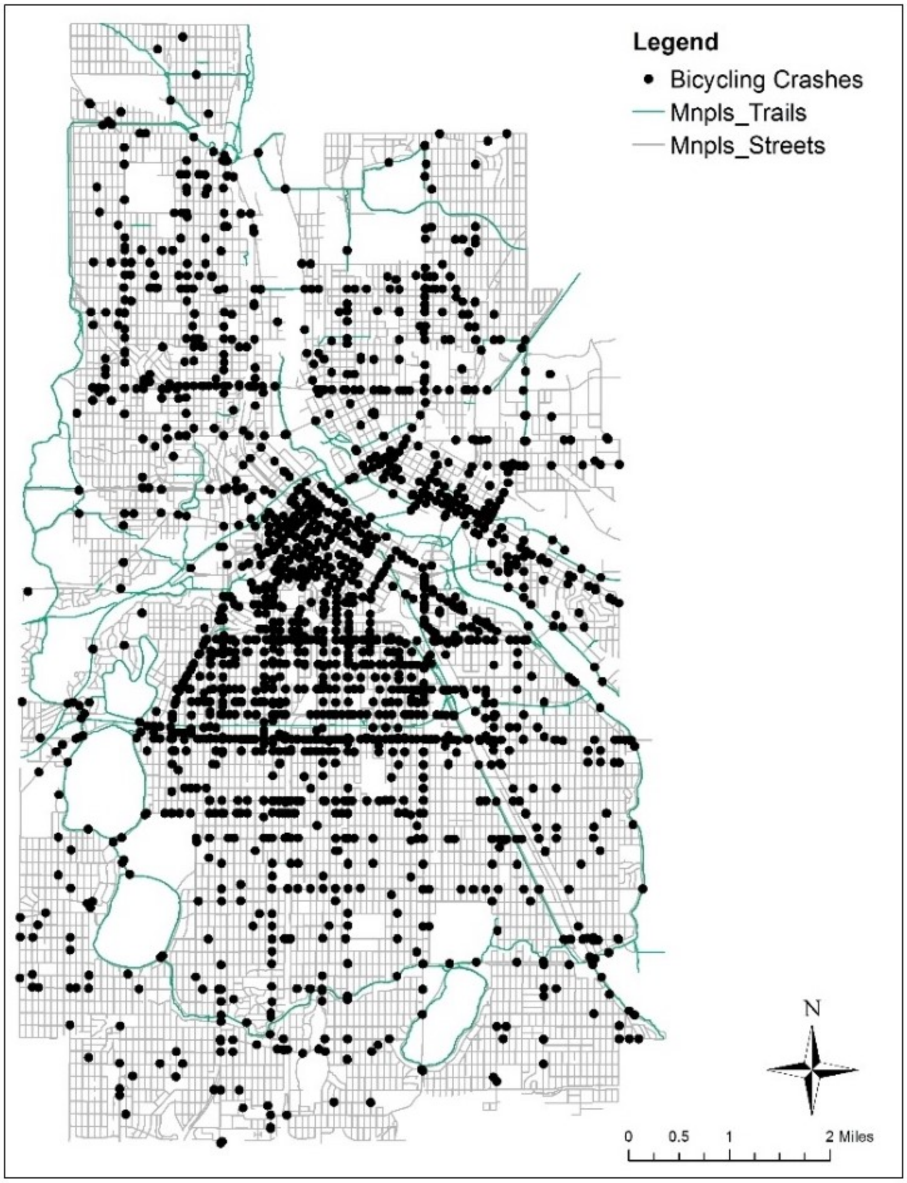


Figure 4.2 Bicycling Crashes in Minneapolis (2005- 2014)

Figures 4.3 and 4.4 provide additional, more detailed information about all bicycle crashes in Minneapolis. On average, the total number of crashes that has occurred annually has been slightly more than 280, with a high of 319 in 2012 and a low of 253 in 2006 (Figure 4.2). The total number of crashes per month over the 10-year period reflects the seasonality of the local climate: bicycle crashes peak in the summer months (July, August, and September) and are lowest in the winter months (December, January, and February). The number of bicycle crashes that occurred in August, for example, was more than 12 times the number of crashes that occurred in January. Most crashes occurred on Fridays and Saturdays, and most occurred between 3:00 p.m. and 6:00 p.m. The disproportionate numbers of crashes at these times on these days also may reflect exposure. Because of limitations of our exposure dataset, these time periods are not reflected in the analyses.

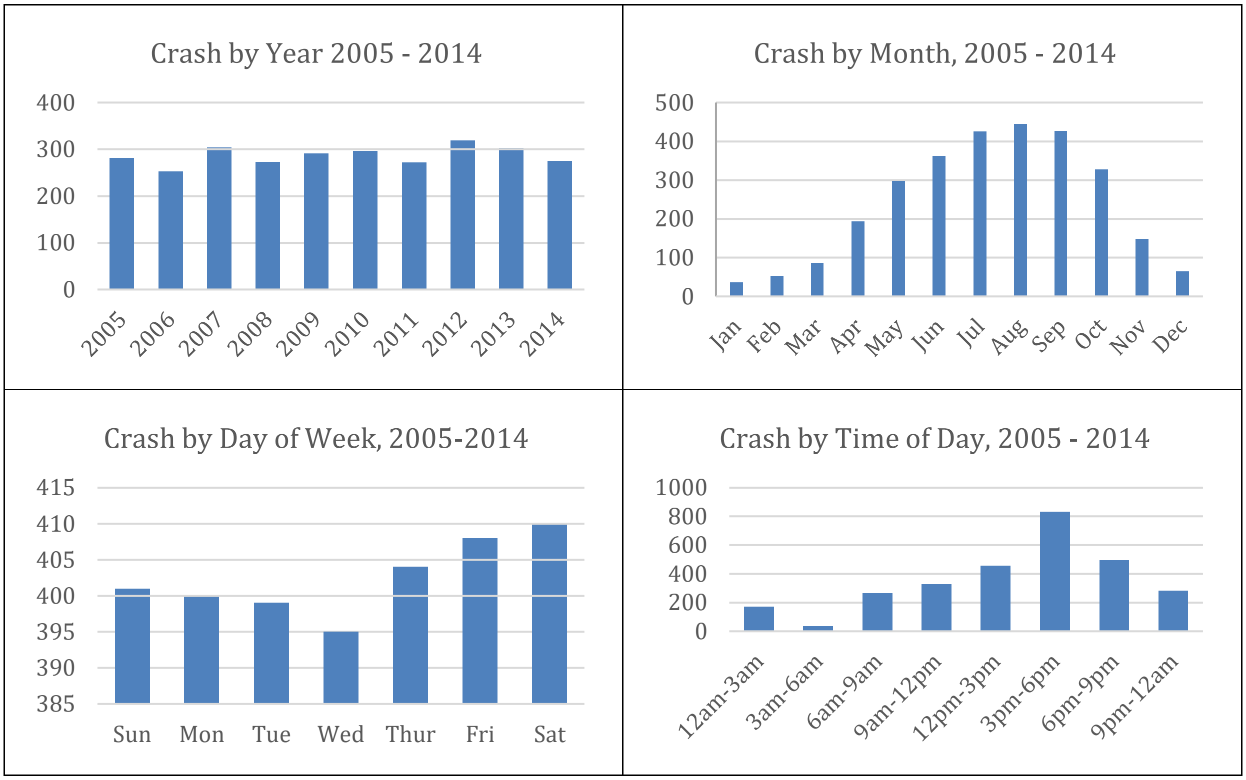


Figure 4.3 Temporal Variation in Bicycling Crashes in Minneapolis

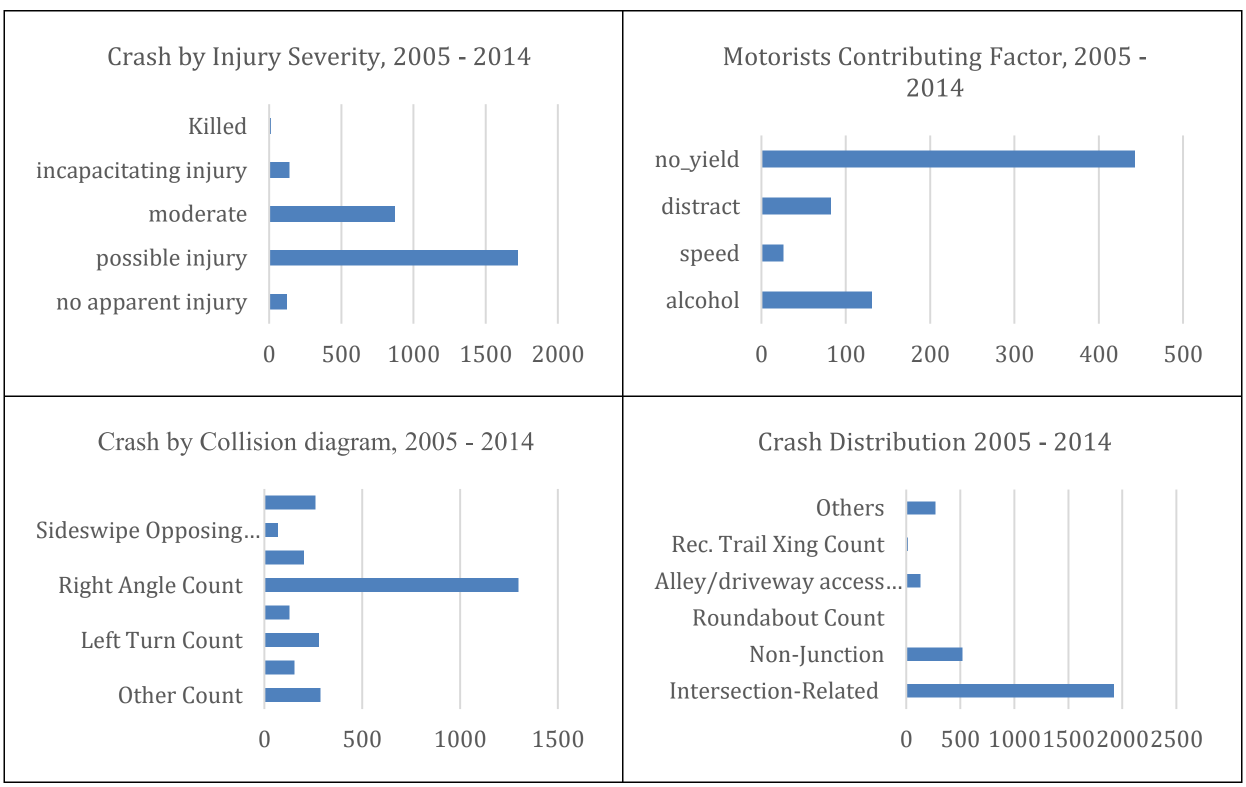


Figure 4.4 Bicycle Crashes in Minneapolis by Injury Severity, Contribution Factors & Location

Some bicycle crashes were associated with fatalities or incapacitating injuries, but most were associated with moderate or slight injuries (Figure 4.4). The most common factor contributing to crashes in which motorists were responsible was failure-to-yield. Alcohol was the second most common contributing factor of bicycle crashes caused by motorists. As noted previously, most crashes were intersection-related, and many were associated with conflicts with vehicles engaged in right-hand turning movement. Few crashes occurred at trail-roadway crossings. Many more males (1,978) than females (749) were involved in crashes, and most crashes involved people between the ages of 16 and 55.

4.2 ASSESSING CRASH RISK IN MINNEAPOLIS

Assessment of crash risk requires crash data and, depending on the analysis, estimates of vehicular exposure (i.e., annual average daily traffic; AADT), bicyclist exposure, or both. All three measures (i.e., crashes, vehicular exposure, and bicyclist exposure) are not available for all locations of interest, so we use a restricted crash dataset for modeling and assessment. Table 4.1 summarizes the crashes used to assess crash risk by year and location (i.e., intersection and segment). This restricted dataset includes 1,666 crashes (63% of total crashes, 6% of crashes involved fatalities), 59% of which occurred at intersections. The average ratio of intersection to street segment crashes in this dataset is 1.4.

Table 4.1 Bicycle Crashes Per Year in Minneapolis Analyzed in the Study.

Year	Crashes At Intersections	Crashes Along Street Segments	Crashes under analysis	Total # of Crashes	Ratio of Intersection to Street Segment Crashes
2005	93	79	172	273	1.2
2006	108	41	149	250	2.6
2007	95	85	180	303	1.1
2008	79	58	137	271	1.4
2009	100	69	169	283	1.4
2010	101	55	156	290	1.8
2011	93	68	161	268	1.4
2012	118	72	190	313	1.6
2013	95	86	181	300	1.1
2014	95	76	171	266	1.3
Total	977	689	1666	2817	1.4
Mean	97.7	68.9	166.6	281.7	--

Notes: 2711 vehicle-related bicycle crashes

We assess crash risk using both the manual peak hour counts of bicyclists completed by DPW (see Section 3.1, Figure 3.1) and our modeled estimates of exposure (see Section 3.2, Figure 3.3), and we assess risk for both segments and intersections. All DPW peak-hour counts were segment counts, and all modeled estimates of exposure were for street segments. To accomplish this, we followed slightly different procedures. When analyzing DPW counts directly, we estimated intersection traffic volumes by aggregating the counts for two, three or four legs as illustrated in Figure 4.5. To approximate the intersection volumes from modeled bicycle volumes, we added the modeled volumes for each leg and divided the total by two (because estimates for each leg of each intersection were available).

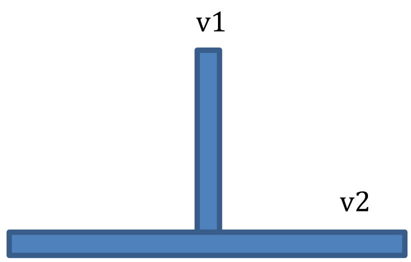
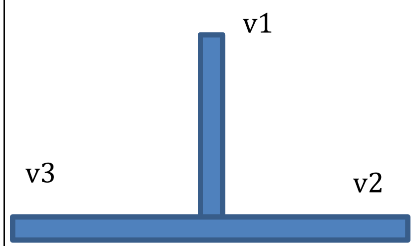
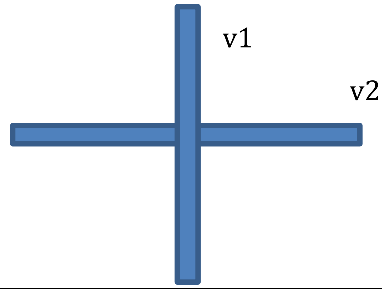
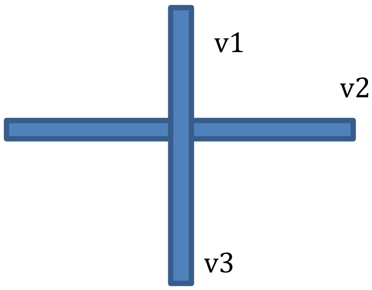
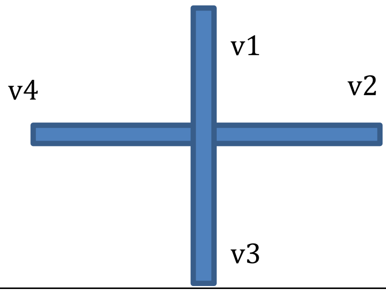
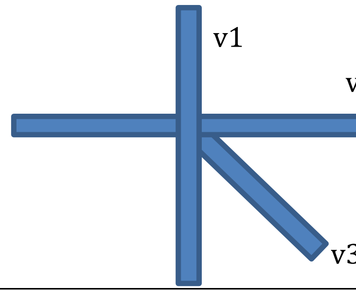
		
Intersection Volume=(v1/2+v2)	Intersection Volume=(v1+v2+v3)/2	Intersection Volume=(v1+v2)
		
Intersection Volume=(v1+v3)/2+v2	Intersection Volume=(v1+v2+v3+v4)/2	Intersection Volume=(v1+v2+v3)

Figure 4.5 Illustration of Obtaining Bicycling Volume for Intersections from Street-Segment Volumes.

We define bicycle crash risk *as the number of bicycle crashes occurring at an intersection or on a street segment between 2005 and 2014, divided by the number of bicyclists cycling through that intersection or segment during a weekday, two-hour peak p.m. period* (i.e., 4:00 – 6:00 p.m.). This measure, or index, of crash risk has a number of limitations. The time periods for the crash dataset and exposure dataset are not consistent, the estimates of exposure are static or time-invariant, and the exposure estimates may come from a single two-hour count. Nonetheless, this measure is useful because it has unusually large geographic scope for a disaggregate analysis and permits testing of hypotheses.

4.2.1 Modeling Bicycle Crash Risk

4.2.1.1 Modeling Approach

In studies of crash risk, crash models may be estimated using numbers of crashes, crash frequencies or rates, or binary or dummy variables in which a location is assigned a value of 1 if a crash has occurred, and a value of zero otherwise. Models that use dummy variables as dependent variables produce estimates of the likelihood of a crash, not estimates of the number of crashes predicted to occur. The choice among approaches depends on the data and the questions of interest. With respect to crash data used in this study, 7% of locations along street segments in the sample used for analysis had one crash, and 0.3% had two crashes, the maximum in any year. At intersections in the sample used for analysis, 22% had one crash in any given year; the maximum number of crashes per year at an intersection was 3 (Figure 4.6). We chose to model crash risk using the binary (dummy) variable approach because of the lack of variability in numbers of crashes at locations and because we think estimating the likelihood of a crash is more consistent with our overall interests and the limitations of our data than trying to estimate numbers of crashes (i.e., using actual crash frequencies). Therefore, in constructing our dependent variable, we assigned values of 1 if a crash occurred at a location in the specific year when the manual counts were conducted and available; we assigned 0 otherwise.

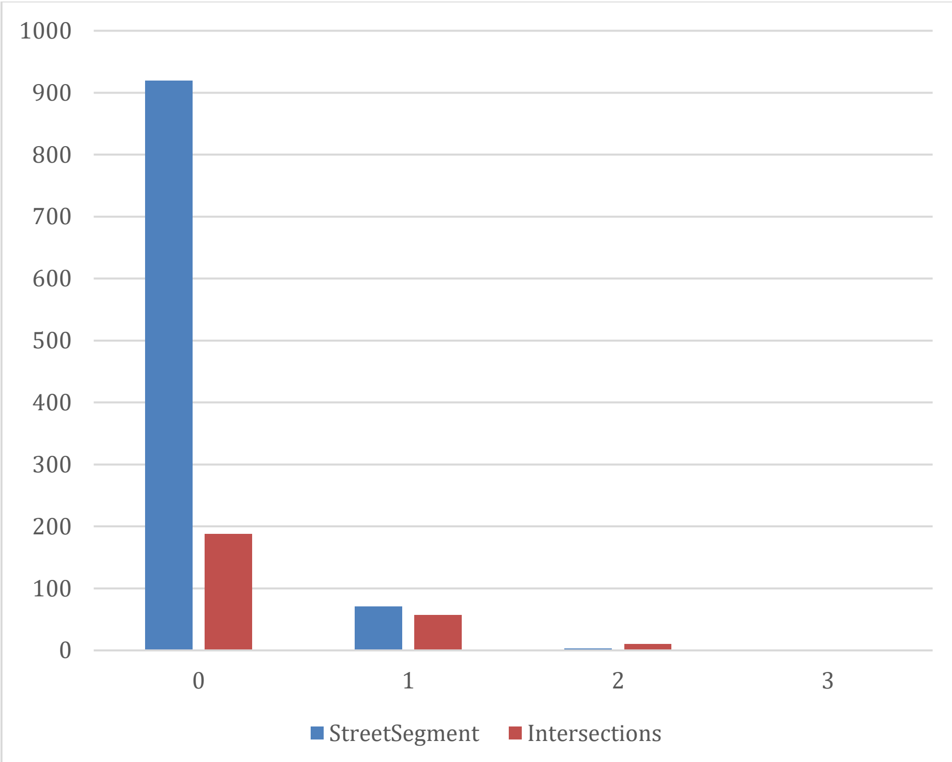


Figure 4.6 Numbers of Street Segments and Intersections by Number of Crashes from 2005 to 2014

A common approach to modeling binary dependent variables is to estimate a logistic regression model with maximum likelihood estimation (MLE). However, because crashes along a street segment or an intersection in any given year are rare events, small sample bias limits the applicability of MLE regression. Firth *(1993)* introduced a penalized MLE procedure into the binary model that can offset the bias involved in MLE. We adopt this penalized-likelihood approach to examine the impacts of explanatory variables on whether there is a bicycling crash or not. To confirm the advantages of the penalized likelihood approach, we estimated models for intersections and street segments using both standard logistic regression and Firth regression modeling procedures. We present only Firth models because diagnostics indicated better fit with the data. Specifically, the Firth models yield lower values for both AIC and BIC, and the standard error of parameter estimates generally were lower, indicating higher accuracy.

4.2.1.2 Correlates of Bicycle Crash Risk

Studies of crash risk have shown that correlates of bicycle crash risk include exposure (both vehicular and bicycle crash traffic volumes), infrastructure characteristics, the built environment or urban form, and weather and temporal variables (Chapter 2). Our focus in this report is on the relationship between crash risk and the measures of exposure described in Chapter 3 while controlling for vehicular exposure and other variables. A limitation of our analyses and models, as previously noted, is that they do not control for specific intersection characteristics or controls.

To estimate vehicular exposure to risk, we obtained 2013 street-segment estimates of annual average daily traffic (AADT) from the Minnesota Department of Transportation (MnDOT) and intersection-level vehicle PM peak-period (4-6PM) traffic from the Minneapolis DPW. Using data from Automatic Traffic Recorders, we calculated the average ratio between PM peak-period (4-6PM) and AADT and applied this ratio to the intersection-level vehicle PM peak-period (4-6PM) traffic counts to get the AADT for the intersections. Figure 4.1a (above) is a map that overlays locations of bicycle counts, the intersections where vehicular intersection counts were taken, and the segments for which estimates of vehicular AADT are available. Because of the limited geographic coverage of the vehicle counts, we had to drop 135 bicycle counts for 87 street segment locations and two modeled bicycle traffic estimates for one intersection from the datasets used to construct our crash probability model. We did not estimate the bicycle crash models on modeled estimates of bicyclist exposure because, for this analysis, we did not want to build the models on modeled data.

Built environment variables were assembled from publicly accessible databases using ArcGIS analysis (Table 4.2). We included population density, job density and job accessibility of all blocks where an intersection or street segment centroid is located. Job accessibility was obtained from the Accessibility Observatory (http://access.umn.edu/). We also incorporated a land use entropy index, the number of intersections, percentage of commercial, office, industrial and open spaces. The land use entropy index, which is used to measure the magnitude of land-use mix within an area, takes on values ranging from 0 to 1. This index was calculated using the following equation *(Frank et al., 2005)*.

$$Land\ Use\ Entropy\ Index = -\sum_{i=1}^{k} P^i Ln\left(P^i\right) \Big/ Ln(k)$$

P^i : the percentage of each land use type *i* in the area
k: the number of land use type *i*

These variables were extracted for two different geographical buffer zones: 100m and 400m Euclidean distance. The objective was to evaluate the impacts of these variables at different distances from the intersection or the street segments; 100-meter buffer is used to examine the impacts of immediate built environment on bicycle crashes while 400-meter buffer is for examining the impacts of macro-level built environment.

To control for presence of bicycle facilities that may affect the likelihood of crashes, we created bike facility dummy variables for intersections and street segments if bicycle infrastructure was present (or not) at the time of a crash. We also created a dummy variable indicating whether there was a trail crossing at an intersection at the time of a crash.

4.2.1.3 Model Estimation Results

Models of the probability of bicycle crashes at intersections and along street segments in Minneapolis are presented in Table 4.3. Both models are parsimonious: we removed independent variables that were insignificant at the 0.1 level. Both models have a large Wald chi-square statistic, indicating that the alternative hypothesis is accepted (i.e., that the probability of a crash is correlated with the independent variables in the model).

Table 4.2 Variable Definitions

Variables	Definition	Intersection Level		Street Segment Level	
		Mean	Standard Dev.	Mean	Standard Dev.
Number of crashes	Number of Crash in 10 years by locations	0.89	1.58	0.123	0.41
Crash Probability	1 if crash occurs at a location in the year count were taken	0.268	0.444	0.08	0.27
Peak hour bicycling Counts	PM peak hour (4-6PM) bicycling Counts	132	144	81	101
Vehicle AADT	Vehicle Average Annual Daily Traffic	25728	12666	10456	6359
Per Bicyclists Crash Risk	Number of Crashes in 10 years divided by PM Peak-Hour Bicycling Volume	0.01	0.019	0.002	0.009
Land Use Attributes					
Pop density	The number of persons per square meters of the block where an intersection or street segment centroid is located.	0.004	0.002	0.003	0.002
Job density	The number of jobs per square meters of the block where an intersection or street-segment centroid is located	0.009	0.023	0.01	0.02
Job accessibility (1000)	The number of jobs within 30-minute walk from the block where an intersection or street segment centroid is located. If the centroid is located at the boundaries of multi-block, add on all the number of jobs.	54	54	50	53
Number of intersection	The number of intersections within 400 meter buffer of an intersection or street segment centroid	27	7	26	9
Land use entropy (100m)	Land use entropy index within 100-meter buffer of an intersection or street segment centroid.	0.47	0.17	0.39	0.20
Land use entropy (400m)	Land use entropy index within 400-meter buffer of an intersection or street segment centroid.	0.667	0.173	0.61	0.16
% commercial (100m)	percentage of commercial land use within 100-meters of an intersection or street segment centroid	0.302	0.260	0.19	0.26
% commercial (400m)	percentage of commercial land use within 400-meters of an intersection or street segment centroid	0.159	0.143	0.13	0.15

Variables	Definition	Intersection Level		Street Segment Level	
% office (100m)	percentage of office land use within 100 meter buffer of an intersection or street segment centroid	0.019	0.076	0.01	0.05
% office (400m)	percentage of office land use within 400 meter buffer of an intersection or street segment centroid	0.023	0.043	0.01	0.04
% industrial(100m)	percentage of industrial land use within 100 meter buffer of an intersection or street segment centroid	0.073	0.205	0.07	0.19
% industrial(400m)	percentage of industrial land use within 400 meter buffer of an intersection or street segment centroid	0.069	0.144	0.08	0.15
% open spaces(100m)	percentage of open space within 100 meter buffer of an intersection or street segment centroid	0.039	0.104	0.14	0.19
% open spaces(400m)	percentage of open space within 400 meter buffer of an intersection or street segment centroid	0.080	0.103	0.16	0.31
Transit stop	1 if there is a transit stop within 15 meter buffer of an intersection or an street segment centroid	0.654	0.477		
Bike facility Variables					
Shared Bike Lane	1 if there is a shared bike lane on a street segment or it is a bike boulevard			0.04	0.19
Bike Lane	1 if there is a bike lane on a street segment			0.20	0.40
Trail	1 if it is on a trail segment			0.21	0.41
Intersection indicators	1 if either leg of an intersection or all legs has bike facilities	0.49	0.50		
Trail indicators	1 if a trailing crossing exists in an intersection	0.07	0.26		

Table 4.3 Firth Logistic Estimation Results

	Intersection Level Model (N=257)		Street Segment Level Model(N=873)	
Variables	Coefficient	P>Z	Coefficient	P>Z
Ln(Peak hour bike Counts)	0.375	0.073	0.718	0.0000
Ln(Vehicle AADT)	1.252	0.000	0.05	0.609
Land Use Attributes				
Job accessibility	0.002	0.088	0.001	0.619
Number of intersection	-0.052	0.058	-0.012	0.562
Land use entropy	0.663	0.515	2.402	0.002
% commercial	-0.369	0.592	1.346	0.007
Bike Facility Variables				
Shared bike lane			0.102	0.908
Bike Lane			-0.070	0.816
Trail			-3.969	0.020
Intersection indicators	-0.278	0.421		
Trail indicators	1.283	0.063		
constant	-14.094	0.0000	-6.76	0.0000
AIC		226.41		370.17
BIC		258.41		408.34
Wald Chi2 (7)		31.20		43.21
Prob>Chi2		0.0001		0.0000

The estimated results at intersections and along street segment in Minneapolis are summarized as following:

$$Y_1 = (0.375)x_1 + (1.252)x_2 + (0.002)x_3 - (0.0.052)x_4 + (0.663)x_5 - (0.369)x_6 - (0.278)x_7 + (1.283)x_8 - 14.09$$

$$Y_2 = (0.718)x_1 + (0.05)x_2 + (0.001)x_3 - (0.012)x_4 + (2.402)x_5 + (1.346)x_6 + (0.102)x_9 - (0.007)x_{10} - (0.3969)x_{11} - 6.76$$

Where:

- y_1: Crash Probability at intersections
- y_2: Crash Probability at street segments
- x_1: Natural logarithm of peak hour bike counts
- x_2: Natural logarithm of vehicle AADT
- x_3: Job accessibility via walking within 30 min
- x_4: Number of intersections within 400 meter buffer
- x_5: Land use entropy within 100 meter buffer
- x_6: percent of commercial land use within 100 meter buffer
- x_7: 1 if either leg of an intersection or all legs has bike facilities

x_8: 1 if a trailing crossing exists in an intersection
x_9: 1 if there is a shared bike lane on a street segment or it is a bike boulevard
x_{10}: 1 if there is a bike lane on a street segment
x_{11}: 1 if there is a trail on a street segment

Note: Firth logistic models only indicate correlation between variables the probability of a crash; they do not imply linear correlations.

As noted, the models include two measures of exposure: actual counts of bicycle traffic volumes and MnDOT/DPW estimates of AADT vehicular traffic volumes. Both measures of exposure are positively correlated with the probability of a bicycling crash occurrence. Both measures are statistically significant at intersections while the estimates of AADT vehicular traffic volumes are not statistically significant along street segments. The three bike facility variables in the street segment model may have absorbed partial effects of vehicle AADT as trails have zero AADT. However, the coefficients of the bicycling and vehicle exposure are different in the intersection and street segment models, indicating that traffic volumes have different magnitudes of effects on the probability of bicycle crashes at intersections and street segments. Vehicle traffic volume is more likely to have larger effect at intersections than along street segments, while bicycle volume is more likely to have a larger effect along street segments than at intersections.

Several land use variables are significantly correlated with the likelihood of a bicycle crash, but the effects are not consistent across the intersection and street segment variables for all model. These variables include job accessibility, number of intersections, land use entropy, and percentage of commercial land use. All the signs on the coefficients are in the expected directions. Job accessibility (i.e., the number of jobs by walking within 30 minutes), has a positive effect on the likelihood of a bicycle crash after controlling for bicycle and vehicular exposure. Job accessibility may be considered as a surrogate measures for exposure in a street network, which may explain the positive correlation. However, the effect is only significant in the intersection model, indicating that bicyclists tend to be more vulnerable at intersections.

A common measure of street connectivity is the number of intersections within a 400-meter buffer of an intersection or a street segment. Street connectivity is hypothesized to have a negative association with the probability of a bicycle crash, possibly because increases in connectivity provide cyclists increased opportunity to avoid locations perceived to be risky or dangerous. However, the correlation between the probability of crashes and street connectivity is significant only in the intersection model. This result is inconsistent with some prior research findings, which found positive relationships between bicycle crash frequency and intersection density/counts *(Siddiqui et al., 2012; Wei & Lovegrove et al., 2012*)

Land use entropy and percentage of commercial land use within a 100-meter buffer area of street segments are significantly and positively correlated with the probability of a crash. However, the correlation is insignificant in the intersection model. This difference in results may be because higher land-use mix and/or more commercial land use on street segments may increase conflicts bicyclists and other street users, thereby increasing the likelihood of crashes.

With respect to the presence of a bicycle facility (i.e., whether a facility is a separated bike lane or a shared bike lane or has no facilities), we found that after controlling exposure, there were no significant effects on bicycling crash occurrence in either of the two models. Trail segments is less likely to have crashes while intersections with a trail crossing were more likely to be associated with crash risk for bicyclists.

4.3 SUMMARY AND CONCLUSION

We used estimates of bicyclist and vehicle exposure to assess bicycle crash risk in Minneapolis. We estimated regression models of the likelihood of bicycle crashes at intersections and along street segments. We found that both bicyclist and vehicular exposure are significantly correlated with bicycle crash risk. This finding is consistent with previous studies (e.g. Strauss, J et al., 2013) and is more evidence of the importance of developing valid measures of exposure. We also found a number of additional built environment variables to be significantly correlated with bicyclist crash risk. Most results were consistent with theory and with previous findings. Street-connectivity, which was inversely correlated with crash risk in our models, has previously been shown to be both negatively and positively associated with crash risk. The inconsistent results may result from two off-setting forces. On one hand, higher street connectivity may slow down vehicle traffic, thereby reducing the probability of crashes. On the other hand, high intersection density may increase the interaction between bicyclists and vehicle traffic, increasing the probability of crashes. As noted, higher street connectivity also provides cyclists greater choice in route selection, thus providing opportunities for to avoid segments or intersections perceived as dangerous.

Limitations of our models are that we are working with incomplete measures of exposure and we are not controlling for site-specific intersection characteristics. None-the-less, we are able to identify correlates of crash risk that may be useful in planning level studies to characterize risk across urban road networks.

CHAPTER 5: EXPOSURE TO RISK AT TRAIL CROSSINGS IN MINNEAPOLIS

Transportation planners and engineers need estimates of exposure to risk and crash risk to assess the need for safety-related interventions, including the need for traffic controls at intersections. The specific type of information required depends on the purpose and level of the study. Exposure data may be sufficient in some circumstances; estimates of crash risk may be required in others. In some intersection specific analyses, exposure data are inputs to calculations.

Shared-use paths, or multiuse trails, are important elements of non-motorized transportation networks in many American cities. Although these networks are small relative to street and sidewalk networks, they often are popular among cyclists and pedestrians, and traffic volumes on them can be substantial. Local planners and engineers are working to reduce conflicts and increase safety at trail-road crossings.

Chapter 5 illustrates how exposure data for multi-use trails can be used as inputs to warrants for traffic controls at roadway-trail crossings in Minneapolis. Section 5.1 provides an overview of our approach. We summarize our results in Section 5.2. We conclude with a brief summary and discussion of findings and limitations. Some of these analyses and preliminary results were presented previously at the 2017 Annual Meeting of the Transportation Research Board (Lindsey et al. 2017).

5.1 APPROACH AND METHODS

Our approach involved:

- Assembling estimates of annual average daily trail traffic (AADTT) for the Minneapolis shared-use path network;
- Inventorying roadway-shared-use path intersections, roadway widths; existing traffic controls; and vehicular AADT;
- Factoring AADTT and AADT to match summertime peak-hour traffic volumes;
- Applying MUTCD warrants to assess the need for traffic signals and pedestrian hybrid beacons, and comparing results with existing controls.

5.1.1 Assembling Trail Traffic Volume Data

In a related project undertaken in 2013 in collaboration with the Minneapolis Park and Recreation Board (MPRB), the Minneapolis Department of Public Works (DPW), and the Minnesota Department of Transportation (MnDOT), members of the research team implemented a program to monitor trail traffic each mile of the city's 80-mile shared-use path network following procedures in the FHWA (2013) Traffic Monitoring Guide. The monitoring network included six permanent reference monitoring sites and 80 short-duration sample sites. All counts were taken with active infrared sensors. Because these sensors do not distinguish between bicyclists and pedestrians, all traffic measures are mixed-mode, or undifferentiated bicyclists and pedestrians. All short-duration counts were taken for at least seven days between April and October, and all counts were adjusted for occlusion. The monitoring results then were used to estimate AADTT for each segment using the day-of-year factoring method proposed by Hankey et al. (2014) and Nosal (2014). Monitoring methods, procedures for estimating AADTT, and results are presented in Hankey et al. (2014), Lindsey et al. (2015b), and Wang et al. (2016).

This research project used the estimates of AADTT produced previously as inputs to new analyses. Specifically, the estimates of AADTT are used to apply MUTCD warrants for traffic controls at trail-road intersections throughout Minneapolis. The idea is that comprehensive exposure data for particular networks can be used in planning-level studies to assess need for interventions and prioritize need for additional, site-specific study.

5.1.2 Inventorying Crossings, Roadway Characteristics, Traffic Signals, and Vehicular AADT

We next inventoried road crossings, roadway geometry, and existing traffic signals, and obtained estimates of motorized annual average daily traffic (AADT) for each street. We used geographic information systems (GIS) to identify 262 at-grade crossings between shared-use paths and other facilities. Of these crossings, 195 were between roads or streets and shared-use paths; 67 were alley-crossings, entrances to parking lots, or railroad tracks. Only the roadway-path intersections were included in the safety assessment. Complete information was not available for all locations, so only 184 crossings are included in the final analyses.

For each of the roadway-path intersections, we then determined or assembled:

- Crosswalk length. Lengths were obtained using Google Earth's measurement tool. Measurements were taken in a straight line from the middle of one curb cut to the other.
- Existing traffic signal. Google Earth (2015-16) was used to determine the presence of any type of existing traffic control, including stop signs, traffic signals, trail crossing signs, and crosswalk markings.
- Vehicular AADT. Most estimates were obtained from the 2013 Minnesota Department of Transportation (MnDOT) vehicular traffic volume databases. When a MnDOT AADT estimate was not available, either a MnDOT AADT estimate for a contiguous segment was held constant and extended a few blocks through the crossing, or a nearby MDPW point estimate located on the same street was used. If estimates were not available from either source (an outcome that occurred mainly on local roads), an AADT of 500 was applied in accordance with guidelines from the MDPW.
- Crossing type. Following Noyce (2013), we classified crossings as midblock, parallel path, or complex crossings. A midblock crossing occurs where a trail crosses a roadway at a distance greater than 100 feet from the nearest intersection. A parallel path crossing occurs where a trail runs alongside a roadway (i.e., parallels it) and later travels across another roadway in close proximity to an intersection. A complex crossing is a trail crossing that does not fall into either of the previous two classifications and has no pre-defined configuration. In many cases, complex crossings result as a consequence of a trail being near to or crossing an intersection with non-standard geometry (i.e., not a four-leg or "T"-intersection).

5.1.3 Factoring AADTT and AADT to Obtain Peak-Hour Traffic Volumes

Application of MUTCD warrants requires estimates of peak-hour vehicular and pedestrian traffic volumes. Standard safety analyses of vehicular traffic focus on weekday traffic. Monitoring of shared-use paths showed, however, that weekend traffic volumes generally were higher than weekday traffic volumes. In addition, non-motorized traffic on shared-use paths varies more seasonally than vehicular traffic, with much higher traffic volumes in summer. Therefore, to assess the need for signals when non-motorized volumes are highest, we estimated peak-hour traffic for weekend days in the summertime. We used standard factoring approaches to calculate and match summertime peak-hour shared-use path and roadway traffic volumes from the annual averages.

To determine peak-hour traffic on shared-use paths we:

- Calculated weekend-weekday average daily traffic ratios for each short duration sample site by adapting procedures developed by Miranda-Moreno et al. (2013). This procedure was possible only because each short-duration sample had a minimum of seven days, including weekend days.
- Determined annual average weekday and weekend average daily traffic volumes using each segment's AADTT and weekend-weekday traffic ratio.
- Reviewed short-duration monitoring results for each segment to determine the hour-of-day and the highest peak-hour percentage on both weekdays and weekend.
- Multiplied peak-hour percentages from each sample count and the weekday and weekend average daily traffic to obtain peak-hour volumes.
- Matched comparable path and vehicular peak-hour volumes for use in safety analyses.

This procedure was completed for summertime traffic volumes on the paths to account for seasonality of use. To obtain average summertime daily traffic on the shared-use paths, we created a summertime-annual ADT ratio by averaging the ratios of summertime ADT to AADTT for the six permanent reference sites. The resulting ratio (2.1) showed that summertime ADT on shared-use paths was slightly more than double AADTT.

We also classified monitoring sites into factor groups by adapting procedures outlined by Miranda-Moreno et al. (2013). This procedure involves determining, in addition to weekend-weekday traffic ratios, weekday a.m. to noon-hour traffic ratios and classification of each site as recreation, mixed-recreational, utilitarian, or mixed-utilitarian. This procedure increases understanding of variation in traffic patterns in the system.

To estimate vehicular summertime peak-hour traffic volumes, we used factors published in "AADT Adjustment Factors for Short Duration Weekday Traffic Volume Counts", a guidance document updated periodically by MnDOT (2014). We supplemented these factors with guidelines from other sources. This approach required that we match roadway vehicular traffic to factor groups. We assumed that all the roads intersecting with paths belonged to the groups titled "Moderately High Weekends" and/or "Moderately High Summer."

The next steps were comparable to those used to estimate peak-hour volumes on shared-use paths. We estimated weekend and weekday average daily traffic from the estimates of AADT, and then used standard assumptions about peak-hour volumes to match peak-hour path volumes. In the absence of site-specific data, MnDOT guidelines recommend assuming that peak-hour vehicular traffic volumes are 10% of AADT. MnDOT does not (Hallenbeck, 1997) publish values for weekend traffic. We assumed that peak-hour weekend traffic is 8% of daily traffic because traffic is more likely to be spread more evenly throughout the weekend days.

5.1.4 Applying MUTCD Warrants

The MUTCD presents warrants for traffic signals and PHBs that require three inputs: vehicular traffic per hour, pedestrian traffic per hour, and road width (see Figure 4C-7 Traffic Signal Warrant and 4F-1 Pedestrian Hybrid Beacon Warrant in USDOT 2009 (FHWA, 2009). The traffic signal warrant establishes 133 pedestrians per hour as the threshold for a signal, regardless of crossing width. The PHB warrant establishes 20 pedestrians per hour as a threshold; the combination of vehicles per hour and pedestrian per hour to warrant consideration of a PHB varies by crossing width. The MUTCD specifies that a warrant is not conclusive proof that a signal or PHB is needed; rather, it indicates that additional site-specific investigations are needed. We used these warrants for mixed-mode traffic counts because pedestrian-only counts are not available and because pedestrians and cyclists cross simultaneously on shared-use paths.

5.2 RESULTS OF APPLICATIONS OF MUTCD WARRANTS

Shared-use path monitoring results (Table 5.1) and roadway crossings are depicted in Figure 5.1. AADTT averaged 954, ranging over three orders of magnitude from nearly 40 to 3,728 (Lindsey, 2015a; Wang, 2016). The median AADTT was 750. As shown in the heat map, AADTT was highest on paths around recreational destinations, including lakes and along the Mississippi River in downtown Minneapolis, relatively high along paths used for commuting to the Minneapolis central business district, and lowest on paths through neighborhoods, especially in North Minneapolis, which is the location of low income, minority populations. Hankey et al. (2014) showed in simulation analyses that the magnitude of error in estimates of AADTT based on day-of-year factoring from 7-day samples during high-volume traffic months (e.g., April – October) may be between 10% and 15%.

Table 5.1 Shared-use Path Monitoring Results by Factor Group

Factor Group	Locations	Mean WWI	Mean AMI	AADT		
				Mean	Min	Max
Utilitarian	18	0.69	1.77	740	39	2,378
Recreational	31	1.35	0.74	1,247	40	3,728
Mixed-Utilitarian	10	0.82	0.73	664	57	3,480
Mixed-Recreational	21	1.70	1.42	843	62	2,052
All Monitoring Sites	80	NA	NA		39	3,728

Based on our criteria for establishing factor groups (Miranda-Moreno, 2013), a plurality of sites (39%) are recreational (Table 5.1). Approximately 26% are mixed-recreational, and an additional 12.5% are mixed-utilitarian. Nearly 23% are utilitarian and characterized by commuting-type traffic flows. Among these four factor groups, mean AADTT is highest at recreational sites, followed by mixed-recreational sites, and then commuting sites. All reference sites, which were established prior to short-duration monitoring, have mixed patterns.

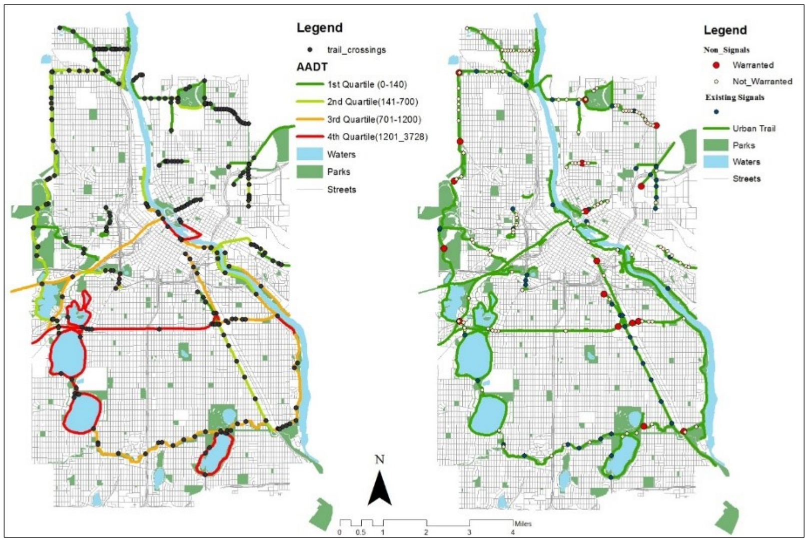


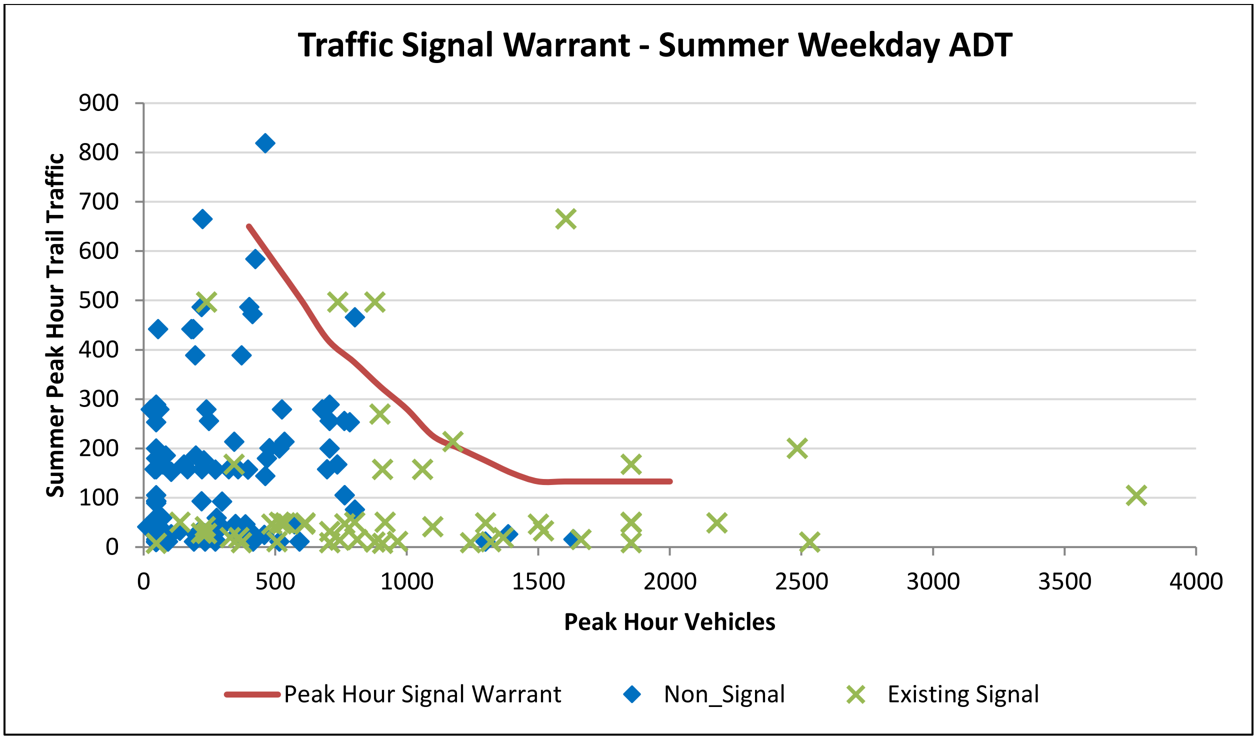
Figure 5.1 Minneapolis Trail Crossings, AADTT by Quartiles, and Crossings that meet Warrants

The locations of crossings reflect the location of shared-use paths within the city's street network. Across the city, there are relatively few crossings on shared-use paths around lakes and along the Mississippi River, and disproportionately more on local streets in residential neighborhoods. This fact affects the likelihood of the potential need for traffic controls: local streets generally have less traffic, and therefore are less likely to need controls.

The results of application of the MUTCD warrants are summarized in Table 5.2 and Figures 5.1, 5.2, and 5.3. Traffic volumes at most (> 93%) roadway-path crossings do not warrant traffic signals, irrespective of whether summertime weekday or weekend peak-hour traffic is considered. Nine crossings (5%) meet warrants for traffic signals based on weekday peak-hour volumes; 12 (6.5%) do so based on weekend traffic flows (Figure 2). Most of the crossings that meet the warrants already have signals. Of the 12 crossings that meet warrants based on weekend peak-hour flows, eight already have signals. Traffic signals may be needed at as many as four crossings.

Many more crossings meet the warrant requirements for PHBs: 25% based on weekend peak-hour traffic volumes and 22% based on weekday peak-hour volumes (Table 5.2, Figures 5.1, 5.3). Among these crossings, the wider the road, the more likely the warrant is met. For example, of the 36 crossings wider than 72 feet, 61% met the requirements of the warrant with summertime, weekend peak-hour traffic volumes; approximately 38% of the crossings between 51 and 72 feet met warrant requirements, while just 24% of crossings between 35 and 50 feet met them. None of the local roads less than 35 feet wide met requirements for PHB warrants. Of the 46 crossings that met requirements of PHB warrants, 63% already have some type of traffic control. As many as 17 crossings, however, may warrant additional investigations to determine if PHB beacons are needed. Several of these are located on the "Grand Rounds" – the flagship trail loop maintained by the Minneapolis Park and Recreation Board; others are along the Midtown Greenway, a rail-trail that runs east-west through the city (Figure 5.1).

The types of crossings the potential need for traffic controls by type are summarized in Table 5.3. The majority of crossings are parallel path crossings. Similarly, the majority of crossings (82%) that meet warrants for traffic controls are parallel path crossings.



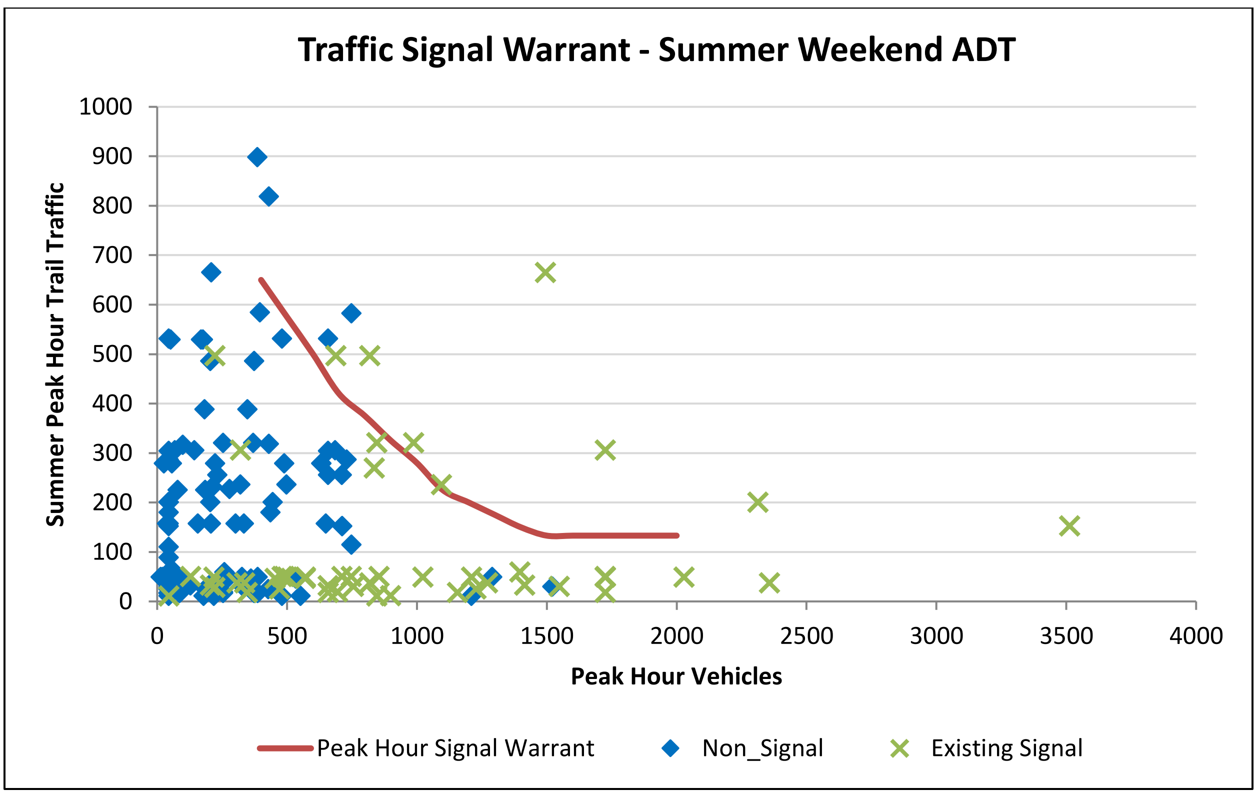


Figure 5.2 Weekday and Weekend Peak-hour Traffic Signal Warrant for All Trail-Crossing

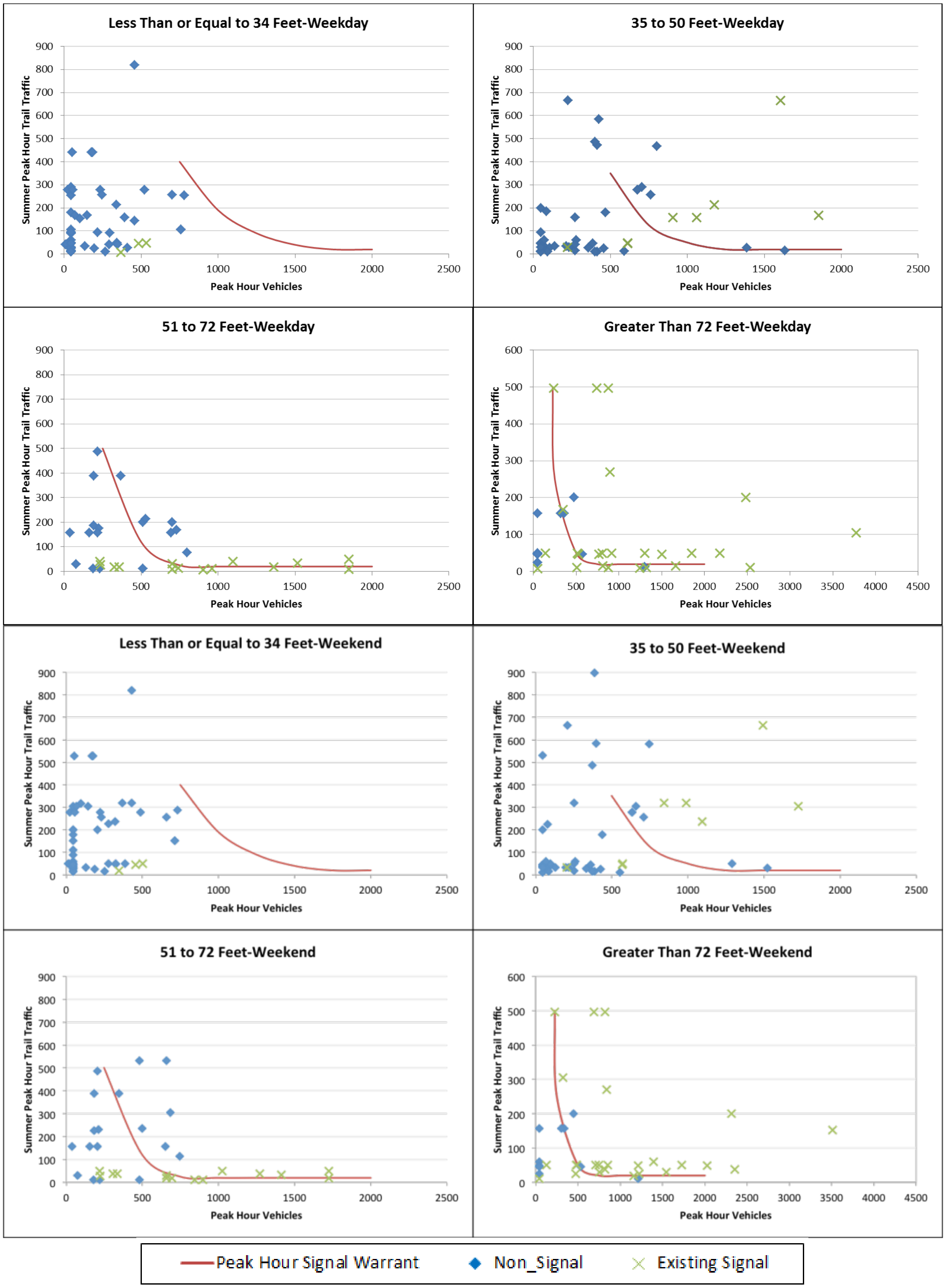


Figure 5.3 Weekend and Weekday PHB Warrants

Table 5.2 Results of Application Warrants for Traffic Signals and PHBs

		Traffic Signal Warrant		PHBs Signal Warrant			
			Total	Less than 35 Feet	35 - 50 Feet	51 - 72 Feet	Greater than 72 Feet
	N	184	184	67	49	32	36
Summer ADT Weekday	Exceed Warrant	9	41	0	11	11	19
	Existing Signal	7	25	0	5	4	16
	Warranted Signals	2	16	0	6	7	3
Summer ADT Weekend	Exceed Warrant	12	46	0	12	12	22
	Existing Signal	8	29	0	5	5	19
	Warranted Signals	4	17	0	7	7	3

Table 5.3 Crossing Categories for Locations Where Warrant is Exceeded and No Signal Exists

		Traffic Signal Warrant	PHBs Signal Warrant				
			total	Less than 35 Feet	35 - 50 Feet	51 - 72 Feet	Greater than 72 Feet
Summer ADT Weekday	N	2	16	0	6	7	3
	Parallel Path	1	13	0	6	4	3
	Midblock	1	2	0	0	2	0
	Complex	0	1	0	0	1	0
Summer ADT Weekend	n	4	17	0	7	7	3
	Parallel Path	2	14	0	7	4	3
	Midblock	1	2	0	0	2	0
	Complex	1	1	0	0	1	0

5.3 SUMMARY AND OBSERVATIONS

Using estimates of exposure developed previously through applications of monitoring procedures outlined in the FHWA's (2013) *Traffic Monitoring Guide*, we analyzed 184 at-grade roadway-path crossings. We found:

- Warrants for traffic controls for shared-use path crossings are more likely to be met using weekend peak-hour traffic flows.
- Traffic volumes at 7% of roadway-path crossings meet warrants for traffic signals.
- Traffic volumes at approximately 25% of crossings meet warrants for PHBs.
- The likelihood that a crossing meets a warrant for a PHB is associated with crossing width: the greater width, the more likely the warrant will be met.
- Eight of the 12 crossings that meet warrants for traffic signals already have signals.
- Approximately 63% of the 46 crossings that meet requirements for PHB warrants already have some type of traffic control.
- Additional investigations of the need for traffic controls may be warranted at as many as 17 crossings (9% of all crossing included in this analysis).

A particularly useful finding is that, for roadway-shared-use path crossings, warrants are more likely to be met on weekends than weekdays. This finding underscores the importance of monitoring non-motorized traffic on both weekends and weekdays, a practice which is not the norm for short-duration monitoring of motorized traffic, at least in Minnesota. Historically, many applications of warrants have been analyses of weekday traffic volumes because this is when vehicular traffic volumes are highest.

Our study has several limitations. Our measures are for mixed-mode traffic. The MUTCD warrants are for pedestrians. Cyclists travel faster than pedestrians at crossings, so, from this perspective, this study may overestimate the need for controls. This fact is one reason why, as specified in the MUTCD, meeting warrants is only one step in determining whether controls are needed. We applied the warrants with mixed-mode traffic because those were the only data available and one of our objectives was to illustrate how monitoring results can be used to characterize conditions and prioritize future investigations. Many jurisdictions use infrared sensors to monitor shared-use paths, so this is likely to be a common limitation and challenge. In the future, as monitoring of bicyclists and pedestrians separately becomes more cost-effective, this approach to applying warrants can be refined.

Another limitation that was unavoidable given the evolution of the monitoring network in Minneapolis is that all six permanent reference sites are characterized by mixed traffic patterns. These monitoring sites were established prior to the short-duration monitoring because program managers were interested in traffic flows at these sites, not because they represented the range of traffic patterns that might exist on shared-use path network. One of the objectives of the short-duration monitoring was to determine if other factor groups exist, which the results showed clearly. The fact that all permanent reference sites have mixed traffic flows means that estimates of AADTT at utilitarian and recreational traffic sites were based on factors from the "wrong" factor group. This procedure potentially introduces error into estimates of both AADTT and peak-hour traffic. In the future, this error could be minimized by establishing permanent monitoring stations at sites known to have utilitarian or recreational traffic patterns. Because this was a planning level study and not a design or site-specific engineering analyses, we think the error introduced by this procedure is acceptable.

The procedure we used to estimate peak-hour traffic volumes and to classify crossings by factor group also has limitations. Both procedures are based on samples of at least seven days. While the duration of these counts is long relative to sample counts taken in motorized traffic monitoring, we used them regardless of the weather during the week the sample was taken. Our use of day-of-year factors controls for weather indirectly in estimation of AADTT, but in these procedures, the implications are that our estimates peak-hour traffic or factor group classification could include error. For example, if for any particular week, the weekend was rainy and the weekdays were sunny, our ratio of weekend to weekday traffic may not be correct. This potential source of error could be addressed through replication of short-duration samples. Resource constraints precluded that in this study.

As already noted, we believe the range of error in our estimates of AADTT to be between 10% and 15%. We have not used this estimate of error directly in our application of the MUTCD warrants, partly because comparable estimates of error are not available for vehicular AADT. In addition, our objectives were to illustrate an approach and to identify crossings that warrant further investigation, not to make decisions about investments in controls. Future studies could use scenario analyses and vary inputs into the application of warrants. However, greater uncertainty is tolerable in planning analyses where assessments are made at the network level to prioritize further study. Our objective was to be inclusive, which, from the perspective of safety, is a conservative approach.

We believe the procedures we followed can be replicated in a straight-forward way by other jurisdictions. As noted, the Mid-Ohio Regional Planning Commission (MORPC), for example, already has replicated the monitoring approach used in Minneapolis and estimated AADTT on 67 segments of a 110-mile shared-use path network in Columbus, Ohio and two surrounding counties (2015b). Both Minneapolis and Columbus began with foundations of a few permanent monitoring stations using infrared monitors, and both completed studies with a part-time graduate students assuming responsibility for short-duration monitoring for periods of six months or less. MORPC has not, to our knowledge, used their monitoring results to assess the need for traffic controls, but data for doing now are available. Our point is that practitioners are adopting practices they find useful. Additional examples in which monitoring results are used to assess safety will lead to adoption of practices in additional communities that, in turn, lead to improvements in both monitoring and assessment of safety.

The choice to assess the need for traffic controls carries with it the possibility that the outcome will indicate the need for new public expenditures. In this case, analyses indicated that additional studies of the need for PHBs may be warranted at up to 17 crossings. The cost of a PHB ranges from $50,000 to $150,000 (Michigan Complete Streets Coalition, 2016) https://michigancompletestreets.wordpress.com/2013/11/26/pedestrian-hybrid-beacons-hawk-signals-explained/), and costs for traffic signals may be two to three times higher. Thus, a possible outcome of the study is that investments of $850,000 to $2.5 million in traffic controls may be warranted. These are significant amounts of money, especially in light of the demands on local government to address other priorities. Given the seriousness of the consequences of not addressing safety concerns and the financial costs of doing so, it is essential planners and engineers provide decision-makers solid evidence to inform decisions.

CHAPTER 6: MODELS OF EXPOSURE TO RISK AND CRASH RISK IN DULUTH

As noted in preceding chapters, transportation planners and engineers need estimates of bicyclist exposure to risk to assess crash risk. Local governments vary in terms of level of bicycle and vehicular exposure, infrastructure and the built environment, data available for assessing risk, and capacity to undertake safety analyses. In this chapter we adapt the approach and procedures used in Minneapolis to estimate exposure to risk (Chapter 3) and assess crash risk (Chapter 4) to develop models of exposure to risk and crash risk for Duluth, Minnesota. The procedures differ from those used in Minneapolis because of differences in the availability of data and because working in a different community provides an opportunity to test a different procedure for modeling exposure.

We begin with a description of bicycle counts in Duluth and our model of bicyclist exposure to risk that subsequently is used to assess exposure risk (Section 6.1). We then summarize available data about bicycle crashes in Duluth and present models of crash risk (Section 6.2). In Section 6.3, we summarize findings and discuss limitations.

6.1 BICYCLIST EXPOSURE TO RISK IN DULUTH

6.1.1 Bicycle Traffic Counts in Duluth

Duluth is a port city on Lake Superior in northern Minnesota with a population of approximately 86,000. Local planners in Duluth have counted bicycle traffic manually using procedures similar to those used by the Minneapolis DPW to characterize summertime peak hour bicycle traffic within the city limits. Between 2012 and 2016, the approach to counting bicycle has changed. In 2012 and 2013, observers (both staff and volunteers) completed intersection counts in which the numbers of bicyclists leaving the final intersection leg were counted. In 2014 and 2015, the counting procedure changed, and observers used the screen-line approach in which the numbers of bicyclists on segments or legs entering or leaving intersections were recorded. These segment counts included directional information. Most of the counts were conducted from 5:00 PM to 7:00 PM. In 2016, City of Duluth also employed the screen-line count approach, recording the number of bicyclists on street segments with directional information in the two-hour PM peak (4 PM - 6 PM).

We filtered the dataset for bicycle counts conducted during both the two-hour AM peak (7:00 AM to 9:00 AM) and two-hour PM peak (4: 00 PM to 6: 00 PM). Because of the differences in count blocks that were used historically, we did not follow strict rules about definitions of peak hours. For example, we used 6:30 AM to 8: 30 AM counts for some locations as the AM peak bicycle traffic volume. We extracted both AM and PM peak hour counts because of the approach used to model exposure (described below).

Overall, between 2012 and 2016, local planners and volunteers completed 85 counts of peak-hour traffic. Forty-seven (55%) of these counts were completed in 2016 with funding from this project in order to obtain a larger dataset that reflected a wider distribution of monitoring locations through the city. Of the 85 counts, 13 were intersection counts with directional data, and 72 count locations were screen-line counts on segments with directional data. In the models of exposure that follow, we use the directional information for each count location and do not aggregate into total counts (as was done in the Minneapolis analyses).

The count locations monitored between 2012 and 2015 were selected purposefully because of local interest in bicycle traffic on specific streets. As shown in Figure 6.1, the locations generally were located downtown, along the lakefront, or near the University of Minnesota Duluth. As a result, these locations mainly were higher-volume locations. To compensate for this bias, the approach used in 2016 to augment the dataset involved stratified, randomized sampling. The idea was to augment the dataset with counts from locations in areas of the city that had not been monitored and might have lower traffic volumes.

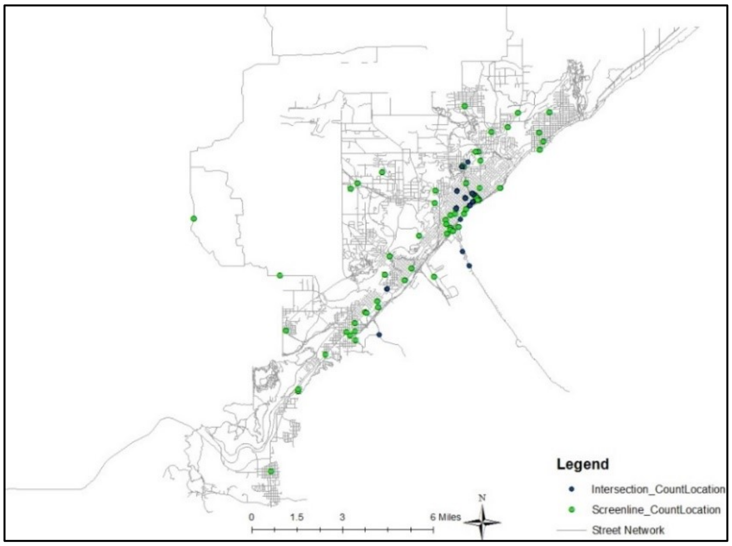


Figure 6.1 Bicycle Traffic Count Locations in Duluth, MN

We summarize mean and median peak hour bicycle counts taken in Duluth between 2012 and 2016 in Table 6.1. Overall, bicycle traffic volumes were modest. The maximum mean peak hour count was 47 in 2015. The most striking observation is the differences in volumes associated with differences in sampling procedures. As noted, the count locations monitored between 2012 and 2015 were purposefully selected because of local interest associated with a planning or engineering project or plan. In 2016, locations were selected randomly within strata specifically to obtain broader geographic coverage on lower volume streets. The mean and median traffic peak hour traffic counts in 2016 were 7 and 4, respectively. These volumes are substantially lower than the volumes at locations sampled in previous years.

Table 6.1 Descriptive Statistics of Peak Hour Bicycle Traffic Counts in Duluth

Year	Intersection Counts			Screen-line Counts		
	N	Mean(Median)		N	Mean(Median)	
		AM Peak	PM Peak		AM Peak	PM Peak
2012	5	23 (18)	27 (18)	-		
2013	8	16 (16)	32 (37)	6	8 (8)	26 (22)
2014	-			12	14 (10)	18 (17)
2015	-			7	32 (14)	47 (14)
2016	-			47	-	7 (4)

6.1.2 Modeling Bicyclist Exposure to Risk in Duluth Using Origin-Destination Centrality

As noted in previous chapters, direct or facility demand models are relatively simple, straightforward tools for estimating exposure to risk on street networks. Challenges to estimation and application of direct demand models includes small or spatially-biased samples of counts for estimation of models and selection or construction of independent variables that reflect the complexity of travel on networks, specifically, the complexity of travel between origins and destinations. To address this latter limitation, we develop and test another independent variable, the origin and destination (OD) centrality index. Use of this index begins to account for network factors analogous to those used in more complex choice modeling (McDaniel et al., 2014) and also enables us to account for information about bi-directional flows available in the count database.

6.1.2.1 Dependent Variable

Our dependent variable in the Duluth exposure model is the directional bicycle count. These counts are not normally distributed, so estimation using ordinary least squares (OLS) regression is inappropriate. Given the non-normal distribution of these count data, we have two options, a Poisson regression model or a negative binomial regression model. A limitation of Poisson regression models with count data is that count data frequently suffer from over-dispersion, which causes large standard errors and low p-values. The negative binomial model generally is preferred because it relaxes the assumption about equi-dispersion. Hankey et al. (2012) compared OLS and negative binomial models on bicycle and pedestrian networks in Minneapolis and showed that negative binomial models produced more accurate estimates of traffic volumes. Wang et al. (2013) reached similar conclusions when modeling mixed-mode traffic on an urban trail network in Minneapolis. We therefore model the counts using negative binomial regression.

6.1.2.2 Explanatory Variables

The OD Centrality Index. The OD centrality index is used to quantify travel patterns between origins and destinations. The logic underlying the index is intuitive: street segments are more likely to be used if they are part of the shortest path between more origins and destinations. In its simplest conception, the index is a frequency of the number of times a segment is on a shortest path between origins and destinations in a network of interest. Many features of transportation networks, however, complicate travel, causing people to deviate from shortest paths when traveling. In addition, the numbers of people originating at or arriving at all destinations are not equal. Accounting for these features (e.g., one-way streets, numbers of intersecting streets, different sizes of households or apartments on a parcel) complicates the development of OD centrality indices for road or street segments.

Analysts typically follow three major steps in calculation of OD centrality indices (Lowry et al, 2012). First, the paths preferred by individuals (in this case, bicyclists) traveling between origins and destinations are selected based on impedance factors. Second, OD pairs are selected based on decisions about reasonable distances individuals are willing to travel by bicycle. Third, multipliers, or weights, are applied to particular origins and destinations when calculating the OD centrality index to account for differences in numbers of individuals likely to depart from or arrive at particular locations.

Impedance factors are factors used to account for features of road segments in addition to length that may affect individuals' propensity to include the segment in a trip. Specifically, the preferred bicycle route between two points in a network is usually determined based on impedance factors. Two different types of impedance factors typically are considered in calculating an OD centrality index: the link impedance for travel through a street segment and the node impedance for travel through an intersection (Lowry et al, 2012). The link impedance is affected by various factors, including lengths of the street segments, existence of bike facilities, vehicle traffic volume, slope, etc. The node impedance is affected by the turn angles, the signal types, and the functional class of the cross street. In this study we use link impedance to define the impedance factors.

The selection of bicyclist OD pairs is complicated because OD pairs vary by time of day and other factors, including distance cyclists are willing to travel. Lowry (2012) observes that the median trip length for bicyclists in the National Household Travel Survey is five miles and recommend this distance be used as the maximum range for calculation of O-D pairs. Longer distances would allow more pairs; shorter distances would allow fewer. We followed this recommendation and constrained pairs to a maximum distance of five miles. To address time of day differences, we developed models to account for two-hour AM peak and PM peak bicycle volumes, respectively. Presumably, most of bicycling trips in the AM peak hours are likely to be from homes to workplaces. However, during the PM peak, bicyclists may come back to homes or to recreation destinations from their workplaces. To address these patterns, we calculated three types of OD centrality: Residential Parcel to Non-Residential Parcel Centrality (RN Centrality) for AM Peak bicycle traffic volume, Non-Residential to Residential Parcel Centrality (NR Centrality) and Non-Residential to Recreation Parcel Centrality (NRecreation Centrality) for PM Peak bicycle traffic volume. The land use parcel data required to estimate these pairs were obtained from the local planning department.

We also included multipliers of origins and destinations when calculating the OD centrality index. The multipliers are used to quantify the potential trips from origins (i.e., production) and trips to destinations (i.e., attractions). For example, a large shopping mall is more likely to attract trips than a small coffee shop. We used the population count as the multiplier for residential parcels, the number of jobs as the multiplier for non-residential parcels, and the number of recreational jobs (retail and entertainment jobs) as the multiplier for recreational parcels. The population and job data are available at the census block level, and were obtained from 2010 decennial survey and the 2013 Longitudinal Employer-Household Dynamics (LEHD), respectively. We used spatial overlay procedures to assign the number of jobs and population estimates at the block level to each land use parcel.

To obtain each of the three OD centrality indices, we used a calculation tool developed by Lowry (2012). The computed centrality values varied greatly, and their distribution was skewed (See Table 6.2). We therefore used the natural logarithm transformation to normalize the distribution of values for the OD centrality variable. We scaled the centrality index by normalizing them to their maximum value and then mapped them. The RN centrality and NR centrality (Figure 6.2A and B) take similar forms. The highest centrality values are concentrated in the multi-use trail segments closest to Lake Superior. However, the N-Recreation Centrality (Figure 6.2C) takes a different spatial form. This index had highest values along segments of the trail with adjacent commercial land uses those local roads that connect the commercial districts in North to the commercial areas in the downtown.

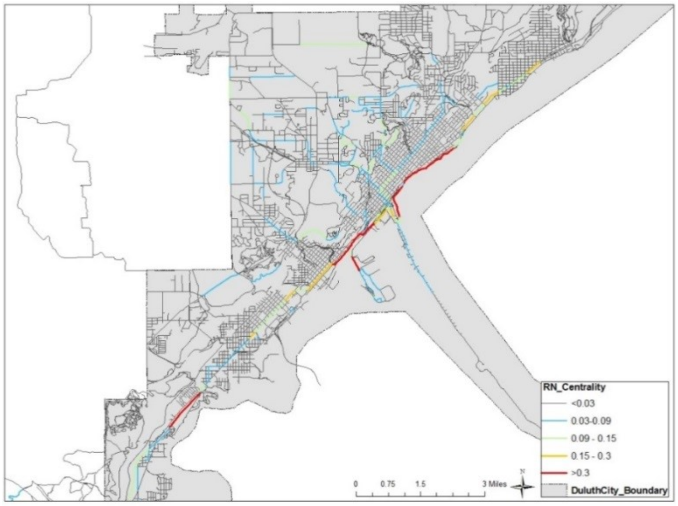


Figure 6-2A: Residential to Non-residential Centrality Index

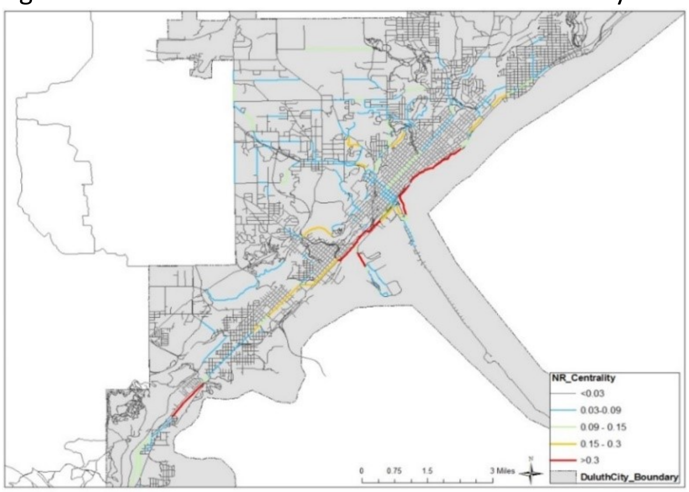


Figure 6-2B: Non-residential to Residential Centrality Index

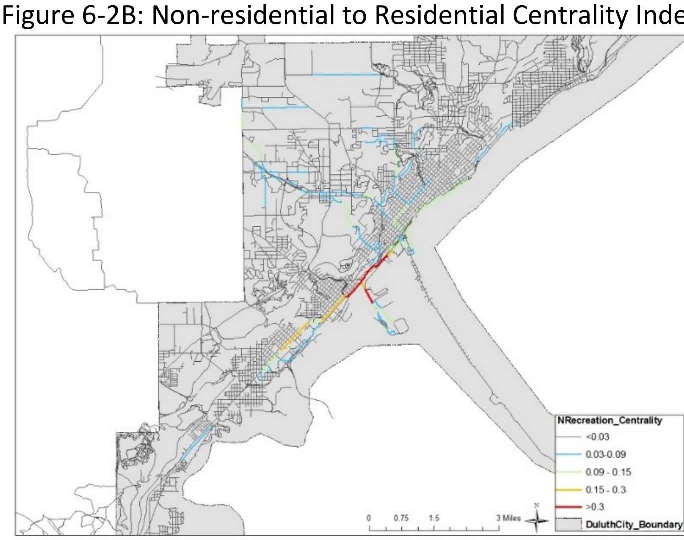


Figure 6-2C: Non-residential to Recreation Centrality Index

Figure 6.2 OD Centrality Index in Duluth

<u>Other explanatory variables</u>. We selected built environment and socio-demographic independent variables (Table 6.2) based on results reported in previous studies of factors that influence bicycle traffic volumes (Hankey et al., 2012; Wang et al 2016). To construct these variables and maximize the potential for replication of this modeling approach in other cities, we relied as much as possible on nationally-available datasets. Our models include four neighborhood socio-demographic variables: percentage of population that is white, percentage of population that is minority, percentage of population with high school degree or below, and median household income. We identified census block group identification number for the location of each count and extracted data from the American Community Survey (2013 Five-Year estimates). We obtained data to create built environment variables from the U.S. Environmental Protection Agency (EPA) 2010 Smart Location database. These variables, which were calculated for census block groups, were: Population Density (Pop density), Job Density (Job density), Employment Diversity Index (used as a proxy for land use diversity) (Table 6.2). Some street segments in Duluth with counts form the boundaries of block groups. For these segments, we considered all the block groups where the count locations were contiguous and computed mean values for further analysis.

Table 6.2 Descriptive Statistics for Explanatory Variables in Duluth Exposure Models

Variable	Description	Mean	Std. Dev.
Dependent Variables			
AM Bicycle	AM Peak Bicycle Volume	6	8.77
PM Bicycle	PM Peak Bicycle Volume	7	11
OD Centrality			
RN Centrality	Residential to NonResidential Centrality	24,355	50,201
NR Centrality	NonResidential to Residential Centrality	65,844	122,960
NRecreation	NonResidential to Recreation Centrality	2198	5535
Socio-Economic Variables			
%NonWhite	% of the Non-White	0.14	0.11
%High School	% of adults with degree below high school	0.075	0.06
Median Income	Median Income	33,342	20,735
Land Use Variables			
Pop density (person/acres)	Population Density	8.4	6.88
Job density (jobs/acres)	Job Density	13.6	19.98
Land use entropy	Employment entropy index based 8-tier classification scheme	0.43	0.24

Prior to estimating the demand models, we computed bivariate correlations between potential explanatory variables to identify potential for multi-collinearity. The correlation coefficients between types of OD centrality and AM and PM peak traffic (our dependent variables) are presented in Table 6.3. The OD centrality indexes are significantly correlated (P>0.000); we therefore incorporate only one OD centrality index into each model. The two-hour AM peak bicycle volume has a higher correlation coefficient is more significantly correlated with the RN centrality index. We therefore included the RN centrality index in our models of AM peak hour traffic. The correlation coefficient between two-hour PM peak bicycle volume and NR centrality is higher and has higher statistically significance, so we used NR centrality in PM peak-hour models. Similar checks of binary correlations for other variables resulted in exclusion of potential variables from the final models. As noted previously, because the dependent variables are count data, we used negative binomial regression.

Table 6.3 Binary Correlations between Bicycle Counts and OD Centrality Indexes in Duluth

	AM bicycle volume	PM bicycle volume	RN centrality	NR centrality
RN centrality	0.3203	0.1340		
	(0.0015)	(0.0737)		
NR centrality	0.0674	0.2326	0.4887	
	(0.5143)	(0.0017)	(0.0000)	
NRecreation	0.0081	-0.0144	0.8261	0.6658
	(0.9378)	(0.8484)	(0.0000)	(0.0000)

Notes: p value in the parentheses

6.1.2.3 Model Results

Demand models of AM and PM peak period bicycle traffic volumes (i.e., exposure) in Duluth are presented in Table 6.4. Both models have reasonable goodness of fit (Cox-Snell R2=0.40 for AM model and Cox-Snell R2=0.45 for PM model). The OD centrality indexes in each model are highly significant (p<0.005), indicating that they are highly correlated with observed variation in bicycle traffic volumes in Duluth. A more general practical interpretation is that those street segments on shortest paths between origins and destinations are more likely to be used by bicyclists. The implication is that planners and engineers can use this information about exposure when assessing safety.

Table 6.4 Models of Two-Hour AM & PM Peak Bicycle Volume (Directional Counts) at Street Segments in Duluth

	AM Peak Model (N=96)			PM Peak Model (N=179)		
	Coefficient	Std. Err.	P>z	Coefficient	Std. Err.	P>z
Log RN centrality	0.11	0.028	0.000**			
Log NR centrality				0.11	0.021	0.000**
% Nonwhite	-2.05	1.087	0.059*	-1.96	0.857	0.022**
% High	-9.51	3.76	0.011**	-11.38	1.927	0.000**
Median Income	0.01	0.007	1.29	0.005	0.005	0.355
Population density	0.05	0.021	0.014**	0.05	0.014	0.001**
Job density	0.024	0.007	0.000**	0.017	0.005	0.000**
Land use entropy	4.44	1.111	0.000**	4.05	0.461	0.000**
Constant	-1.45	0.668	0.030**	-0.667	0.439	0.129
Cox-Snell R2			0.40			0.45

Notes: ** significant at p<0.0; * significant at p<0.1

With respect to the socio-demographics of neighborhoods around count locations, measures of race and education are highly correlated with observed bicycle traffic volumes. Specifically, the percentages of non-white population and population with a high school degree or below have significant negative associations with both AM and PM peak bicycle volume. Median household income is not significantly correlated with observed bicycle traffic volumes in either the AM peak or PM peak model.

Consistent with previous findings in other studies, each of the built environment variables (i.e., population density, job density and land-use mix) is positively and significantly correlated with observed bicycle traffic volumes in both models. That is, bicycle volumes tend to be higher in areas with higher population and job densities and greater land-use mix.

To assess the predictive capability of the models, we used them to predict the AM and PM peak-hour traffic, respectively, and then plotted the predicted traffic volumes against the actual counts (Figure 6.3). The OLS regression line between the actual and predicted counts is an indicator of the validity of each model. The R2 values are measures of the strength of covariation between the predicted and actual counts. The AM peak hour model performs slightly better (R2 = 0.62) than the PM peak hour model (R2 = 0.44), but the results indicate that overall, each demand model has moderate predictive capacity.

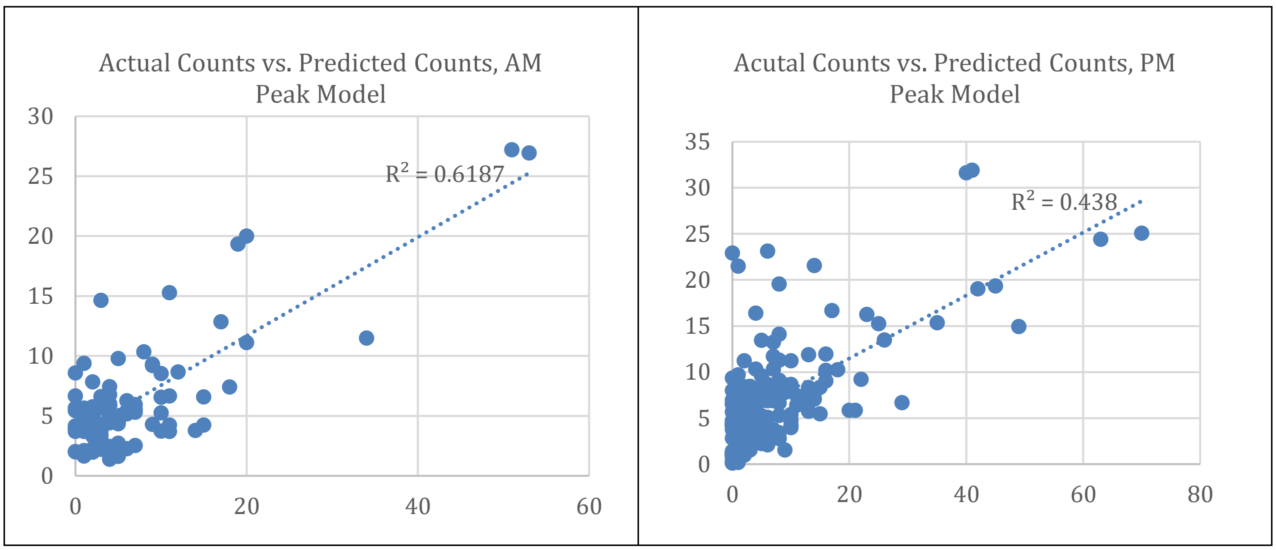


Figure 6.3 Scatterplots between Actual Counts and Predicted Counts

6.1.2.4 Estimated Bicycle Volumes in Duluth

We next used the models to estimate AM and PM peak hour bicycle traffic volumes for each direction of each segment in Duluth. To facilitate mapping and subsequent analyses, we then aggregated the unidirectional bicycle volume to the total AM and PM peak hour bicycle volume for each segment. Figure 6.4 presents heat maps of predicted volumes. As is evident in the maps, the predictive capacity of the models appears limited. Although corridors of highest use are along the lakefront and near University of Minnesota as expected, unexpectedly high estimates occur in some outlying areas in the northern sections of the city.

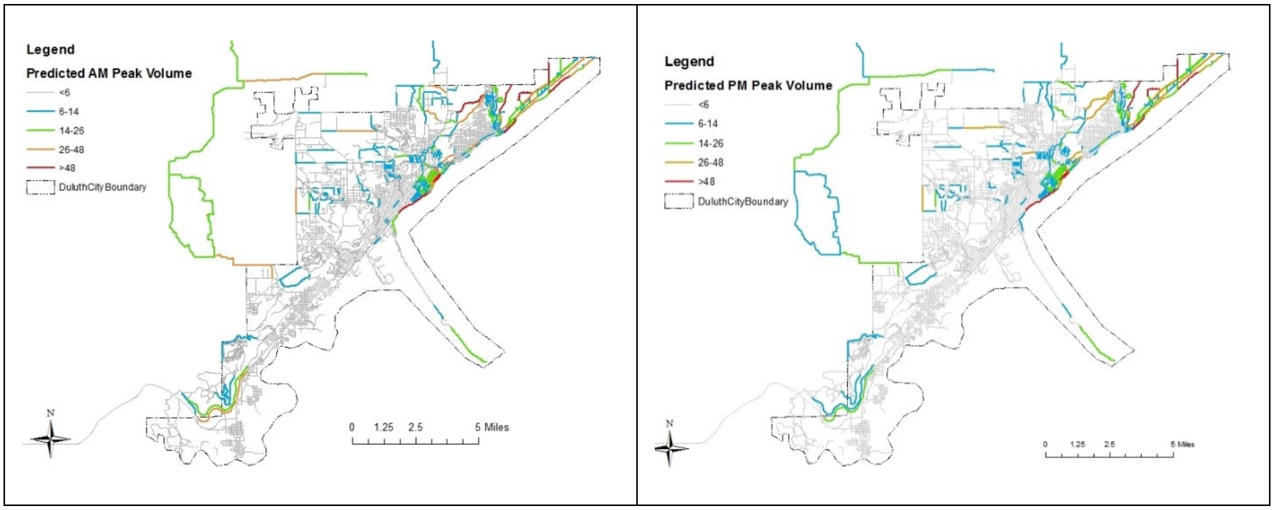


Figure 6.4 Predicted Bicycle Volume in Duluth

6.2 BICYCLE CRASHES AND CRASH RISK IN DULUTH

To test whether bicyclist exposure is correlated with the probability of crashes in Duluth, we assembled information about crashes in Duluth and then estimated crash models using bicyclist and vehicular exposure as explanatory variables.

6.2.1 Bicycle Crashes in Duluth

Between 2005 and 2014, 135 crashes involving bicyclists were reported in Duluth; nearly all of these (132) involved crashes with vehicles. The number of crashes per year ranged from a low of 6 in 2008 to a high of 25 in 2009, with an average of just over 13 crashes per year (Figure 6.5). Crashes by month adhere closely to local climate conditions in Minnesota and the seasonality of bicycle traffic volumes. Crashes were least prevalent in the winter, increased in the spring, peaked in the summer and decreased in the autumn. No crashes were reported in January or February, and about 80% crashes occurred between June and October. More crashes occurred on weekdays than weekends. Crashes on weekends were below fifteen. Crashes on weekdays were most common on Thursdays and Fridays, with more than 20 crashes on these days. In terms of time of day, crashes were more likely to occur from 3 PM to 6 PM, similar to the pattern in Minneapolis. Crashes increased throughout the day, peaked in the late afternoon and decreased in the evening, generally matching daily bicycle traffic patterns.

Information about the severity of injuries, contributing factors, and location of bicycle crashes is summarized in Figure 6.6. The crashes resulted in one fatality and eight incapacitating injuries. The majority of injuries were classified as moderate or below. For motorists, failure to yield was most prevalent contributing factor associated with crashes (n-63). Distraction contributed to 19 crashes. Speed and alcohol each contributed to eight crashes. Most of crashes were related to right angle movements at intersections. Males were disproportionately involved in crashes: 111 males compared to 24 females. Most of the crashes involved people between 16 and 55 years of age. Ninety-three (93) of 135 crashes were related to intersections.

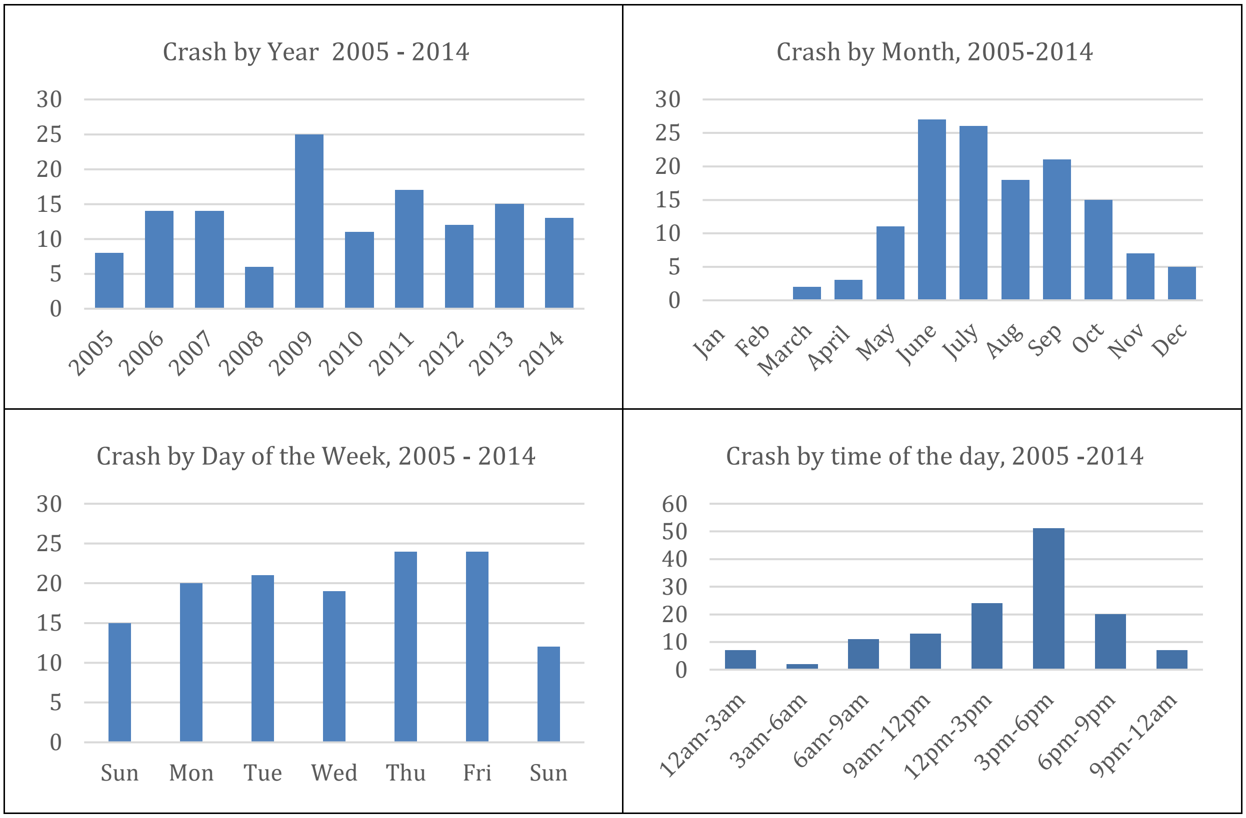


Figure 6.5 Temporal Variation in Bicycling Crash in Duluth

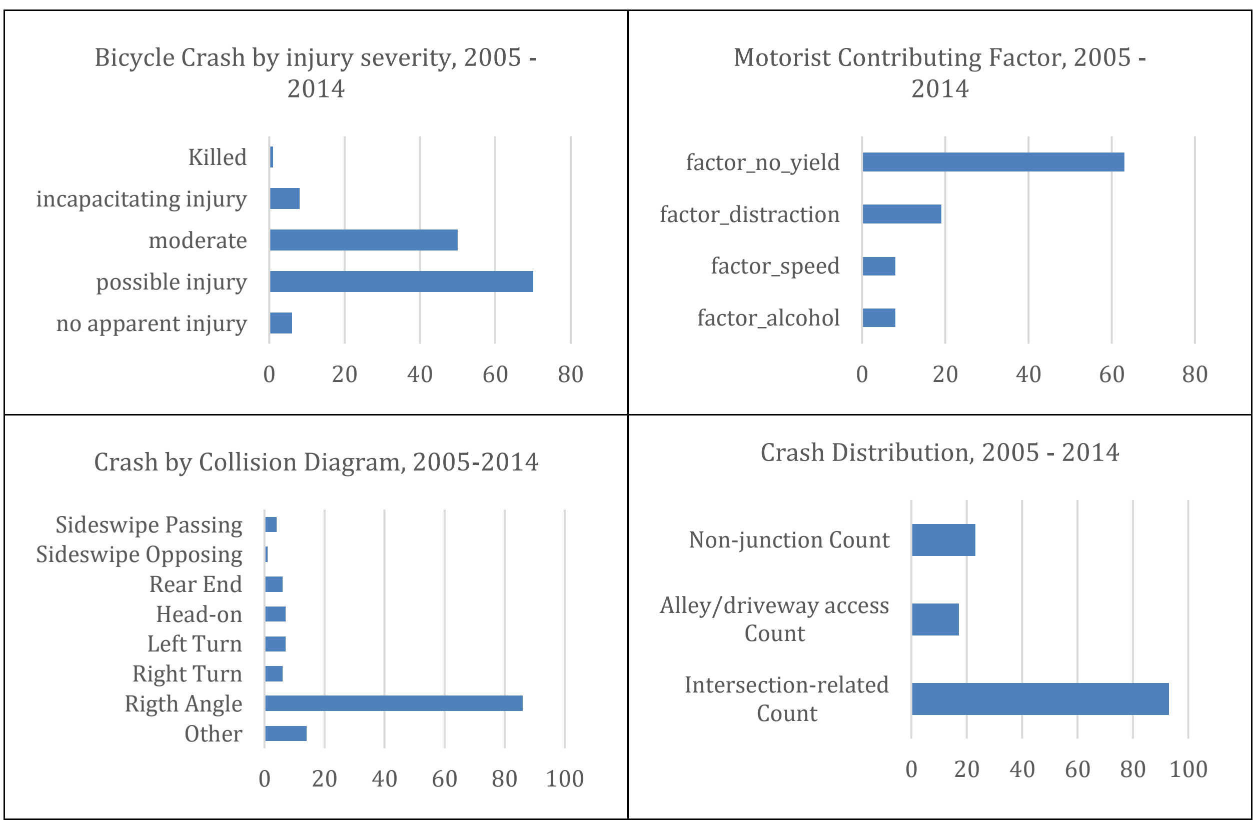
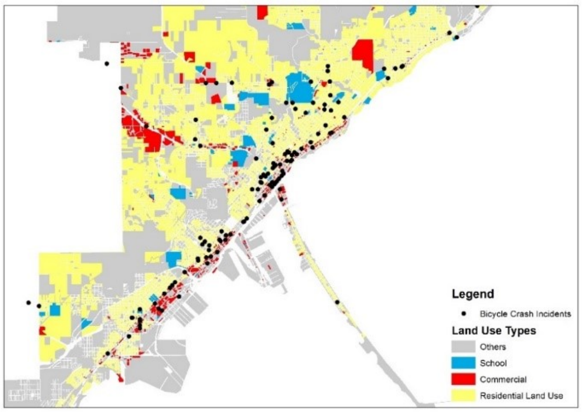


Figure 6.6 Bicycle Crash in Duluth by Injury Severity, Contribution Factors & Locations

Figure 6.7 depicts the spatial distribution of bicycling crashes in Duluth. Most of crashes occurred at intersections along arterial and collector streets along the lakeshore where commercial and recreational land uses are concentrated. A number of crashes also occurred close to University of Minnesota, Duluth campus. Corridors with higher numbers of crashes included East/West Superior St, Grand Ave and East 4 street. Crashes were assigned to a specific corridor based on 25-meter distance threshold; some crashes were assigned to two corridors because they occurred at intersections).



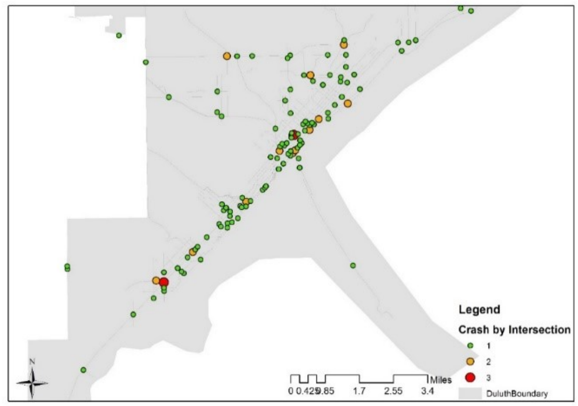


Figure 6.7 Bicycle Crash Distribution in Duluth

6.2.2 Bicycle Crash Risk in Duluth

We modeled bicyclist crash risk as a binary (0-1) variable, with values of 1 assigned to locations where a crash had occurred. The probability of a crash was estimated as a function of our modeled estimates of bicyclist exposure and vehicular exposure. Estimates of vehicular annual average daily traffic (AADT) for street segments were obtained from MnDOT. We assigned the value of 300 for vehicle AADT to local streets for which estimates were not available. Models for both AM and PM peak periods were estimated using the penalized MLE procedure introduced by Firth (1993) (Table 6.5). The models have low Wald chi-square statistics, and we fail to reject the null hypothesis that bicyclist and vehicular exposure are not significantly correlated with the probability of crashes. These models thus provide no evidence that our estimates of exposure are related to crash risk. We did not introduce additional independent variables into these models because our principal interest lies in the relationship between exposure and risk, and none was identified in these models.

Table 6.5 Estimated Results in Firth Logit Modeling Bicycling Crashes at Segment Level in Duluth

	AM Peak Model (N=49)		PM Peak Models (N=94)	
	Coefficients	P-value	Coefficient	P-values
Log(Peak Hour Bicycling Counts)	-0.200	0.684	0.25	0.286
Log(AADT)	1.267	0.098	0.58	0.403
Constant	-11.78	0.056	-7.06	0.038
Pro> Wald-Chi Square	0.1717		0.1802	

The fact that we cannot reject the null hypothesis, however, does not necessarily mean there is no relationship between exposure and risk. The low explanatory power of these models could be caused by the bicycle crash distribution in Duluth. In the AM peak model, only six street segments had at least one bicycle crash, while in the PM peak model, only 12 street segments had at least one bicycle crash. The estimates also could be affected by the quality of the bicyclist exposure estimates: as noted, the exposure models had only moderately good fit. Error in estimates of exposure from our models could limit their accuracy and reduce their validity as correlates of crash risk.

6.3 SUMMARY AND OBSERVATIONS

We estimated bicyclist exposure to risk in Duluth and, using those estimates of exposure, developed simple models of crash risk. The count database in Duluth was small, and, even with additional counts commissioned to augment existing data, still did not provide systematic coverage through the city at desirable densities. We estimated separate models for AM and PM peak periods, and, in additional to built environment and socio-demographic variables, introduced origin-destination (OD) centrality indices as independent variables. Although the models overall performed only moderately well, the OD centrality indices were statistically significant, indicating these measures have potential to capture network and land use effects on bicyclist exposure.

We next summarized available crash data. The number of crashes that occur annually in Duluth is a relatively small number: about 13 per year. The fact that there are so few crashes complicates that challenge of modeling crash risk. We modeled the probability of a crash as a function of bicyclist and vehicular exposure and found no significant relationships. Data limitations may be a factor in this outcome. Additional analyses with better data are warranted.

CHAPTER 7: EXPLORATORY STUDIES IN BEMIDJI

Our research proposal noted the importance of exploring exposure to risk in smaller communities and identified Bemidji, Minnesota (population 13,431) as a community for investigation. We collected available bicycle counts in Bemidji and conducted exploratory analyses. The available data, however, were too limited to support informative analytic approaches to assessment of exposure and the relationship between exposure and risk. We describe here the data that were collected for Bemidji and the analyses that were completed. The results, while useful for Bemidji, provide few insights that are generalizable. We also identified the village of Grand Marais (population 1,341) as a potential site for study, but only two crashes were we reported in Grand Marais, and few counts were available, so no results are presented.

7.1 BICYCLIST EXPOSURE TO RISK IN BEMIDJI

7.1.1 Bicycle Traffic Counts in Bemidji

Local planners in Bemidji have been involved in the Minnesota Bicycle and Pedestrian Counting Initiative led by MnDOT and initiated activities to conduct bicycle and pedestrian counts. However, counts were available for only 17 locations in Bemidji at the time of this study. Three of these locations involved automated counts on trails and are not included in this analysis because the focus is extrapolation of peak-period, manual counts. A limitation of the manual counts that are available is that observers only recorded the total number of bicyclists without providing directional information. The limited size of the sample makes the regression-based approach to estimating exposure difficult to implement. Table 7.1 summarizes the mean and median count data available from Bemidji. The mean traffic volumes were low: 16 cyclists in 2012 and 22 cyclists in 2014. Figure 7.1 shows the count locations in Bemidji. The coverage was very limited. No counts were completed for the residential areas in northeast and southwest and the commercial areas in southeast.

Table 7.1 Descriptive Statistics of PM Peak Bicycle Traffic Counts in Bemidji

Year	N	Mean (Median)
2012	13	16 (14)
2014	14	22 (24)

7.1.2 Modeling Bicyclist Exposure to Risk in Bemidji Using Origin-Destination Centrality

The initial plan to modeling bicyclist exposure to risk in Bemidji was to mirror the approach used in Duluth. Specifically, the plan was to use a similar dependent variable (i.e., bicycles in the peak-period) and the same explanatory variables in demand models, including origin-destination centrality indices. However, as explained below, because no meaningful correlations were observed between the bicycle count volumes and the OD centrality indices, no fully-specified demand models were estimated. Table 7.2 summarizes descriptive statistics for traffic counts and OD centrality indices calculated for Bemidji. (See section 6.1.1.2 above for a complete description of the approach.)

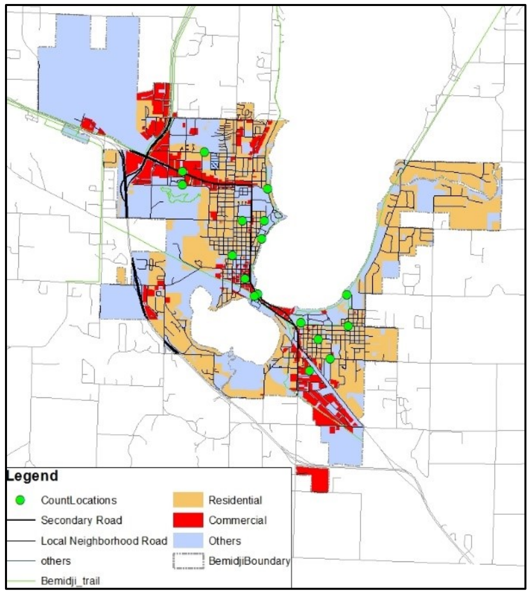


Figure 7.1 Count Locations in Bemidji

Table 7.2 Descriptive Statistics of Explanatory Variables in Bemidji

Variable	Description	Mean	Std. Dev.
Dependent Variables			
AM Bicycle	AM Peak Bicycle Volume	na	na
PM Bicycle	PM Peak Bicycle Volume	18	11.63
OD Centrality Indices			
RN Centrality	Residential to NonResidential Centrality	32504.47	68325.84
NR Centrality	NonResidential to Residential Centrality	77375.6	166308.4
NRecreation	NonResidential to Recreation Centrality	2429.43	3802.71

Figure 7.2 are maps of the RN and NR centrality indexes in Bemidji. The RN centrality index is highest for the street segments, local roads, and trails in northwest Bemidji where there are concentration of commercial land use. The NR centrality is comparable in form with the RN centrality index. However, the spatial patterns of the NRecreation centrality index is different: street segments, connecting more recreational or entertainment jobs tend to have higher NRcreation centrality. For instance, local street segments adjacent to commercial land use in the west and southeast of Bemidji that provide access to recreation tend to have higher NRecreation centrality index values.

Table 7.3 presents binary correlations between PM peak period bicycle traffic volumes and the three OD centrality indices. None of the correlations is significant, indicating no association between observed count volumes and the indices. This is likely because the count dataset includes only 17 observations. No additional analyses involving other independent variables were undertaken because of the limitations imposed by the small dataset.

Table 7.3 Binary Correlations between Counts and OD Centrality Indexes in Bemidji

	RN centrality	NR centrality	NRecreation
PM bicycle volume	0.2272 (0.3805)	0.1975(0.4473)	0.106 (0.6855)

Notes: p value in the parentheses

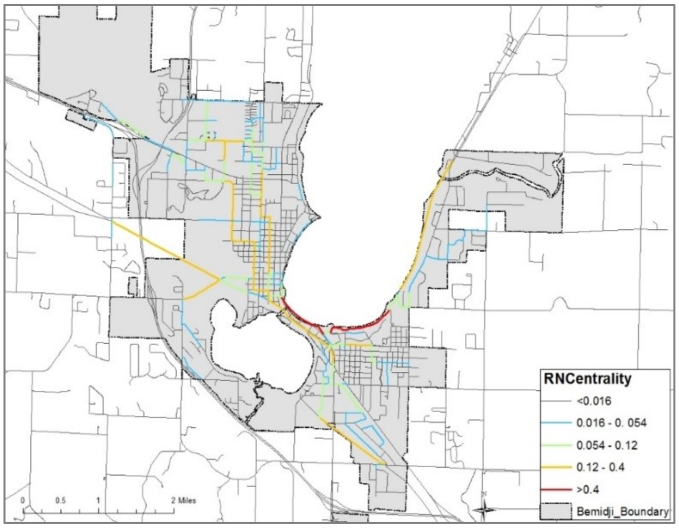


Figure 7-2 A: Residential to Non-residential Centrality Index in Bemidji

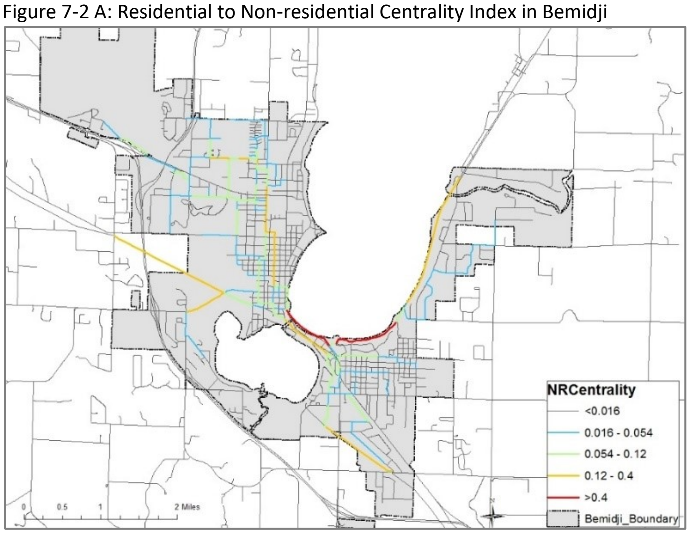


Figure 7-2B: Non-residential to Residential Centrality Index in Bemidji

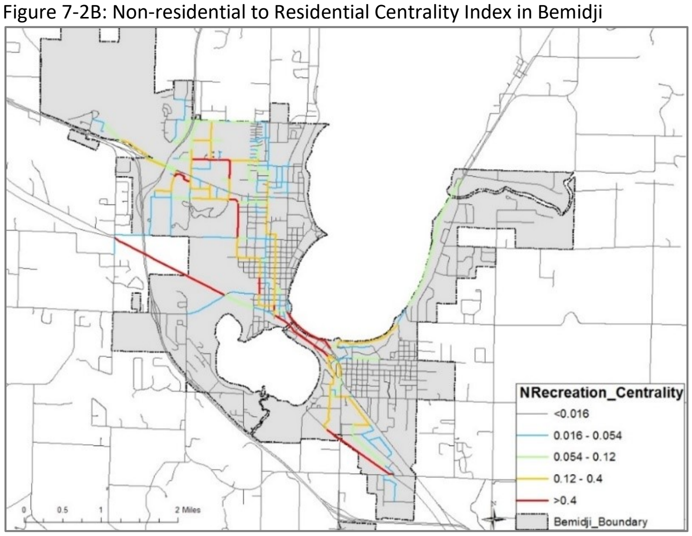


Figure 7-2C Non-Residential to Recreation Centrality Index in Bemidji

Figure 7.2 OD Centrality Index in Bemidji

7.2 BICYCLE CRASHES IN BEMIDJI

Between 2005 and 2014, 27 bicycle crashes occurred in Bemidji (Figure 7.3). The two years with the highest number of crashes were 2008 and 2009: six crashes occurred in each year. Crashes by month closely followed local climate conditions in Minnesota and seasonal bicycle traffic patterns. Crashes occurred least in the winter, increased in the spring, and peaked in the summer. No crashes were reported in the months of February and March. The months with the highest number of crashes were June and August. More crashes occurred on weekdays than weekends; none were reported on Sundays. Tuesday had the highest number of crashes. Similar to Minneapolis and Duluth, crashes steadily increased through the morning, peaked in the afternoon, and decreased at night. The highest number of crashes occurred between 12 PM to 3 PM.

All bicycle crashes were involved vehicles . No fatalities were reported, one crash caused an incapacitating injury, and the severity of the remaining 26 crashes was reported as below moderate. Failure to yield and distraction were the main two contributing factors. Right angle, right turn and left turn crashes accounted for 90% of the crashes (Figure 7.4). Among 27 crashes, 14 females and 13 males were involved, and most people involved in crashes were between the ages of 16 and 55. Spatially, bicycle crashes were concentrated in the commercial areas in Northwest, and commercial and school areas along the lakeshore (Figure 7.5). No estimates of bicycle crash risk were developed in Bemidji because estimates of exposure were inadequate to support specification and estimation of crash models.

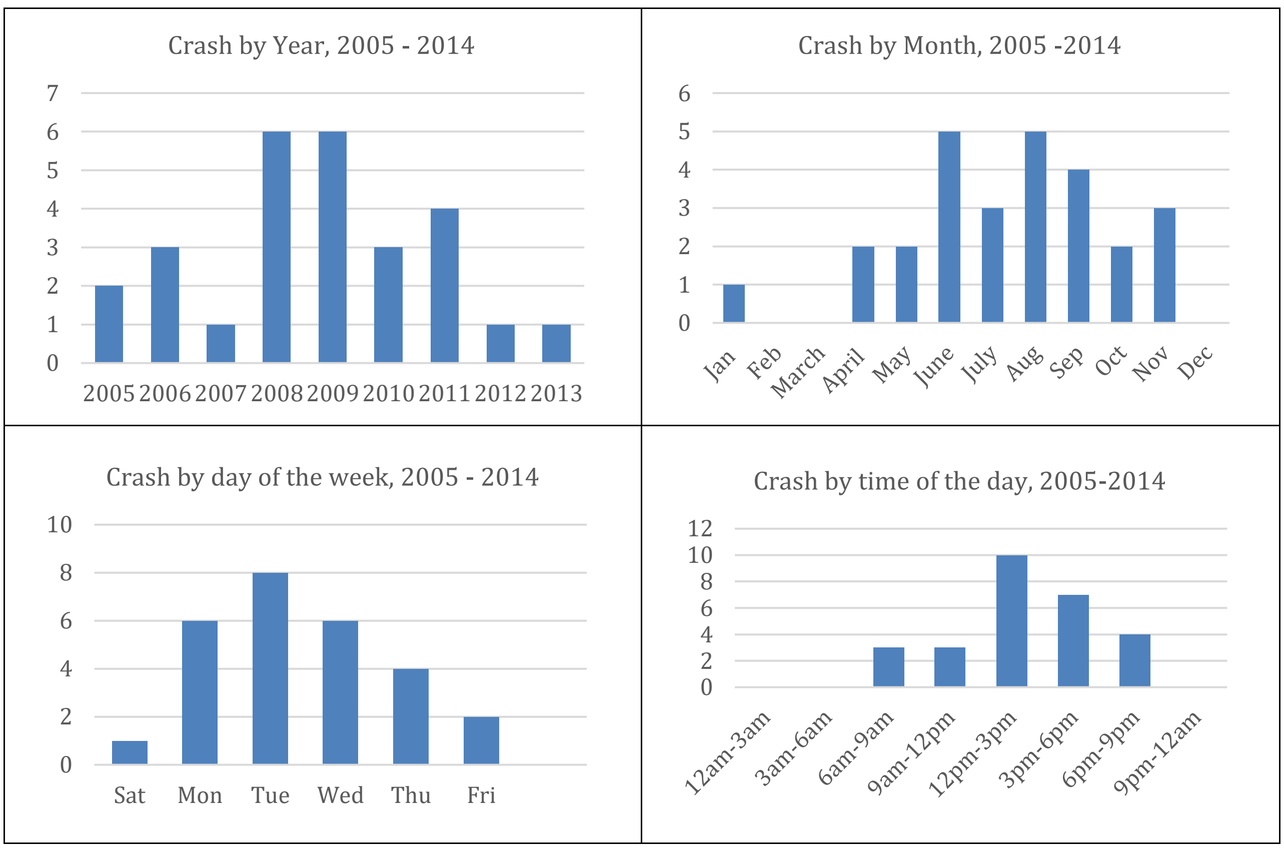


Figure 7.3 Temporal Variation of Bicycling Crash in Bemidji

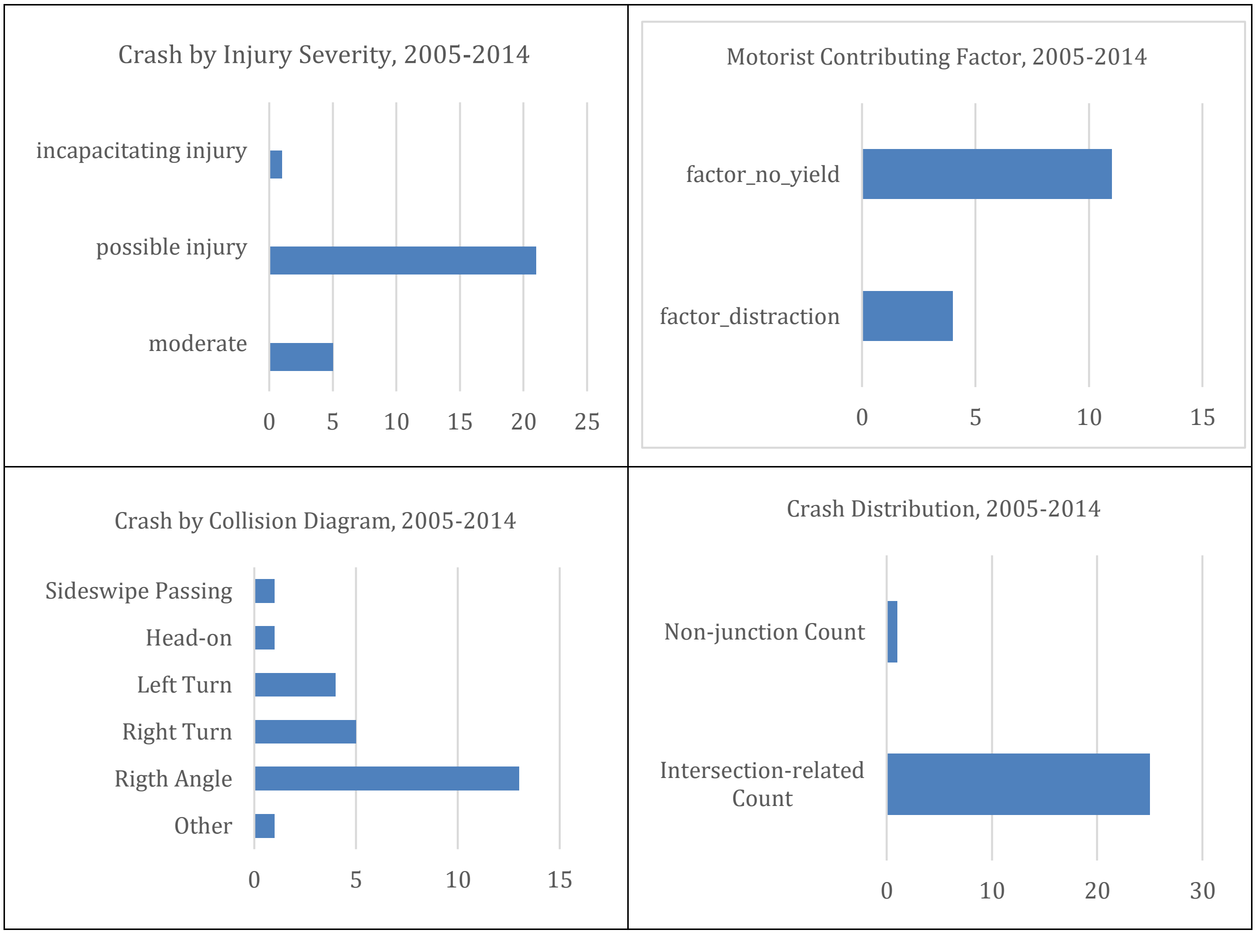


Figure 7.4 Bicycle Crashes in Bemidji by Injury Severity, Contribution Factors &Locations

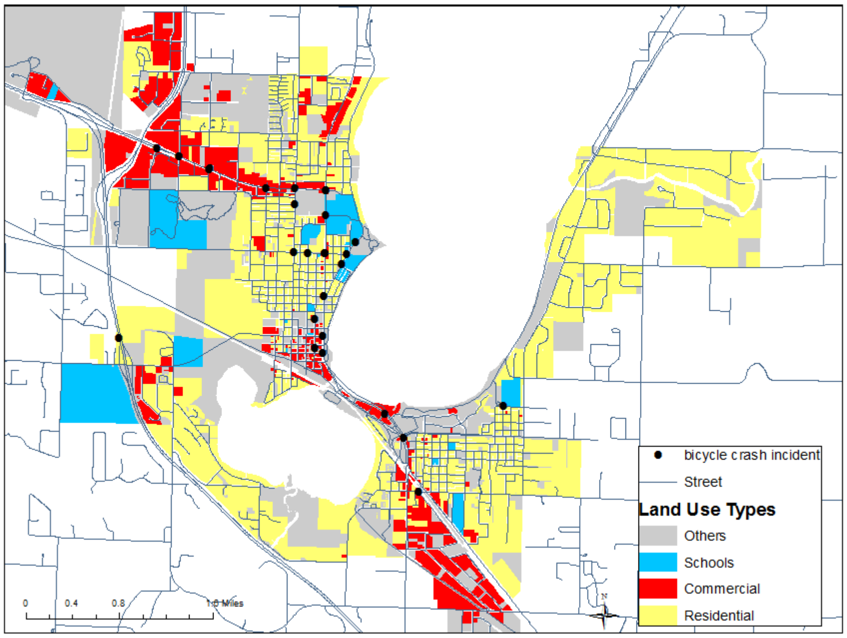


Figure 7.5 Spatial Distribution of Bicycle Crashes in Bemidji

CHAPTER 8: OBSERVATIONS AND CONCLUSIONS

The objectives of this research project were to develop methodologies and tools for estimating bicyclist exposure to risk (i.e., bicyclist demand, or traffic volumes) and to illustrate, through case studies, how these measures can be used to assess crash risk and incorporated into planning level studies of the need for countermeasures to increase safety. Following a literature review that summarized recent advances in demand modeling, estimating exposure to risk, and assessing crash risk, we:

- Developed new bicycle demand models for estimating bicyclist exposure to risk in Minneapolis from a large database of PM peak-period bicycle counts (Chapter 3);
- Developed regression models to assess the probability of crashes in Minneapolis (Chapter 4);
- Demonstrated how estimates of traffic on multiuse trails in Minneapolis can be used as estimates of exposure and incorporated into safety assessments, specifically, warrants for traffic signals and pedestrian hybrid beacons at roadway-path crossings (Chapter 5);
- Tested the use of origin-destination (OD) centrality indices as explanatory variables in count-based demand models for Duluth, Minnesota, and then used estimates of exposure to assess associations with crashes (Chapter 6);
- Completed exploratory analysis of available count and crash data in Bemidji, Minnesota (Chapter 7).

Our bicycle demand models in Minneapolis produced new estimates of weekday, PM peak-period exposure that, when extrapolated to the city street network, illustrated variation in exposure throughout the city. Exposure is highest in the central business district, along arterials and collectors, in higher-density residential neighborhoods, and along multiuse trails and bicycle boulevards that link neighborhoods and recreational areas throughout the city. These demand models for bicycle traffic show the importance of traffic generators (e.g., job accessibility, population density), destinations (e.g., open space, retail area), aspects of the transportation network (i.e., off-street trails, on-street facilities), and weather parameters (i.e., temperature and precipitation) as correlates of exposure. The models are limited in that they reflect only PM peak-period traffic, do not reflect seasonal variation in traffic (e.g., July volumes could be higher) and do not reflect the variation in traffic that naturally occurs at each location. Nonetheless, they provide consistent, comprehensive estimates of bicycle volumes throughout the network that can be used in planning-level studies where exposure is relevant.

Our probability models of crash risk were estimated using the penalized maximum likelihood estimation technique. We found that both bicyclist exposure and vehicular exposure were associated with the likelihood of a bicycle crash at both intersections and along street segments. We also identified several other land use-related variables that were positively and significantly correlated with the probability of crashes. Factors associated with crashes at intersections included land-use mix, percentage of commercial land use, number of intersections within a 400-meter buffer, and presence of trail crossings. Job accessibility was significantly correlated with the probability of crashes along street segments. In addition to the limitations associated with our estimates of exposure, our models of crash risk have other limitations. Most importantly, they do not account for site-specific factors that contribute to particular crashes. These factors include, for example, roadway geometry, signalization, and turning movements. This limitation introduces error and uncertainty into our estimates and limits their applicability for site-specific analyses and design of countermeasures. Despite these limitations, these estimates of exposure can be used in planning-level studies to understand the spatial distribution of crash risk and to assess issues such as the equity of distribution of crash risk throughout the city.

Our use of exposure estimates to assess the need for countermeasures at 184 roadway-trail crossings in Minneapolis has a number of implications for current practice. First, we showed that warrants for traffic controls for shared-use path crossings are more likely to be met using weekend peak-hour traffic flows. Engineers historically have completed studies for weekday peak-hour periods when vehicle volumes are highest. Our exposure data show that non-motorized traffic volumes are highest on weekends and that analyses should include both weekdays and weekends. We showed that most locations that meet warrants for either traffic signals or pedestrian hybrid beacons already have signals, but that as many as 17 crossings (9% of all crossings) warrant site-specific analyses. A limitation of this assessment was that the estimates of exposure were for mixed-mode, non-motorized traffic (i.e., undifferentiated bicycle and pedestrian traffic). Despite this limitation, the analysis demonstrates the value of consistent estimates of exposure in a network-wide assessment of the need for countermeasures on an important type of facility.

We developed count-based models of bicyclist exposure for Duluth and tested the correlation between measures of exposure and crashes. Both analyses were limited because of data limitations; despite augmentation with addition counts, the spatial distribution of counts across the city was limited, and there were comparatively few crashes available for analysis. We used introduced OD centrality indices as explanatory variables in our demand models following procedures recommended by Lowry (2012), and showed that these measures correlated positively and significantly with counts. However, the measures of bicyclist exposure did not correlate with bicycle crashes, and we therefore did not estimate crash models. The failure to identify correlations between bicyclist exposure and crashes may be because of data limitations.

We collected bicycle counts, estimated an exposure model for Bemidji, and collected crash data. However, because of limited observations, we were unable to assess crash risk.

In summary, we completed a set of analyses that involved collection of bicycle counts, modeling bicyclist exposure to risk, and using measures of exposure to apply warrants at roadway-trail crossings and to assess crash risk on street networks. We showed that crash risk is associated with exposure, but that data limitations affect the inferences that can be drawn about particular locations. The analyses presented here can be used in planning-level studies where consistently estimated measures of exposure or risk are needed. More detailed site-specific data or estimates will be needed for studies to assess the need for countermeasures at particular locations. These studies underscore the need for public and nonprofit organizations to continue efforts to collect and make available estimates of exposure.

Additional research can build on these findings and address some of their limitations. Collection of data on weekend traffic would enable estimation of additional exposure models that would provide insights into differences between weekday and weekend traffic and the probability of crashes on streets. These types of analyses would provide a more complete picture of exposure to risk and would provide insight into whether different types of factors affect the probability of crashes during different periods of the week. Our analyses of the use of exposure data in applications of warrants could be extended to on-street facilities. Although research of this type would require substantial efforts in data collection, the research could have significant implications for standard evaluations of the need for traffic controls. Relative to studies in large communities, studies in small communities remain rare. Our analyses produced few results for the smallest communities; these limitations might be overcome by pooling data for small communities. Our analyses could be extended to pedestrian traffic, which generally is greater than bicycle traffic. More comprehensive models that include bicycle, pedestrian, and vehicle exposure would be interesting and could provide insights into interactions among modes. Last, our models of the likelihood of crashes could inform analyses of equity that are of increasing importance to managers of transportation systems.

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