Hennepin County Pedestrian Crash Study

Humphrey School Capstone Report

The Hubert H. Humphrey School of Public Affairs
The University of Minnesota

Ryan Ackerman
Isak Johnson
Daniel Murphy
Tristan Trejo

PA 8081 Capstone Workshop
Section 003
Instructor: Greg Lindsey, Ph.D.

Spring 2023

Hennepin County Public Works

Subject Keywords:
Crash, Risk, Exposure, Negative Binomial Regression, Safety Performance Function, Towards Zero Deaths, Crash Prediction, Crash Risk, Exposure to Risk

Abstract (250 words or less):
Our study analyzed historical pedestrian crashes throughout Hennepin County and ranked crash locations based on crash occurrence over a ten-year period (2012-2021). For analysis purposes, crashes were split into two categories: intersections and midblocks. Crashes primarily occurred in urban areas, and collisions resulting in fatal injuries were rare. We created a tiered ranking system to group together locations with similar levels of crash occurrence to guide potential county improvement projects. Using ArcGIS Pro, we developed crash point maps to spatially represent crash locations and severity in each Hennepin County Commissioner District. We then created Safety Performance Functions (SPFs) by conducting a statistical analysis of crash data using a Negative Binomial Regression model. The variables we chose for statistical analysis were identified in previous studies as statistically significant variables that influenced pedestrian crashes. We used our SPFs to predict future crash locations and crash severity at intersections and midblocks over the next ten years. Our SPFs predicted fewer crashes at intersections and midblocks over the next ten years than the actual number of crashes over the ten-year study period. This can be partially attributed to our model, which was relatively weak, but can also be attributed to a lack of data. In particular, pedestrian count data would likely have increased the accuracy of our model, but this is not easily accessible. Our study opens the door to future research by transportation planning professionals who can make proactive, informed decisions about reducing pedestrian crash risk throughout Hennepin County based on our research.

Executive Summary

Graduate students from the University of Minnesota conducted an analysis of pedestrian crash risk, severity, and occurrence on the Hennepin County road network in order to inform Hennepin County transportation planning officials and assist them with planning for Towards Zero Deaths initiatives. Our study analyzed historical pedestrian crashes throughout Hennepin County and ranked crash locations based on crash occurrence over a ten-year period (2012-2021). For analysis purposes, crashes were split into two categories: intersections and midblocks. Crashes primarily occurred in urban areas, and collisions resulting in fatal injuries were rare. We created a tiered ranking system to group together locations with similar levels of crash occurrence to guide potential county improvement projects. Using ArcGIS Pro, we developed crash point maps to spatially represent crash locations and severity in each Hennepin County Commissioner District. We then created Safety Performance Functions (SPFs) by conducting a statistical analysis of crash data using a Negative Binomial Regression model. The variables we chose for statistical analysis were identified in previous studies as statistically significant variables that influenced pedestrian crashes. We used our SPFs to predict future crash locations and crash severity at intersections and midblocks over the next ten years. Our SPFs predicted fewer crashes at intersections and midblocks over the next ten years than the actual number of crashes over the ten-year study period. This can be partially attributed to our model, which was relatively weak, but can also be attributed to a lack of data. In particular, pedestrian count data would likely have increased the accuracy of our model, but this is not easily accessible. Our study opens the door to future research by transportation planning professionals who can make proactive, informed decisions about reducing pedestrian crash risk throughout Hennepin County based on our research.

Contents

List of Figures

List of Tables

List of Abbreviations

AADP - Average Annual Daily Pedestrians

AADT - Average Annual Daily Traffic

AASHTO - American Association of State Highway and Transportation Officials

EB - Empirical Bayes

GIS - Geographic Information Systems

HC - Hennepin County

HCPW - Hennepin County Public Works

NBR - Negative Binomial Regression

OLS - Ordinary Least Squares

SPF - Safety Performance Functions

TPD - Transportation Planning Division

Introduction

In 2021, five pedestrians were killed, and an additional nineteen were seriously injured in crashes on Hennepin County roads. This was the highest number of pedestrian deaths since at least 2012, and the highest number of serious injuries since 2019. The Transportation Planning division (TPD) of Hennepin County Public Works (HCPW) is committed to its goal of achieving zero deaths and serious injuries on the county transportation system (Hennepin County, 2013; Hennepin County, 2018). TPD is eager to understand which factors influence the risk of pedestrian fatalities and injuries, and where in Hennepin County increased risk exists. To that end, TPD enlisted our team of four graduate students from the University of Minnesota's Humphrey School of Public Affairs to undertake this work.

It is important to have some contextual information about Hennepin County before diving deeper in the report. As of the 2020 United States Census, Hennepin County had a population of 1,281,568 people living in an area of 554 square miles, with a population density of 2,313 people per square mile. More than one in five Minnesotans live in Hennepin County, in 45 cities of varying populations, ranging from 340 in Medicine Lake to 428,403 in Minneapolis. There are 571 centerline miles of roadway under the county's jurisdiction, 3,591 intersections with at least one county road, and 4,171 midblocks in the space between intersections.

Our primary objective was to create intersection and midblock safety performance functions (SPF) for Hennepin County that can be used to further their efforts toward achieving zero deaths. At the most basic level, a safety performance function is a crash prediction model that relates various site characteristics to crashes. Building off previous research in the field, the team incorporated site characteristics found to be significant in previous crash studies into the SPFs for this analysis. The need for a deeper analysis of crash risk than that provided by simple observation stems from the fact that one cannot simply look at locations of crashes to determine risk, because the same factors that are associated with crash risk at one location also exist at locations where zero crashes have occurred. Since the vast majority of pedestrian crossings see no crashes at all, the safety performance functions provide a method for overcoming this problem and identifying risks at all locations, regardless of crash history.

We separated our analysis units into two separate categories: intersections and midblocks. This division was created because of the different ways in which pedestrians and vehicles interact at the two types of crossings. At intersections, pedestrians are often crossing in a crosswalk, traffic signals of some kind are often present, and turning movements by drivers are common. At midblocks, pedestrians may not have a designated crosswalk to use, traffic control signals may not be present, and vehicles are generally moving in straight lines rather than turning. The differences between the two crossing types were notable enough that we deemed it necessary to split them up for a portion of our analysis.

The crash data utilized for our analyses come from law enforcement personnel's data input whenever authorities were called to the scene of a crash. Pedestrian crashes that did not involve law enforcement, such as crashes where the pedestrian is not injured and both parties leave the scene are not included in this study. Therefore, there may be some intersection and midblock locations where the number of crashes does not reflect every pedestrian crash over the study period. Additionally, annotating if the injury suffered by the pedestrian was a serious vs. minor injury is left up to the law enforcement officer. The subjective nature of what one might consider a "serious" or "minor" injury may vary upon the judgment of the individual completing the crash form.

We used Geographic Information Systems (GIS) analysis and negative binomial regression analysis to answer five research questions posed by TPD staff:

Question I: Which pedestrian crossings on Hennepin County Roads see the highest number of pedestrian crashes?

Question II: Which pedestrian crossings see the highest number of fatalities and/or severe injuries?

Question III: How do street characteristics (e.g., street width, speed limit, etc.) and local area characteristics (e.g., land uses, population density/make-up, etc.) correlate with the number of crashes?

Question IV: Which built environment characteristics seem to increase/decrease the severity of those crashes?

Question V: Based on the identified characteristics that correlate with higher numbers of pedestrian crashes (and higher numbers of fatalities/severe injuries), which intersection and midblock locations appear to be at higher risk of pedestrian crashes?

We find that crashes occur more frequently on roadways in more densely populated portions of Hennepin County. Among all municipalities in Hennepin County, the City of Minneapolis has by far the highest number of crashes. These crashes are concentrated on a few high traffic thoroughfares in the city, including, but not limited to, Lake Street, West Broadway, Franklin Avenue, Lyndale Avenue, and Cedar Avenue. The intersections and midblocks that saw the highest number of fatal or serious injury crashes included those roadways, as did the intersections and midblocks that our SPFs predicted to be at the highest risk for future crashes. Statistically significant predictors of crash risk at intersections included the presence of a stoplight, the presence of a transit stop, total population, average annual daily traffic (AADT), the share of the population living at or below 185 percent of the poverty level, the presence of a bike facility, female population, divided roadways, and open space land uses. At midblocks, statistically significant predictors of crash risk included non-white population, total population, the share of the population over 65, and the presence of a bike facility.

Past Pedestrian Crash Research

Components of Pedestrian Crash Risk Modeling

Pedestrian safety has been an area of significant academic and practice-based research since at least the turn of the 21st century. The period from 2010-2021 saw a steady increase in publications in the issue area, with 470 works related to pedestrian safety published in 2021 alone (Ma et al., 2022). Government agencies in the transportation sector at the local, regional, and federal levels have also waded into the field and sponsored research on the safety risks posed to pedestrians (City of Minneapolis, 2017; Metropolitan Council, 2021; Turner et al., 2018). A Minneapolis pedestrian crash study assessed trends, contributing factors, and characteristics of pedestrian crashes in Minneapolis from 2007-2017 to better understand where these crashes occurred in the city. In Minneapolis, 85 percent of pedestrian crashes occurred at intersections, while the remaining 15 percent occurred at midblock locations (City of Minneapolis, 2017). While signal-controlled intersections represented only 12 percent of city intersections, 68 percent of pedestrian crashes occurred at those intersections. Seventy-two percent of Minneapolis's 25-highest pedestrian crash intersections featured Hennepin County roads (City of Minneapolis, 2017). At the regional level, the Metropolitan Council (Met Council) identified that Hennepin County had the highest serious and non-serious crash numbers of any county in the Twin City metro area in 2021 (Metropolitan Council, 2021).

Some of these agencies have also published guidance on the development of crash modeling scenarios intended to determine risk factors on roadways. These crash models most often take the form of mathematical equations known as Safety Performance Functions (SPFs). SPFs nearly always control for traffic volume (average annual daily traffic, AADT) and may include any number of site characteristics, such as traffic controls, lane width, or intersection type. The result of the SPF is an estimate of the number of expected crashes over a period of time at a given site with given conditions (Srinivasan and Bauer, 2013; AASHTO, 2010). The Highway Safety Manual published by the American Association of State Highway and Transportation Officials (AASHTO) identifies three (out of many) potential uses for SPFs: screening the road network for locations with promise, where safety treatments could be beneficial; estimating the average expected crash frequency among a set of alternatives; and evaluating the effect of a design treatment for a particular roadway (Srinivasan and Bauer, 2013; AASHTO, 2010).

To identify pedestrian SPFs that have been estimated in other contexts, we began our process by identifying search terms to emphasize as we combed through the literature in the field. Since our intention was to find and evaluate all factors that may affect crashes, we search for terms related to crashes and the built environment, roadway infrastructure, and demographics. In total, we reviewed 28 pieces of literature. The majority were scholarly articles, and the remainder were crash studies commissioned by public agencies. As we reviewed the literature, we noticed that studies consistently framed their research around two terms: exposure and risk. One study defined exposure as “a measure of the degree of opportunity for a crash to occur”, and defined risk as “a measure of the probability of a crash per unit of exposure” (Merlin et al, 2020), while another defined “exposure to risk” as “the number of potential opportunities for a crash to occur” (Tao et al, 2021). The two are intimately related when it comes to crash modeling, and the simplest description of the nature of their relationship is such that when pedestrians are exposed to motor vehicle traffic, the risk of a crash, injury, or fatality is created (Schneider et al, 2021). The level of risk created depends on the specific conditions of the studied area, which leads to the inclusion of site characteristics in most SPFs to create more accurate models. With these two categories in mind, we established our inclusion criteria as articles that addressed the relationship between exposure, risk, and the built environment. From there, we examined the variables found to be significant in those models and reviewed different modeling techniques.

We group these variables into three categories: built environment/land use; roadway infrastructure; and demographics.

Built Environment/Land Use Characteristics

Certain built environment and land use characteristics have been found to be statistically significant in previous studies. Population density (Tao et al., 2021; Miranda-Moreno et al., 2011), density of development (Tao et al., 2021; Wang et al., 2016), commercial land uses (Schneider et al., 2021; Lin et al., 2019) and activity near transit stops (Tao et al., 2021; Thomas et al., 2017) were found to have positive correlations with pedestrian crash risk. In general, land use characteristics that allow for the shared occupation of space by pedestrians and vehicles increases levels of exposure, which increases the risk of a crash.

Roadway Infrastructure

Many factors of roadway design have an influence on pedestrian crashes. The presence of a traffic signal, number of intersection legs, number of main roads, number of secondary roads were all found to be statistically significantly related to pedestrian crashes (Tao et al., 2021; Ukkusuri et al., 2012). Other studies have found that intersection design, road widths and lengths, and crosswalk availability were found to be a major factors that influenced pedestrian crash risk (Ukkusuri et al., 2012; Wang et al., 2016; Miranda-Moreno et al., 2011; Cottrill and Thakuriah, 2010; Thomas et al., 2017; Kumfer et al., 2019; Merlin et al., 2020; Schneider et al., 2021; Tao et al., 2021; Ammar et al., 2022). Street lighting has also been found to be a determinant to pedestrian crash risk (Lin et al., 2019; Ammar et al., 2022).

Demographics

Although state departments of transportation have started to invest more resources into pedestrian safety in recent years, disparities in safety outcomes remain between income and racial groups. Areas with high concentrations of people of color and low incomes see higher rates of crashes between motorists and pedestrians (Cottrill and Thakuriah, 2010; Thomas et al., 2017; Lin et al., 2019; Kumfer et al., 2019; Schneider et al., 2021). Higher unemployment rates, low levels of education, and low English proficiency were found to be significant in some studies (Cottrill and Thakuriah, 2010; Thomas et al., 2017; Lin et al., 2019; Kumfer et al., 2019).

Statistical Models of Pedestrian Crash Risk

Ordinary Least Squares Regression

Studies have utilized a variety of analysis methods to understand the factors that influence pedestrian crashes. An early study used an ordinary least squares (OLS) analysis to examine the relationship between the number of people walking and bicycling and the frequency of crashes between motorists and walkers and bicyclists (Jacobsen, 2003). OLS is not widely used for analyses of crash risk due to limitations posed by the skewed distribution of crash data and because, from a mathematical perspective, not well suited to handle the complications of working only with count data.

Negative Binomial Regression

Negative binomial regression (NBR) is more commonly employed by researchers to determine the influencing factors of crashes, particularly when there are not many crashes per unit of analysis (Ukkusuri et al., 2012; Thomas et al., 2017; Tao et al., 2021). Using NBR, Ukkusuri et al. found a clear link between built environment, transit, road design characteristics and fatal pedestrian-motorist crashes, as well as that results' accuracy increased with finer levels of geographic data aggregation. Thomas et al. used NBR in a Seattle-based study to offer recommendations for proactive action based on identified crash risk indicators. They found that numerous built environment and socioeconomic variables including total population and building volume, mean income, and larger intersections contributed to increased crash risk (Thomas et al., 2017). Similarly, Tao et al. analyzed the importance of including pedestrian and bicycle exposure variables when determining crash risks for pedestrians and bicyclists in Minneapolis. Ultimately, they used pedestrian/bike counts modeled from some real data and concluded that including these respective exposure variables in their NBR crash risk analysis improved the accuracy of their crash risks predictions. (Tao et al., 2021). Other studies that utilized NBR for at least part of their findings were Miranda-Moreno et al., 2011 and Lin et al., 2019 when determining which built environment, demographic and roadway characteristics most impact pedestrian crash frequency at signalized intersections and low-income areas, respectively - further demonstrating the usefulness of this technique.

Poisson-gamma and Poisson-lognormal Regression

A Poisson regression model is used to model count data, model contingency tables, and find outcomes to low numeric-based variables. Since the majority of intersections see zero crashes during a given study period, and most intersections that do see crashes at most have only one or two, a Poisson regression is a more suitable approach to predicting outcomes. One group of researchers utilized the Poisson-gamma and Poisson-lognormal models to account for the small sample size and skewed mean in the crash data (Schneider et al., 2021). Another study utilized the Poisson-lognormal regression model to create a new method of crash prediction (Mukherjee et al., 2021). In a study investigating occurrence of fatal pedestrian crashes in urban settings, researchers developed a three-components mixture model. This model was an attempt to create an alternative to the single equation prediction model which has been typically used in similar studies. The three-component mixture model utilized three different sources of risk factors, instead of one, and was found to result in more accurate crash predictions (Mukherjee et al., 2021).

This study synthesizes the best practices utilized by previous studies in the field. The focus of our analysis is on variables identified as statistically significant in previous studies and uses statistical models that best account for challenges in the data. As a condensed approach to understanding the wide range of analyses previously undertaken, Table 1 below describes analysis units, considered exposure to risk, and significant variables found in similar studies. More specific characteristics of each study are grouped in four categories: pedestrian and vehicle exposure to risk, built environment, traffic facility, and demographic variables.

Table 1: Significant Variables Identified in Literature

			Exposure to Risk Considered		Significant Variables			
Studies	**Analysis Unit Type**	**Analysis Unit**	**Pedestrian**	**Vehicle**	**Exposure to Risk**	**Built Environment**	**Traffic Facilities**	**Demographic**
Cotrill and Thakuriah (2010)	Area-Wide	Census Tract	Population	AADT	***Population per square mile***	***Commercial land uses,*** *no. of schools,*	***Transit availability,*** *Length of road*	Crime rate, pedestrian accessibility index, Pct. who speak limited or no English, no car households
Miranda-Moreno et al. (2011)	Facility Specific	Signalized Intersections	AADP	AADT	***AADP***, *AADT*	***Commercial land use***, no. of jobs, *no. of schools*	***Presence of metro station, no. of bus stops,*** *Pct. of major arterials*, average *street length*	-
Ukkusuri et al. (2012)	Area-Wide	Census Tract and Zip Code	Population	-	***Population***	Industrial/***Commercial land use***	***Transit ridership/ subway stations***, *4-5 legged intersections*, no. *of lanes/road width*	-
Zegeer et al. (2012)	-	-	-	Vehicle speeding	-	Surrounding Urban Environment		*Pedestrian Age*

Wang et al. (2016)	Area-Wide	Traffic Analysis Zones	Population	-	***Population***	Area of Traffic Analysis Zone	*Length of major/minor arterials*, Road density, average intersection spacing, Pct. *of 3-legged intersections*	-
Thomas et al. (2017)	Facility specific	Intersection	AADP	AADT	***AADP***	***Total pop.,*** Total building volume, ***Commercial building volume, Transit stop***	*Traffic signal,* ***no. of total legs,*** *no. local legs, no. lanes total, no. thru lanes, no. main roads, parking on any leg*	Mean income
Kumfer et al. (2019)	Facility Specific	Intersection	AADP	AADT	***AADP***	***Transit stops,*** Land use density	*No. of lanes,* type of lanes, type of medians, speed limits, *traffic control type*	Mean income
Lin et al. (2019)	Area wide	Census Block Group	Population	-	***Population***	***Densities of certain commercial uses***	*Traffic signals,* ***Bus stops,*** *Pct. of major roads*	*Pct. seniors, Pct. transit or bike commuters, Pct. low education level, Pct. no car households*

Mukherjee et al. (2021)	Crash/Incident Specific	Intersection	-	Vehicle Speed	-	Crossing Presence, ***Land Use***	*Road Width*, Pavement Condition	*Pedestrian Age*, Pedestrian Gender
Schneider et al. (2021)	Facility Specific	Multi-use trail/Road Crossing	Trail User AADT	AADT	*AADT*, Average Annual Daily Trail Traffic	***Crosswalk length***	Trail crossing perpendicular to road at 3-way intersection	-
Tao et al. (2021)	Facility Specific	Intersection	Ped Count, Bike Count	AADT	***Ped. Count,*** *AADT*	***Pop. density***, Job density ***Transit stop,*** Pct. open space	*Traffic Signal, no. of legs, no. of main roads, no. of secondary roads*	*Pct. seniors*, Average Household Size
Ammar et al. (2022)	Crash/Incident Specific	Intersection	Pedestrian Pre-motion	Vehicle Type, Pre-motion Speeding Indication	-	Lighting Condition	*No. of Lanes*	*Pedestrian Age*, Driver Age
Ghomi & Hussein (2023)	Facility Specific	Midblock	No. of Walking Trips	AADT	-	***No. of bus stops,*** *No. of schools,* Bike-share stations, Playgrounds, Parking lots, Trails, ***Restaurants, Convenience stores***	-	-

Italics indicates similar variables concluded to be a significant crash risk predictor by 3-5 studies

Bold italics indicates similar variables concluded to be a significant crash risk predictor by more than 5 studies

Crash Modeling Methods

GIS Analysis

Hennepin County TPD provided pedestrian crash data for a 10-year period and authorized analyses for the entire period. This data included crash location, crash severity, time of day, intersection type, and other relevant information about the crash. Pedestrian crashes in Hennepin County over this period for both intersections and midblocks occurred predominantly in urban areas. We used ArcGIS Pro to integrate land use, road, Census Bureau (block group level), transit stop occurrence, average annual daily traffic (AADT), and municipal/county boundary data into intersection and midblock crash data. Land use data at intersections and midblocks were summarized as the most dominant land use type at a specified buffer. If there were multiple land use types within an intersection or midblock buffer, the land use type with the highest area in that location was chosen to represent the crash buffer. Demographic data at the Census block group level was summarized the same way as land use types.

If there were multiple block groups within an intersection or midblock buffer, the block group with the highest area in that location was chosen to represent the crash buffer. We defined an intersection crash as a crash within 20 meters of the center of an intersection and a midblock crash as a crash outside of the 20-meter intersection buffer. A 15-meter buffer from the road centerline was utilized for midblock segments in order to help capture surrounding land use and other demographics of those locations. A 20-meter intersection buffer and a 15-meter midblock buffer were the most efficient distances tested in our analysis. Buffers greater than 20-meters caused issues of overlap where crash point data were counted twice and produced inaccurate results. While the vast majority of intersections meet with non-county roads, all intersections were treated equally regardless of connecting roadway categorization.

Tiered Crash Ranking

Once the crash data were acquired for intersections and midblocks, the data were sorted based on the sum of crashes that occurred at intersections and midblocks in the study period (2012-2021). Each intersection and midblock was assigned a unique intersection/midblock ID, where incident IDs (documented crashes) were assigned based on spatial location. Once sorted by the number of crashes, intersections and midblocks were placed into four different tiers. Tier 1 intersections and midblocks had the highest number of crashes, followed by tiers 2, 3 and 4. Tiers were separated based on natural breaks in crash numbers, where crashes per individual intersection/midblock IDs were fewer than the preceding tier.

Tiered ranking breaks for intersection and midblock locations are presented in Table 2:

Tier	Number of Intersection Crashes	Number of Midblock Crashes
1	≥10	6-9
2	5-9	3-5
3	2-4	2
4	1	1

Table 2: Tiered Crash Ranking Divisions

This created a ranking where the most dangerous intersections and midblocks for pedestrians were in the same tier so Hennepin County professionals could prioritize safety improvements for a specific tier instead of individual locations. Tables 3 and 4 present the intersections and midblocks with the highest number of reported crashes over the study period. The full tiered crash rankings for intersections and midblocks are included as supplements to this report and are available upon request from TPD.

Intersection Crash Tiered Ranking

Intersection Crash Tiered Ranking

Tier 1 - Tier 2 - Tier 3 - Tier 4

Tier	County Road Number	County Road Local Name	Intersecting Road	Commissioner District	Number of Crashes	Number of Serious Injuries	Number of Fatalities
T1	81	W Broadway Avenue	Lyndale Avenue North	2	30	3	-
T1	3	Lake St W	CSAH 22 (Lyndale Avenue South)	3	17	3	-
T1	5	Franklin Ave E	Chicago Avenue	4	15	-	1
T1	5	Franklin Ave	Nicollet Avenue	3	14	-	-
T1	3	Lake St W	Pillsbury Avenue	3	13	-	-
T1	3	Lake St W	Blaisdell Avenue South	3	12	1	-
T1	2	Penn Ave N	CSAH 153 (Lowry Avenue North)	2	10	1	-
T1	3	Lake St E	Bloomington Avenue South	4	10	1	1
T1	5	Franklin Ave E	CSAH 35 (Portland Ave)	4	10	2	-
T2	3	Lake St E	1st Avenue South	3	9	1	-
T2	152	Cedar Ave	4th Street South / Riverside Avenue	3	9	1	-

Table 3: Intersection Crash Tiered Ranking

Midblock Crash Tiered Ranking

Midblock Crash Tiered Ranking

Tier 1 - Tier 2 - Tier 3 - Tier 4

Tier	County Road Number	County Road Local Name	Closest Intersections	Commissioner District	Number of Crashes	Number of Serious Injuries	Number of Fatalities
T1	152	Cedar Ave	S of 7th St S to Riverside Ave	4	9	3	-
T1	152	Washington Ave N	23rd Ave N to CSAH 66 (West Broadway)	2	8	2	-
T1	22	Lyndale Ave S	CSAH 3 (Lake St W) to 26th St W	3	7	1	-
T1	152	Washington Ave S	W of I-35W Ramp to I-35W E Ramp	4	6	-	-
T2	20	Blake Rd	Excelsior Blvd to 2nd St NE	6	5	1	-
T2	37	4th St SE	I-35W Frontage Rd E to I-35W	4	5	-	-
T2	152	Cedar Ave	Regent Ave N to 207' S of Regent Ave N	1	4	1	-
T2	2	Penn Ave N	CSAH 153 (Lowry Ave N) to 35th Ave N	2	4	-	-
T2	81	W Broadway Avenue	CSAH 152 (Washington Ave N) to I-94 W Ramp	2	4	1	-
T2	35	Portland Ave	CSAH 5 (Franklin Ave E) to 18th St E	4	3	-	-
T2	2	Penn Ave N	36th Ave N to Dowling Ave N	2	3	1	-

Table 4: Midblock Crash Tiered Ranking

Safety Performance Functions

Once the built environment, traffic facility, and demographic characteristics were assigned to their appropriate locations via GIS, the study used the following method to analyze which variables were statistically significant predictors of crashes or fatalities/serious injuries in order to create our safety performance functions (SPFs). As described in the Literature Review, one method of statistical analysis that has proven to be highly useful with regards to pedestrian crash studies is negative binomial regression (NBR). NBR is commonly used when the dependent variable in question has higher variance than its mean (Tao et al., 2022, UCLA: Statistical Consulting Group, n.d.). In other words, for the thousands of Hennepin County intersections and midblock locations in this study, most will have either zero or one crash associated with them so the average number of crashes per location will be very low; however, there are numerous locations that have a noticeably higher number of crashes so the variation of crashes in the whole set is much higher than the average number of crashes.

For this reason, we employed NBR to determine which independent variables contributed increased risks for pedestrian crashes. The regression analysis was conducted in Stata where the SPF took the form:

$$Y = e^{(int.+b_1X_1+b_2X_2...+b_nX_n)} \quad (1)$$

where X_i is the independent variable (built environment, roadway or demographic characteristic described above) and b_i is that variable's corresponding coefficient (UCLA: Statistical Consulting Group, n.d.)).

Using equation 1, we estimated three separate SPFs: two where Y was the number of pedestrian crashes (separately for intersections and midblocks) and the one where Y was the number of fatalities or serious injuries as a result of those crashes. For the fatality regression, we ran a single analysis for intersections and midblocks combined in order to increase the sample size. All dependent variables were consistent across the regressions with the exception of a dummy variable (i.e., a binary variable with values of either 0 or 1) for indicating if the intersection was a four-way intersection in the intersection crash analysis. This variable was changed to length of the midblock and a dummy variable indicating whether the fatality/serious injury occurred at an intersection (rather than a midblock) in their respective regressions and resulting SPFs. The full list of the variables used in our analyses to create the SPFs, as well as some brief descriptive statistics for each variable, is given in Table 5. As noted previously, this list was determined largely by which variables were commonly found to be significant predictors of crashes in other studies; another limiting factor when deciding which variables to use was data availability and accessibility.

Empirical Bayes Estimation Functions

Once we determined how our variables influenced the number of crashes, we used the SPFs to predict future crashes and fatalities/serious injuries at all locations. While our initial estimate of future crashes employed Equation (1), this method can struggle to accurately represent locations that were outliers with large crashes numbers; therefore, an additional step was taken via Empirical Bayes Estimation (EB) to provide a more definitive crash estimate that incorporates historical crash data as well (Training - Safety | Federal Highway Administration, 2013). This takes the form of the following equations:

$$EB = wP + (1 - w)x \quad (2)$$

where *EB* is the new crash estimate from the Empirical Bayes method, *P* is the original estimate of crashes calculated from Equation (1), *x* is our historical crash data values, and *w* is a weight assigned to *P* and *x* for the estimation. The way to calculate this weight, w, is given by:

$$w = \frac{1}{\left(1 + \frac{P}{k}\right)} \quad (3)$$

where *k* is the inverse of the dispersion factor that is determined by the original NBR (Tao et al., 2021; UCLA: Statistical Consulting Group, n.d.). Given the fact that our historical crash data comes from a 10-year period of time, our final *EB* crashes values will serve as estimated crashes for each location over the next ten years.

Table 5: Variables Chosen for Analysis

		Intersections *(n = 1,148)*			Midblocks *(n = 347)*			Fatalities and Serious Injuries *(all locations, n = 249)*		
Variable	**Unit**	**Minimum**	**Maximum**	**Mean**	**Minimum**	**Maximum**	**Mean**	**Minimum**	**Maximum**	**Mean**
Crashes or Fatalities	Integers	1	30	2.076	1	9	1.372	-	-	-
Fatalities	Integers	-	-	-	-	-	-	0	4	0.3089
Four-way intersection	Dummy	0	1	0.6184	-	-	-	-	-	-
Midblock Length	Meters	-	-	-	16.73	1267.82	174.03	-	-	-
Intersection	Dummy	-	-	-	-	-	-	0	1	0.6861
Pct. of Crashes Daylight	Percent	0	100%	52.44%	0	100%	50.26%	0	100%	51.76%
Number of Lanes	Integers	0	8	3.389	2	8	3.468	0	8	3.414
Presence of Traffic Signal	Dummy	0	1	0.5714	0	1	0.2253	0	1	0.4628
Speed Limit	MPH	0	55	32.35	0	55	33.24	0	55	32.63
Commercial Land Use	Dummy	0	1	0.1555	0	1	0.1542	0	1	0.1551

Industrial Land Use	Dummy	0	1	0.0036	-	-	-	0	1	0.1439
Office Land Use	Dummy	0	1	0.0108	-	-	0.0040	0	1	0.0074
Open Space Land Use	Dummy	0	1	0.3544	0	1	0.4506	0	1	0.2444
Total Block Group Pop.	Integers	0	3,129	1,286	0	4,665	1,244	0	4,665	1,280
Pct. of Pop. Female	Percent	0	72.37%	48.91%	0	73.79%	48.64%	0	73.79%	48.83%
Pct. of Pop. Under 18	Percent	0	49.00%	19.37%	0	49.40%	20.60%	0	49.40%	19.76%
Pct. of Pop. 65 and Over	Percent	0	65.00%	11.67%	0	64.67%	13.04%	0	65.00%	12.57%
Pct. of Pop. Non-white	Percent	0	94.00%	40.46%	0	94.49%	42.58%	0	94.49%	41.13%
Median Household Income	Dollars	0	$250,001	$70,278	0	$250,001	$71,321	0	$250,001	$70,605
Pct. of Pop. ≤185% Poverty Rate	Percent	0	94.4%	31.43%	0	94.4%	31.12%	0	94.4%	31.34%
Presence of Transit Stop	Dummy	0	1	0.5696	0	1	0.3360	0	1	0.4963

Divided Roadway	Dummy	0	1	0.2604	0	1	0.3043	0	1	0.2742
Presence of Bike Facility	Dummy	0	1	0.4051	0	1	0.3557	0	1	0.3896
AADT	Integers	1,300	38,500	14,383	2,900	37,000	14,704	1,300	38,500	14,484

Trends, SPFs, and Predicted Crashes

Descriptive Results

Intersections

1,148 crashes occurred at intersections over the ten-year study period, an average of about 115 crashes per year. Intersection crash locations in Hennepin County were not evenly distributed across municipalities. The vast majority of intersection crashes occurred in Minneapolis, which had over three times the number of crashes than the cumulative total of every other city in Hennepin County. The densest concentrations of crashes occurred on major thoroughfares in the heart of Minneapolis, on roadways such as Lake Street, Lyndale Avenue, Franklin Avenue, and West Broadway (Figure 1).

Intersection Pedestrian Crashes, Hennepin County (2012-2021)

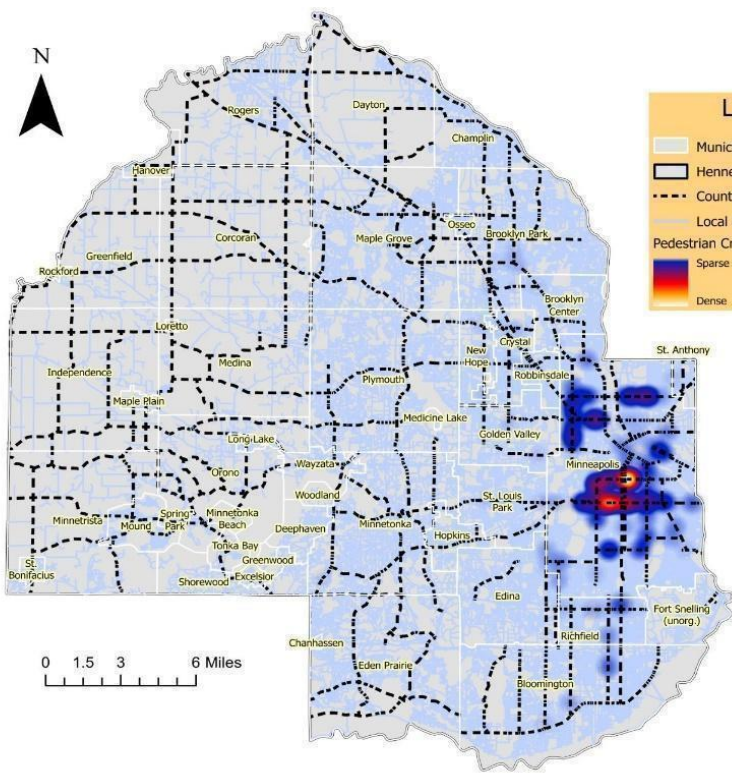


Figure 1: Intersection Pedestrian Crash Distribution

Intersection Crash Severity

Crash severity at intersections varied by crash category throughout the study period. The highest number of fatalities occurred in 2021, while the highest number of serious injuries occurred in 2019. Minor injuries and possible injuries varied during the study period, until both categories experienced a steep decline from 2019 to 2021, though 2021 levels of minor injuries were similar to those reported in 2018 and 2015. There were never more than five fatalities at intersections in a given year (Figure 2).

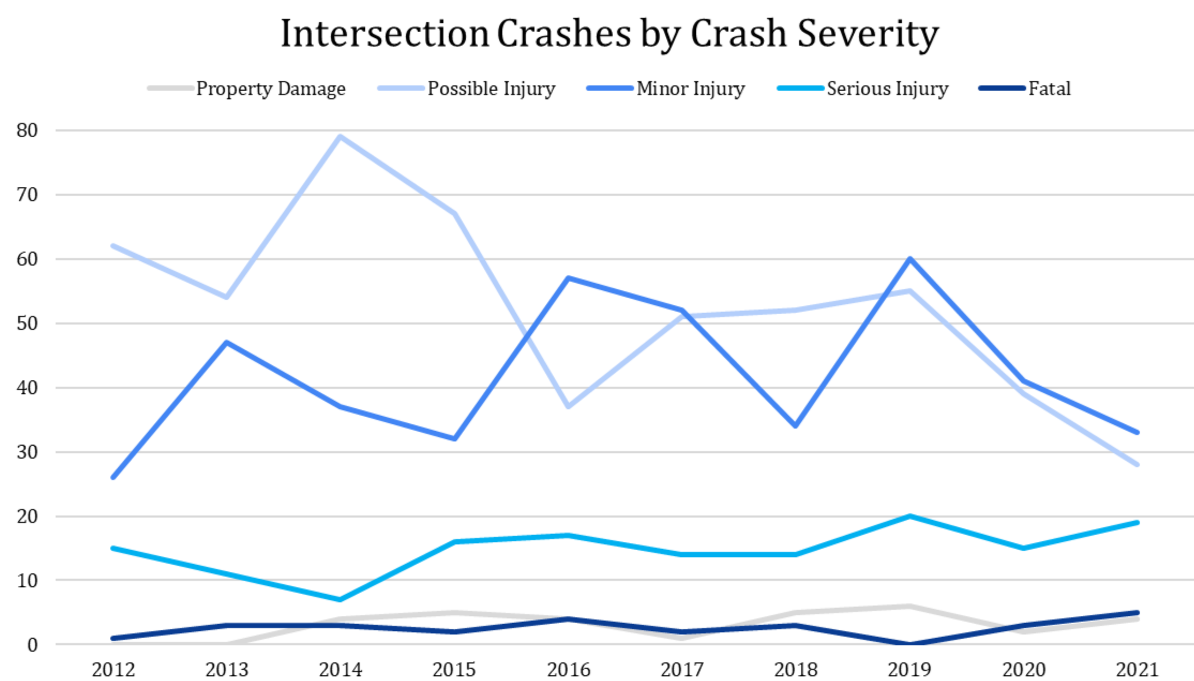


Figure 2: Intersection Crashes by Crash Severity

Midblock Locations

347 crashes occurred at midblocks over the ten-year study period, an average of about 35 crashes per year. In a similar pattern to intersections, crashes at midblocks were not evenly distributed throughout the county. The densest concentrations of midblock crashes were in Minneapolis, which had over one and a half times the number of midblock crashes than the cumulative total of every other city in Hennepin County. Within the City of Minneapolis, the distribution of midblock crashes mirrors that of intersection crashes, but there are notable concentrations of midblock crashes in the northwestern suburbs of Crystal, Brooklyn Center, and Brooklyn Park that are absent for intersection crashes (Figure 3).

Midblock Pedestrian Crashes, Hennepin County (2012-2021)

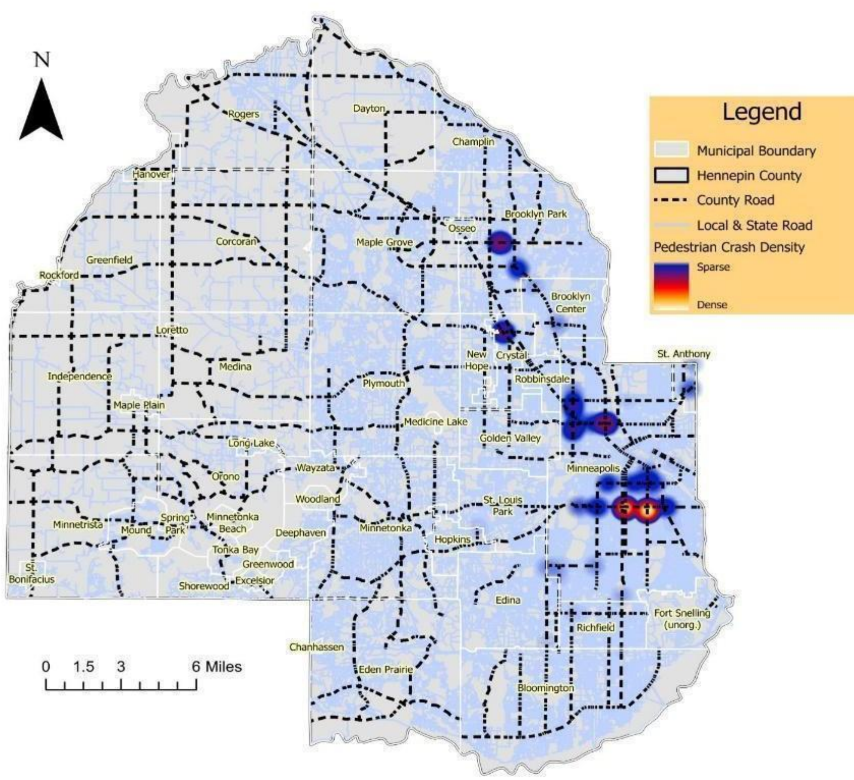


Figure 3: Midblock Pedestrian Crash Distribution

Midblock Crash Severity

Crash severity at midblocks varied by crash category throughout the study period. The highest number of both serious injuries and fatalities occurred in 2017, while the highest number of minor injuries occurred in 2019. Crashes resulting in minor injuries saw a sudden spike in 2019 but returned to 2018 levels in 2020. There were never more than three fatal crashes at midblocks in a given year (Figure 4).

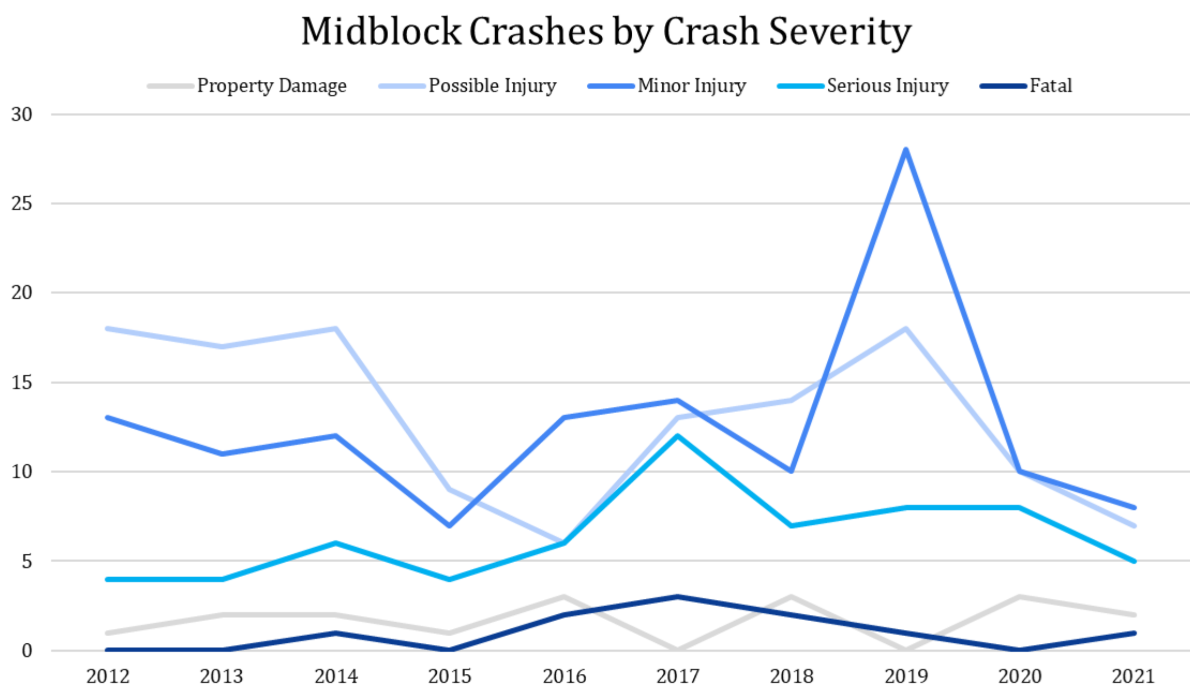


Figure 4: Midblock Crashes by Crash Severity

Annual Total Crashes

Intersection and midblock crashes per year remained relatively consistent throughout the study period. The period from 2012 to 2018 saw an average of 117 intersection crashes and 34 midblock crashes, before a sizable increase in 2019 to 141 intersection crashes and 55 midblock crashes. This was followed by a steep decline to below average levels in 2020 that continued into 2021. This may be attributable to the COVID-19 pandemic, though we can't say for certain what caused the decline (Figure 5).

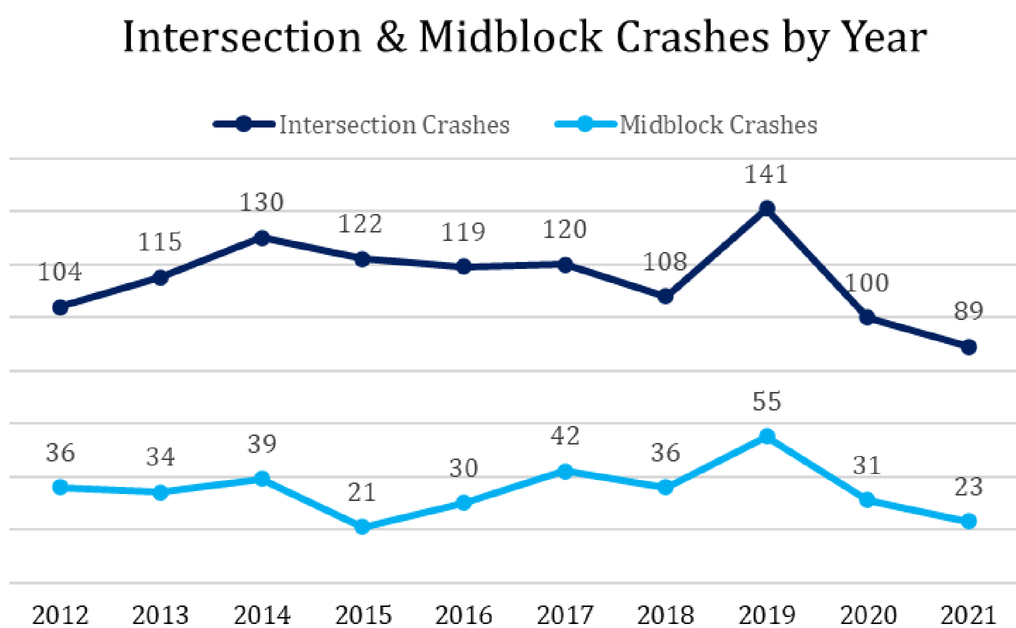


Figure 5: Crashes by Year

Crashes by Commissioner District

Crashes within the seven Hennepin County Commissioner Districts were not evenly distributed. The more densely populated Commissioner Districts containing portions of Minneapolis and inner-ring suburbs had many more crashes than the less densely populated districts containing outer-ring suburbs, exurban, and rural areas. Commissioner District 4 (University of Minnesota, Downtown, Cedar-Riverside, and South Minneapolis) had the highest total number of crashes, as well as the most intersection and midblock crashes among the seven districts. Commissioner District 3 (Downtown, Uptown, Southwest Minneapolis, and St. Louis Park) had the second highest number of crashes, while District 2 (North and Northeast Minneapolis, Golden Valley, and Plymouth) ranked third in total crashes. District 7, on the other hand, had the fewest number of intersection and midblock crashes due to its predominantly exurban and rural character (Figure 6).

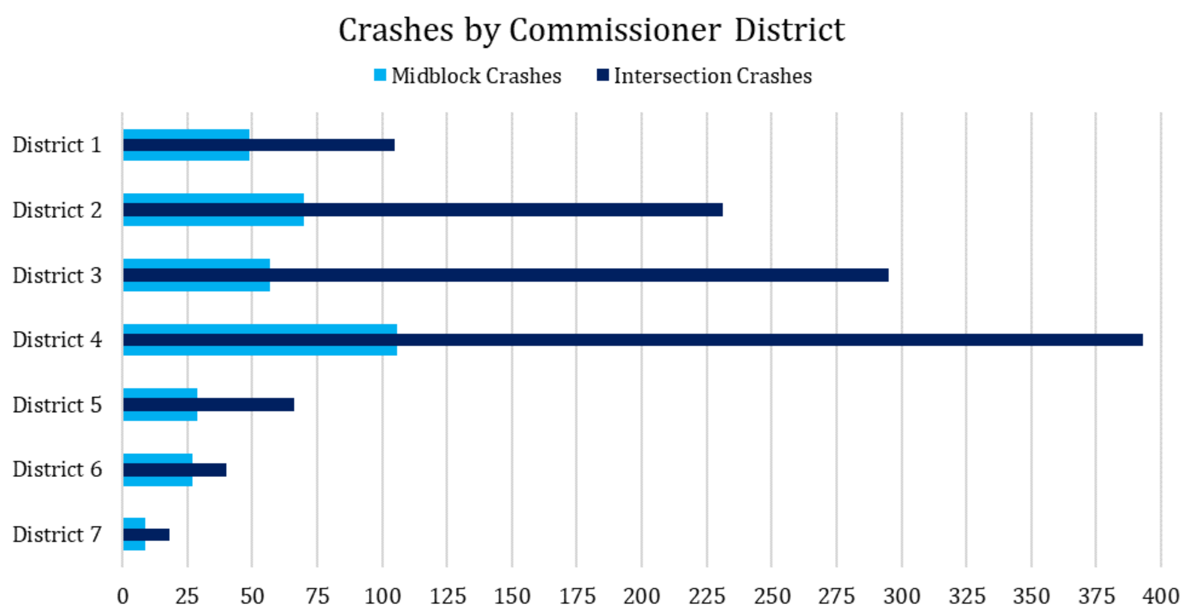


Figure 6: Crashes by Commissioner District

Safety Performance Functions — Assessment of Significant Variables

Intersections

The following represents the results of our NBR analyses. Table 6 represents the coefficients that will later be used in Equations (1) through (3) to predict the number of crashes and fatalities/serious injuries at each location.

Of the twenty-one independent variables included in the intersection SPFs, nine were found to be significant at the 5% level or below (no variables were significant at only the 10% level, where descending levels indicate increasing statistical significance). SPF results for all variables are summarized in Table 5 where asterisks denote statistical significance (i.e., found to be more strongly associated with predicting the number of crashes or fatalities/serious injuries). Additionally, the values listed are the coefficients (b_i) used in Equation (1) where the presence of that variable (such as a traffic signal) or an increase in a variable (such as AADT) caused an increase or decrease in the predicted number of crashes by that value depending on the sign of the coefficient.

Table 6: SPFs for Intersections, Midblocks and Fatal/Serious Injuries

Variable	Unit	Intersection Crashes pseudo-R^2 = 0.1022	Midblock Crashes pseudo-R^2 = 0.038	Fatality/Serious Injury (both locations) pseudo-R^2 = 0.0572
Four-way intersection	Dummy	0.0205		
Midblock Length	Meters		$-8.52\text{x}10^{-5}$	
Intersection	Dummy			-0.0656
Pct. of Crashes Daylight	Percent	-0.0391	-0.0467	-0.5964***
Number of Lanes	Integers	0.0145	-0.0116	0.1832***
Presence of Traffic Signal	Dummy	0.4287***	0.3008**	0.1193
Speed Limit	MPH	0.0008	-0.0047	-0.0013
Commercial Land Use	Dummy	0.1387	0.0243	-0.1313
Industrial Land Use	Dummy	-05449	-	-0.2860

Office Land Use	Dummy	-0.2163	0.1353	-0.4434
Open Space Land Use	Dummy	-0.2079***	0.0973	0.0326
Total Block Group Pop.	Integers	0.0002***	-5.5×10^{-5}	0.0002
Pct. of Pop. Female	Percent	-0.9297**	0.0260	-0.1484
Pct. of Pop. Under 18	Percent	-0.1698	-0.8814	0.1544
Pct. of Pop. 65 and Over	Percent	-0.5632	-0.7381	-0.3981
Pct. of Pop. Non-white	Percent	0.1649	0.5062	0.7881*
Median Household Income	Dollars	1.6×10^{-6}	1.36×10^{-6}	2.59×10^{-6}
Pct. of Pop. ≤185% Poverty Rate	Percent	1.076***	0.4213	0.1829
Presence of Transit Stop	Dummy	0.1978***	0.1352	0.2462*
Divided Roadway	Dummy	-0.3323***	-0.0551	-0.1904
Presence of Bike Facility	Dummy	-0.2869***	-0.1145	-0.4504***
AADT	Integers	3.02×10^{-5}***	2.46×10^{-6}	7.93×10^{-6}

Notes: *,**, and *** indicate statistical significance at the 10%, 5% and 1% levels respectively; Industrial land use was omitted by the regression software in the midblock analysis due to lack of crashes near those midblock locations and residential land uses were omitted due to collinearity; All percentages, except percent of crashes in daylight, are a percentage of the total population of the block group; Positive coefficients indicate an increased number of crashes and negative coefficients indicated a reduced number of crashes.

In general, higher AADT, greater census block group population, presence of stoplights, presence of transit stops and larger proportion of the population living at or below 185% of the federal poverty level were factors found to be correlated positively with numbers of pedestrian crashes. Conversely, the predicted number of crashes decreases when the dominant land use around an intersection is open space, when divided roadways or bike facilities are present, or when the proportion of the female population of a block group increases. Essentially, with all else being equal, a block group with a higher proportion of females will see fewer predicted intersection crashes than a block group with a lower proportion of females.

Statisticians use measures of "goodness of fit" to describe how well models fit and describe the data of interest. For example, the standard measure of goodness-of-fit used in OLS regression is the R^2 which has a range of 0-1, with values closer to 1 indicating a better overall fit. The standard measure of goodness of fit for NBR analysis is known as McFadden's pseudo-R^2 which does not operate on the same scale as the standard R^2. In McFadden's words, a pseudo-R^2 of 0.2-0.4 represents an excellent fit of the model (McFadden, 1979). The value of McFadden's R^2 for our intersection model was 0.1022, which likely represents a weak-to-good overall fit, but not an excellent fit. In similar work, Tao et al., 2021 determined that the addition of direct pedestrian counts produced more accurate crash risk predictions, so it is likely that this pseudo-R^2 could be improved in the future with the addition of direct pedestrian exposure data. Other general limitations, and some potential recommendations for improving the fit of all of these models, will be given after our conclusions.

Midblock Locations

In the midblock regression, using the same independent variables (with the exception of midblock length, which took the place of intersection type), only one variable – the presence of a stoplight - was found to be a significant indicator of predicting the number of crashes (Table 5). This indicates that our chosen variables of study are better at predicting intersection crashes than crashes at midblock locations. Future pedestrian crash studies will require additional consideration as to what are the fundamental characteristics of midblock locations, how they differ from intersections, and how pedestrians and vehicles interact in those spaces.

This NBR model yielded a McFadden's' pseudo-R^2 of 0.038. Applying the same reasoning described above for Intersection Crashes, this model acts as a weak overall predictor of crash risk for midblock locations using the present data. It is possible that the future inclusion of direct pedestrian counts – or other characteristics – could improve this model; it should also be noted that there were far fewer reported crashes at midblock locations compared to intersections in this dataset (347 at midblocks and 1,148 at intersections), so it is possible that the smaller sample size impacted the results.

Fatalities and Serious Injuries (Both Locations)

Of the total 1,495 crashes at all intersections and midblock locations (n=805, combined), there were a total of 249 serious injuries or fatalities. Separately, there were 27 fatalities and 148 serious injuries at intersections (n= 552), and 10 fatalities and 64 serious injuries at midblock locations (n=253). Therefore, we combined the two location types and created a single index of 'fatalities plus serious injuries' in order to increase the sample size for the third SPF. Additionally, we used a dummy variable to differentiate intersections from midblock locations; this variable took the place of the four-way intersection dummy variable and midblock length in their respective crash regressions.

Two variables were significant predictors of reduced fatality/serious injury risk - both at the 1% level - and three variables were determined to be significant predictors of increased risk. The two variables that reduced the predicted fatalities/serious injuries were presence of a bike facility and the percentage of crashes that occurred in daylight (i.e., if a crash occurred in daylight conditions, it was less likely to yield a fatality or serious injury). An increased number of fatalities or serious injuries are predicted when a transit stop is present or when the proportion of a block group's population that identifies as non-white increases (i.e., all else being equal, a block group with a higher proportion of non-white residents is predicted to have more fatalities/serious injuries than a block group with a lower proportion of non-white residents). The pseudo-R^2 value for this regression was 0.0561, again indicating a fit that is not particularly strong.

Regression Results — Assessment of Crash Potential

We applied Equations (1) through (3) to all locations along Hennepin County roads using the appropriate coefficients of the three SPFs listed in Table 5 to arrive at EB-predicted numbers of crashes and fatalities/serious injuries for each location. These results represent a predicted value for the next 10 years given that the historical data was from a 10-year period. A full display of the estimated crash results would be too cumbersome to include here - there are a total of 3,591 intersections and 4,171 midblock locations on Hennepin County roads. Instead, we provide the overall top 10 intersections and midblocks by EB-predicted crash numbers (Tables 6 and 7) as well as the top 10 intersections and midblocks by EB-predicted numbers of fatalities/serious injuries to contextualize the results (Tables 8 and 9). The top 10 predicted crashes at intersections and midblocks for each Commissioner District were provided to TPD. Figures of these Commission District-specific crash predictions are also provided in Appendix C.

Intersection Crashes

Table 7 presents descriptive results and the top ten intersections by EB estimated crashes in Hennepin County. Previously, the intersection with the historically highest number of crashes was W Broadway Avenue and Lyndale Avenue N in District 2 at 30 crashes. However, rounding to the nearest integer, our regression results from Equation (1) predicts 6 crashes. This is one-fifth the historical value, but this intersection is by far the most notable outlier. Using the EB method, which assigns weights to both the historical values and initial estimates, this intersection is adjusted to 15 predicted crashes (again rounding to the nearest integer). Both the estimates from Equation (1) and Equation (2) determine this intersection to be the location with the most risk, and many intersections that were historically prone to crashes remain so in the predictions, though the order is not necessarily identical. No intersections see predicted crashes quite as high as the number of crashes historically recorded due to the nature of predicting outlier cases. However, higher predicted crash locations are generally more likely to be found in urban areas rather than in the suburban or rural sections of Hennepin County.

Predicted Intersection Crash Ranking

Rank	Location	Predicted Crash Total	2012-21 Crash Total
1	West Broadway & Lyndale Ave	15	30
2	Lake St & Lyndale Ave	9	17
3	Franklin Ave & Nicollet Ave	9	14
4	Lake St & Blaisdell Ave	8	12
5	Lake St & 1st Ave	7	9
6	Franklin Ave & Chicago Ave	7	15
7	Lyndale Ave & 24th St	7	8
8	Lyndale Ave & 22th St	7	8
9	Franklin Ave & Park Ave	7	8
10	Franklin Ave & Portland Ave	6	10

Table 7: Predicted Intersection Crash Ranking

Midblock Crashes

Similarly, for midblock locations, our results of the top ten midblock locations by EB estimated crashes are presented in Table 8. The midblock location with the overall highest number of predicted crashes is West Broadway Ave between Logan Ave and Penn Ave at three crashes when rounding to the nearest integer. This is different from the location with the historical highest crash value of nine along Cedar Ave between 7th St S and Riverside Ave. The caveat for interpreting the intersection predictions holds true for midblocks as well. No midblock location had an EB-predicted number of crashes higher than three due to the nature of predicting outlier cases. However, we again see more high crash midblock locations in urban areas of Hennepin County along roads such as Franklin Ave, W Broadway Ave and University Ave.

Predicted Midblock Crash Ranking

Rank	County Road	Closest Intersections	Predicted Crash Total	2012-21 Crash Total
1	West Broadway	Logan Ave to Penn Ave	3	2
2	Penn Ave	West Broadway to Lowry Ave	3	2
3	Cedar Ave	26th St to 24th St	3	3
4	Lyndale Ave	Lake St to 26th St	2	7
5	West Broadway	Washington Ave to I-94 W Ramp	2	4
6	Franklin Ave	Lyndale Ave to Nicollet Ave	2	3
7	Lyndale Ave	26th St to Franklin Ave	2	2
8	University Ave	I-35W to I-35W Frontage Rd	2	3
9	Cedar Ave	23rd Ave to West Broadway	2	8
10	University Ave	15th Ave to Oak St	2	1

Table 8: Predicted Midblock Crash Ranking

Fatalities and Serious Injuries (Intersections and Midblocks)

For the third SPF related to predicted fatalities/serious injuries, we indicate the top ten intersections and midblocks on the following page in Tables 9 and 10, respectively. While the pseudo-R^2 for this SPF was higher than that of the midblock SPF, there are some important notes to keep in mind with these particular predictions. Our historical data saw no more than four fatalities or serious injuries combined at any particular intersection or midblock. Furthermore, most locations had zero fatalities or serious injuries regardless of the number of crashes; and after zero, the next most common number of fatalities/serious injuries was one. It is largely for this reason that no location sees an EB-predicted number of fatalities or serious injuries higher than one. However, these predictions, along with the previous crash number predictions, can still offer a general indication of which intersections and midblocks appear to be at increased risk of harm.

Predicted Intersection Serious Injury & Fatality Ranking

Rank	Location	Predicted Crash Total	2012-21 Crash Total
1	Portland Ave & 78th St	0.98	0
2	Brooklyn Blvd & 62nd Ave	0.91	0
3	Old Shakopee Rd & Nesbitt Ave	0.81	0
4	Bass Lake Rd & Rhode Island Ave	0.78	0
5	Cedar Ave & 26th St	0.75	4
6	Old Shakopee Rd & Dupont Ave	0.74	0
7	Lake St & Chicago Ave	0.74	1
8	Cedar Ave & 28th St	0.73	0
9	Brooklyn Blvd & 60th Ave	0.72	0
10	Brooklyn Blvd & 62nd Ave	0.71	0

Table 9: Predicted Intersection Serious Injuries and Fatalities

Predicted Midblock Serious Injury & Fatality Ranking

Rank	County Road	Closest Intersections	Predicted Crash Total	2012-21 Crash Total
1	Portland Ave	77th Ave to 78th Ave	0.90	0
2	66th St	Richfield Pkwy to 16th Ave	0.86	0
3	Bass Lake Rd	Rhode Island Ave to Quebec Ave	0.85	0
4	Lyndale Ave	Lake St to 26th St	0.79	0
5	Cedar Ave	20th Ave to 19th Ave	0.79	0
6	Brooklyn Blvd	62nd Ave to 63rd Ave	0.78	0
7	Brooklyn Blvd	61st Ave to 62nd Ave	0.78	0
8	Old Shakopee Rd	Aldrich Ave to Lyndale Ave	0.76	0
9	Old Shakopee Rd	Lyndale Ave to Grand Ave	0.74	0
10	West Broadway	Penn Ave to 29th Ave	0.73	0

Table 10: Predicted Midblock Serious Injuries and Fatalities

Conclusions and Limitations

Conclusion

In this study we examined how exposure, risk, and built environment characteristics influence pedestrian crashes at intersections and midblocks in Hennepin County. We framed our study around five questions:

Question I: Which pedestrian crossings on Hennepin County roads see the highest number of pedestrian crashes?

We used GIS to identify and analyze locations and corridors in the county with high crash frequencies. We found that the City of Minneapolis has by far the highest number of crashes among the municipalities in Hennepin County, and that crashes that occur in Minneapolis are concentrated on a few high traffic corridors. This is unsurprising given that Minneapolis is the most urbanized portion of Hennepin County and also has the highest volume of pedestrian traffic.

Question II: Which crossing locations see the highest number of fatalities and/or serious injuries as a result of those crashes?

The intersections with the three highest number of fatalities and/or serious injuries were:

- Cedar Ave S and E 26th St (7 total crashes, 4 serious/fatal)
- E Lake St and 12th Ave S (4 total crashes, 3 serious/fatal)
- W Broadway and Lyndale Ave N (30 total crashes, 3 serious/fatal)

The midblocks with the three highest number of fatalities and/or serious injuries are:

- Cedar Ave S - 7th St to Riverside Ave (9 total crashes, 3 serious/fatal)
- Washington Ave N - 23rd Ave N to W Broadway Ave (8 total crashes, 2 serious/fatal)
- Lyndale Ave S - W Lake St to W 26th St (7 total crashes, 1 serious/fatal)

Question III: How do street characteristics (e.g., street width, speed limit, etc.) and local area characteristics (e.g., land uses, population density/make-up, etc.) correlate with the number of crashes?

We utilized negative binomial regression to model historic crashes and create safety performance functions that then were used to predict the number of crashes expected at an intersection or midblock, given the values taken on by 20 different variables. We found that at intersections, five variables were positively correlated with the number of historic crashes at sites, while three were negatively correlated. At midblocks, only one variable was found to be positively correlated, while three were found to be negatively correlated. Both models had relatively weak pseudo-R^2 values, though the intersections model was stronger than the midblocks model.

Question IV: Which characteristics seem to increase/decrease the severity of those crashes?

At intersections, the following characteristics were significantly positively correlated with crash risk:

- Presence of a stoplight
- Total population
- Percentage of the population below 185% of the federal poverty level

- Presence of a transit stop
- AADT

Conversely, the following characteristics were significantly negatively correlated with crash risk at intersections:

- Female population percentage
- Divided roadways
- Presence of a bike facility
- Open space land uses

At midblocks, fewer variables were found to have statistical significance. Only non-white population percentage was significantly positively correlated with crash risk, while total population, age 65 and over population, and the presence of a bike facility were significantly negatively correlated with crash risk.

Question V: Based on the identified characteristics that correlate with higher numbers of pedestrian crashes (and higher numbers of fatalities/severe injuries), which intersection and midblock locations appear to be at higher risk of pedestrian crashes? We used the three SPFs to predict crashes at all intersections and all midblocks in Hennepin County and to estimate crash severity and all intersections and midblocks combined.

The three intersections at the highest risk of pedestrian crashes are:

- West Broadway Ave and Lyndale Ave N (15.3 predicted crashes)
- W Lake Street and Lyndale Ave S (8.8 predicted crashes)
- W Franklin Ave and Nicollet Ave (8.7 predicted crashes)

The three midblocks at the highest risk of pedestrian crashes are:

- West Broadway Ave between Logan Ave N and Penn Ave N (2.7 predicted crashes)
- Penn Ave N between Logan Ave N and West Broadway Ave (2.6 predicted crashes)
- Cedar Ave S between E 24th St and E 26th St (2.5 predicted crashes)

Limitations

The wide range of studies undertaken on pedestrian crash risk has produced a wide range of crash risk and crash exposure variables, so it is difficult to include all variables that may impact crashes and risk. While the variables that were most commonly determined to be statistically significant in other studies were used in this study, these likely are not the only variables that foster influence. The availability of data is another factor which influenced the determination of variables utilized in this study, as well as the scope of this research. Additionally, the timeframe of much of the data used to construct explanatory variables in our analyses does not fully cohere or align with the 10-year period used for the crash analysis. During this timeframe, roadway infrastructure may have deteriorated, received infrastructural improvements, and/or been completely rebuilt. Our data only contained roadway conditions at the time of the crash and does not contain any information of roadway quality changes. Therefore, an intersection which may appear to have a large number of crashes, may be due to a prior infrastructural system which no longer pertains today. Since crash reports are filled out manually, there are many instances where data is missing; or if multiple crashes occurred at the same intersection, each person manually filling out the same data points might interpret the surroundings differently. These two facts create some difficulty in assessing certain crash variables.

Our measure of presence of a transit stop simply tells us if a stop was present at some point in the last 10 years - meaning a stop that was present at some location in 2013 might have been taken out of service or rerouted in 2018. Additionally, our chosen measure did not go into further detail about how many transit stops were within our buffers, how many routes served those stops, or how many riders used those routes. This again, was partially due to data availability and the aforementioned 10-year timespan of our crash data. Future studies incorporating more detailed transit related information when available could provide a more accurate picture of how many pedestrians are present in or pass through a given area.

Perhaps the most notable limitation of this work is the absence of direct pedestrian count volumes for our analyzed locations. Other studies have emphasized the growing importance of the inclusion of pedestrian volume counts to give an indication of the level of pedestrian exposure to risk (Merlin et al., 2020; Tao et al., 2021). However, this kind of data is rarely as widely available as its vehicular counterpart, AADT. Traditional methods of obtaining direct counts of pedestrians and cyclists for planning and/or safety studies often utilize manual or automated counts at specific locations - although proxies such as population and/or employment density can be used (Tao et al., 2021).

In efforts to increase the scale of data collection, researchers are increasingly turning to crowdsourced pedestrian/bicycle count data from sources which passively gather data via GPS (or similar location services) such as StreetLight Data Inc., by first verifying the accuracy of these crowdsourced data compared to baseline direct counts in cities (Turner et al., 2020; Cheng et al., 2022). Some examples include Cheng et al., who determined that StreetLight data can offer a suitable alternative to permanent counters. Furthermore, they created a method to adjust the crowdsourced StreetLight data into AADT equivalents for pedestrian and bike modes (Cheng et al., 2022). Similarly, Turner et al. evaluated several crowdsourced forms of data for both pedestrian and bicycle-related counting compared to direct counts. They found that the Miovision traffic signal system was accurate enough to have potential for use in future studies - particularly for pedestrian exposure in crash studies - and that bicycle count data from StreetLight were well correlated with baseline direct counts (and very well correlated with estimates from other sources like Strava) (Turner et al., 2022). While this work did not employ any form of direct pedestrian count data, these studies help to demonstrate the potential avenues to improve the accuracy of future results should this work be recreated in the future.

References

American Association of State Highway and Transportation Officials. "AASHTO - Highway Safety Manual - Home," 2010. https://www.highwaysafetymanual.org/Pages/default.aspx.

Ammar, Dania, Yueru Xu, Bochen Jia, and Shan Bao. "Examination of Recent Pedestrian Safety Patterns at Intersections through Crash Data Analysis." *Transportation Research Record: Journal of the Transportation Research Board* 2676, no. 12 (December 2022): 331–41. https://doi.org/10.1177/03611981221095513.

Cheng, Wen, Yongping Zhang, and Edward Clay. "Comprehensive Performance Assessment of Passive Crowdsourcing for Counting Pedestrians and Bikes." *Mineta Transportation Institute Publications*, February 1, 2022. https://doi.org/10.31979/mti.2022.2025.

City of Minneapolis. "City of Minneapolis Pedestrian Crash Study," 2017. https://www2.minneapolismn.gov/government/departments/public-works/tpp/data-research/pedestrian-crash-study-2017/.

Cottrill, Caitlin D., and Piyushimita (Vonu) Thakuriah. "Evaluating Pedestrian Crashes in Areas with High Low-Income or Minority Populations." *Accident Analysis & Prevention* 42, no. 6 (November 1, 2010): 1718–28. https://doi.org/10.1016/j.aap.2010.04.012.

Ghomi, Haniyeh, and Mohamed Hussein. "Analyzing the Safety Consequences of Pedestrian Spatial Violation at Mid-Blocks: A Bayesian Structural Equation Modeling Approach." *Transportation Research Record: Journal of the Transportation Research Board* 2677, no. 1 (January 2023): 1–13. https://doi.org/10.1177/03611981221097964.

Hennepin County. "Pedestrian Plan." County of Hennepin, 2013. https://www.hennepin.us/-/media/hennepinus/residents/transportation/documents/pedestrian-plan.pdf.

"Incorporated Places in Hennepin (Minnesota, USA) - Population Statistics, Charts, Map, Location, Weather and Web Information." Accessed April 11, 2023. https://www.citypopulation.de/en/usa/minnesota/27053__hennepin/.

Jacobsen, P. "Safety in Numbers: More Walkers and Bicyclists, Safer Walking and Bicycling." *Injury Prevention* 9, no. 3 (September 2003): 205–9. https://doi.org/10.1136/ip.9.3.205.

Kang, Mingyu, Anne Vernez Moudon, Haena Kim, and Linda Ng Boyle. "Intersections and Non-Intersections: A Protocol for Identifying Pedestrian Crash Risk Locations in GIS." *International Journal of Environmental Research and Public Health* 16, no. 19 (September 24, 2019): 3565. https://doi.org/10.3390/ijerph16193565.

Kumfer, Wesley, Libby Thomas, Laura Sandt, and Bo Lan. "Midblock Pedestrian Crash Predictions in a Systemic, Risk-Based Pedestrian Safety Process." *Transportation Research Record: Journal of the Transportation Research Board* 2673, no. 11 (November 2019): 420–32. https://doi.org/10.1177/0361198119847976.

Lin, Pei-Sung, Rui Guo, Elzbieta Bialkowska-Jelinska, Achilleas Kourtellis, and Yu Zhang. “Development of Countermeasures to Effectively Improve Pedestrian Safety in Low-Income Areas.” *Journal of Traffic and Transportation Engineering (English Edition)* 6, no. 2 (April 1, 2019): 162–74. https://doi.org/10.1016/j.jtte.2019.02.001.

Ma, Wanjing, Philip Kofi Alimo, Ling Wang, and Mohamed Abdel-Aty. “Mapping Pedestrian Safety Studies between 2010 and 2021: A Scientometric Analysis.” *Accident Analysis & Prevention* 174 (September 2022): 106744. https://doi.org/10.1016/j.aap.2022.106744.

McFadden, Daniel. “Quantitative Methods for Analysing Travel Behaviour of Individuals: Some Recent Developments.” In *Behavioural Travel Modelling*. Routledge, 1979.

Merlin, Louis A., Erick Guerra, and Eric Dumbaugh. “Crash Risk, Crash Exposure, and the Built Environment: A Conceptual Review.” *Accident Analysis & Prevention* 134 (January 1, 2020): 105244. https://doi.org/10.1016/j.aap.2019.07.020.

Metropolitan Council. “Regional Pedestrian Safety Action Plan,” May 5, 2021. https://metrocouncil.org/Transportation/System/Bicycle-and-Pedestrian/Studies/Regional-Pedestrian-Safety-Action-Plan.aspx.

Miao, Mingyue, Yanqun Yang, and Yu Liang. “Pedestrian Crash Risk Assessment and Intervention.” *Advances in Mechanical Engineering* 8, no. 7 (July 2016): 168781401665329. https://doi.org/10.1177/1687814016653296.

Miranda-Moreno, Luis F., Patrick Morency, and Ahmed M. El-Geneidy. “The Link between Built Environment, Pedestrian Activity and Pedestrian–Vehicle Collision Occurrence at Signalized Intersections.” *Accident Analysis & Prevention* 43, no. 5 (September 2011): 1624–34. https://doi.org/10.1016/j.aap.2011.02.005.

Mukherjee, Dipanjan, and Sudeshna Mitra. “Investigating the Fatal Pedestrian Crash Occurrence in Urban Setup in a Developing Country Using Multiple-Risk Source Model.” *Accident Analysis & Prevention* 163 (December 2021): 106469. https://doi.org/10.1016/j.aap.2021.106469.

Ragland, David R., Offer Grembek, Phyllis Orrick, and Grace Felschundneff. “Roadway and Infrastructure Design and Its Relation to Pedestrian and Bicycle Safety: Basic Principles, Applications, and Benefits,” July 1, 2013. https://escholarship.org/uc/item/9qg3s59b.

Schneider, Robert J., Frank R. Proulx, Rebecca L. Sanders, and Hamideh Moayyed. “United States Fatal Pedestrian Crash Hot Spot Locations and Characteristics.” *Journal of Transport and Land Use* 14, no. 1 (2021): 1–23.

Schneider, Robert J., Andrew Schmitz, Greg Lindsey, and Xiao Qin. “Exposure-Based Models of Trail User Crashes at Roadway Crossings.” *Transportation Research Record* 2675, no. 8 (August 1, 2021): 468–80. https://doi.org/10.1177/0361198121998692.

Srinivasan, Raghavan, and Karin Bauer. “Safety Performance Function Development Guide: Developing Jurisdiction-Specific SPFs | FHWA.” Federal Highway Administration, September 2013. https://highways.dot.gov/safety/data-analysis-tools/rsdp/rsdp-tools/safety-performance-function-development-guide-0.

Sun, Ming, Xiaoduan Sun, and Donghui Shan. "Pedestrian Crash Analysis with Latent Class Clustering Method." *Accident Analysis & Prevention* 124 (March 1, 2019): 50–57. https://doi.org/10.1016/j.aap.2018.12.016.

Tao, Tao, Greg Lindsey, Jason Cao, and Jueyu Wang. "The Effects of Pedestrian and Bicycle Exposure on Crash Risk in Minneapolis." *Journal of Transport and Land Use* 14, no. 1 (November 5, 2021): 1187–1208. https://doi.org/10.5198/jtlu.2021.1980.

Thomas, Libby, Bo Lan, Rebecca L. Sanders, Alexandra Frackelton, Spencer Gardner, and Michael Hintze. "Changing the Future?: Development and Application of Pedestrian Safety Performance Functions to Prioritize Locations in Seattle, Washington." *Transportation Research Record* 2659, no. 1 (January 1, 2017): 212–23. https://doi.org/10.3141/2659-23.

Training—Safety | Federal Highway Administration. (2013, October 4). U.S. Department of Transportation. https://safety.fhwa.dot.gov/local_rural/training/fhwasa14072/sec9.cfm

Turner, Shawn, Michael Martin, Greg Griffin, Minh Le, Subasish Das, Ruihong Wang, Bahar Dadashova, and Xiao Li. "Exploring Crowdsourced Monitoring Data for Safety," March 2020. https://rosap.ntl.bts.gov/view/dot/50717.

Turner, Shawn, Ipek Sener, Michael Martin, L.D. White, Subasish Das, Robert Hampshire, Mike Colety, Kay Fitzpatrick, and Ravi Wijesundera. "Guide for Scalable Risk Assessment Methods for Pedestrians and Bicyclists | FHWA." Texas A&M Transportation Institute, July 2018. https://highways.dot.gov/safety/pedestrian-bicyclist/safety-tools/guide-scalable-risk-assessment-methods-pedestrians-and-0.

UCLA: Statistical Consulting Group. (n.d.). Negative Binomial Regression | Stata Data Analysis Examples. Retrieved April 24, 2023, from https://stats.oarc.ucla.edu/stata/dae/negative-binomial-regression/

Ukkusuri, Satish, Luis F. Miranda-Moreno, Gitakrishnan Ramadurai, and Jhael Isa-Tavarez. "The Role of Built Environment on Pedestrian Crash Frequency." *Safety Science* 50, no. 4 (April 2012): 1141–51. https://doi.org/10.1016/j.ssci.2011.09.012.

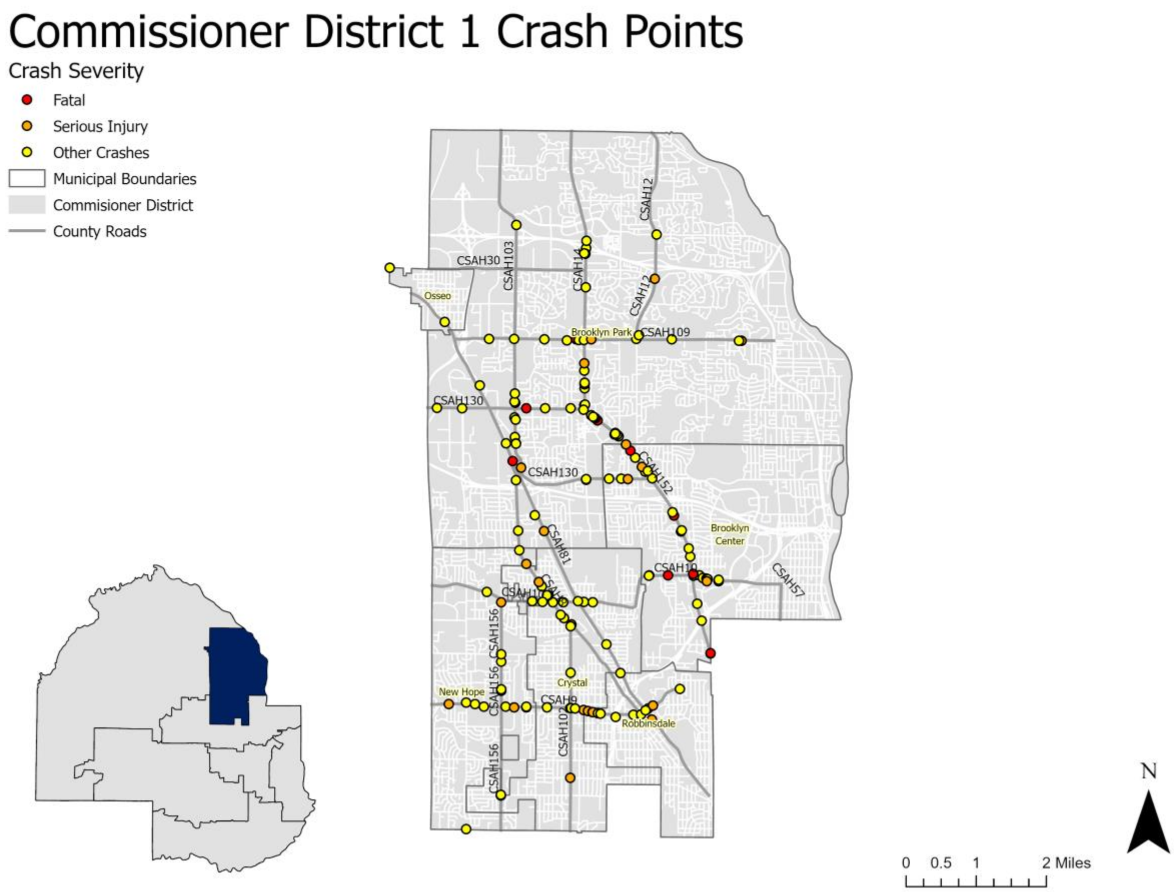
"U.S. Census Bureau QuickFacts: Hennepin County, Minnesota." Accessed April 11, 2023. https://www.census.gov/quickfacts/hennepincountyminnesota.

Wang, Xuesong, Junguang Yang, Chris Lee, Zhuoran Ji, and Shikai You. "Macro-Level Safety Analysis of Pedestrian Crashes in Shanghai, China." *Accident Analysis & Prevention* 96 (November 2016): 12–21. https://doi.org/10.1016/j.aap.2016.07.028.

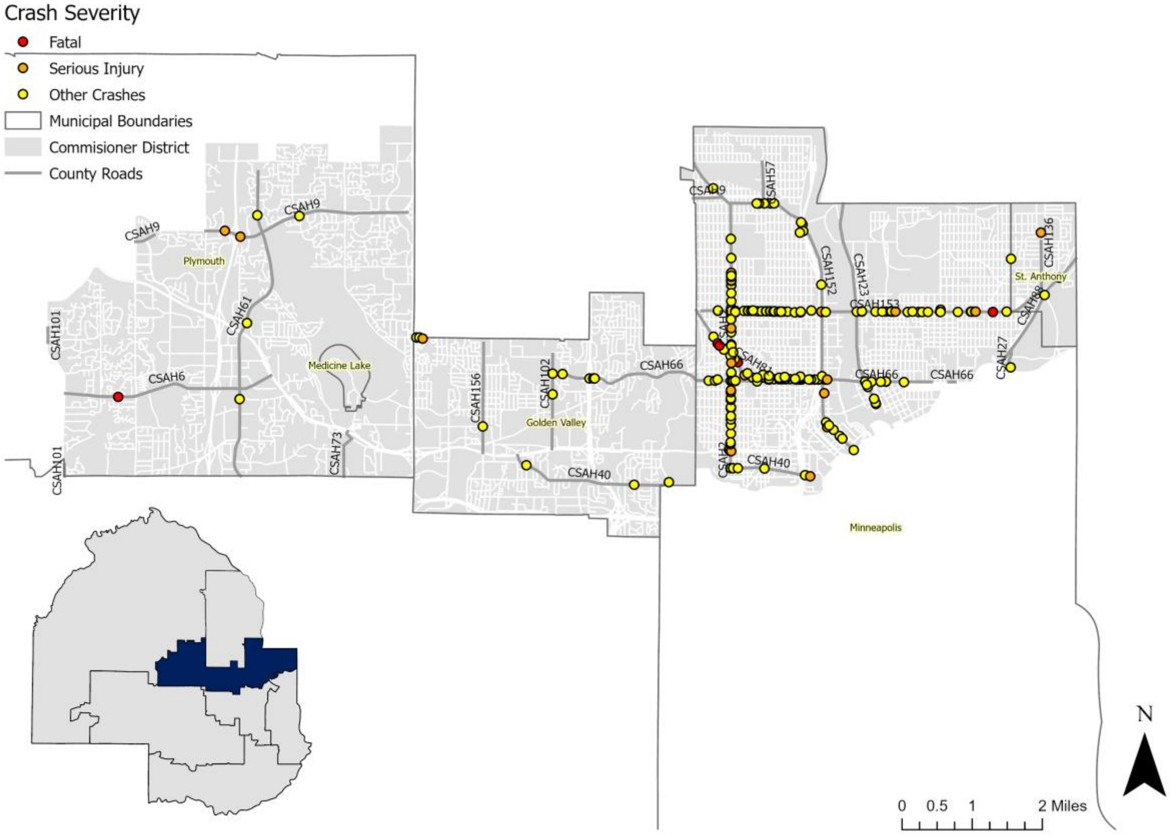
Zegeer, Charles V., and Max Bushell. "Pedestrian Crash Trends and Potential Countermeasures from around the World." *Accident Analysis & Prevention*, Safety and Mobility of Vulnerable Road Usears: Pedestrians, Bicyclists, and Motorcyclists, 44, no. 1 (January 1, 2012): 3–11. https://doi.org/10.1016/j.aap.2010.12.007.

Appendices

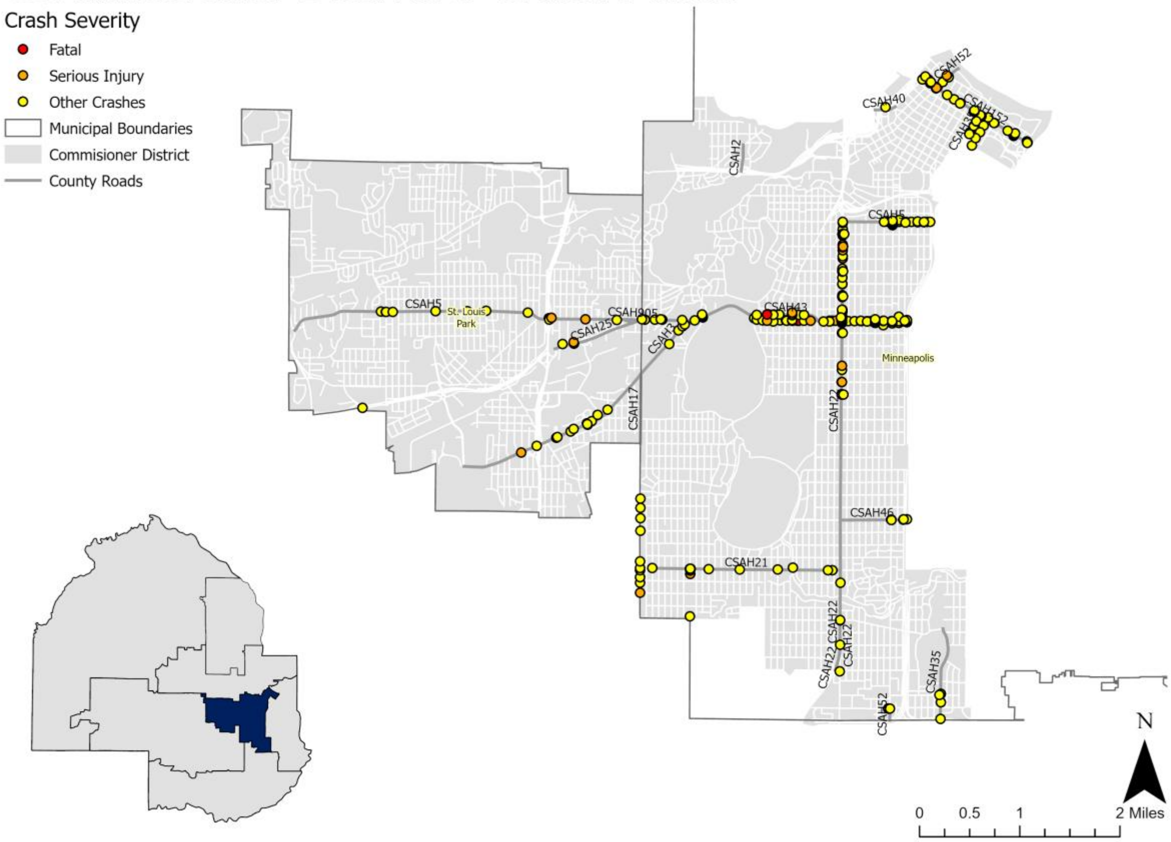
Appendix A: Pedestrian Crashes by Commissioner District

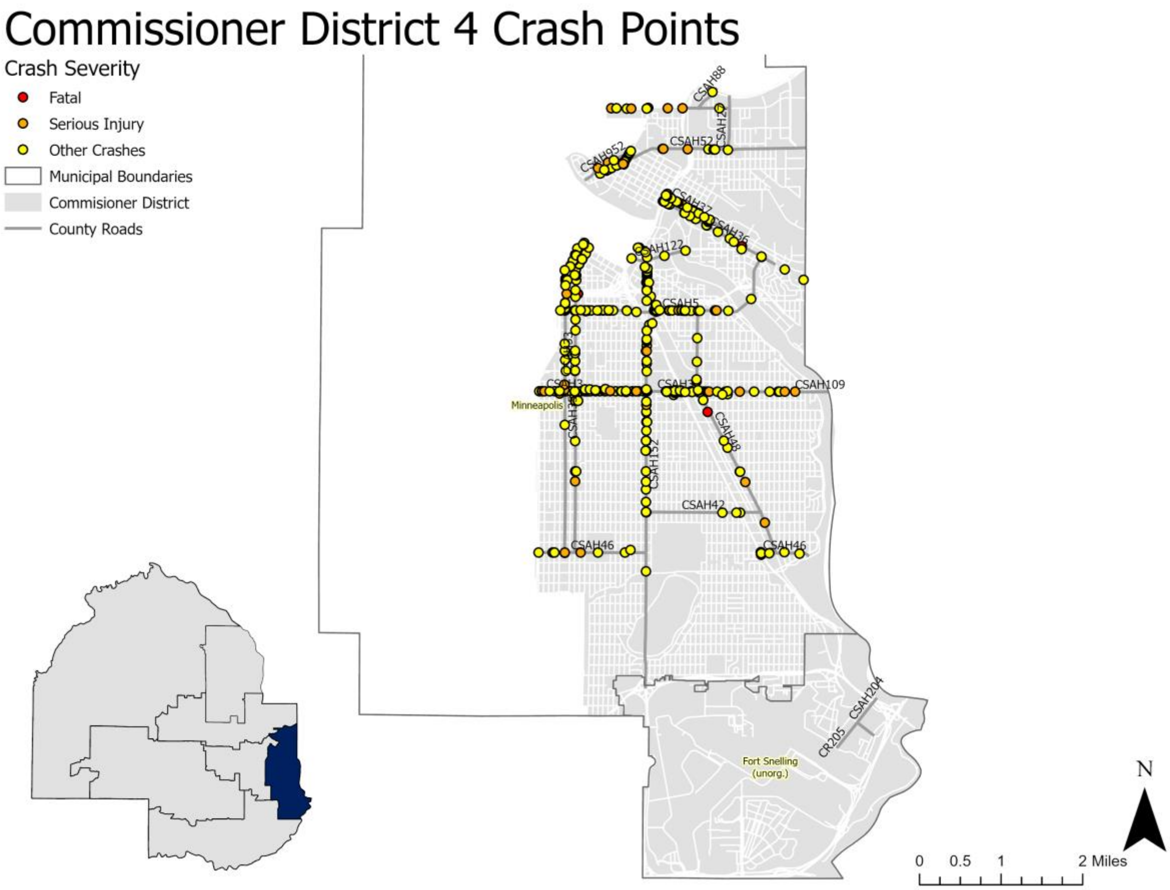


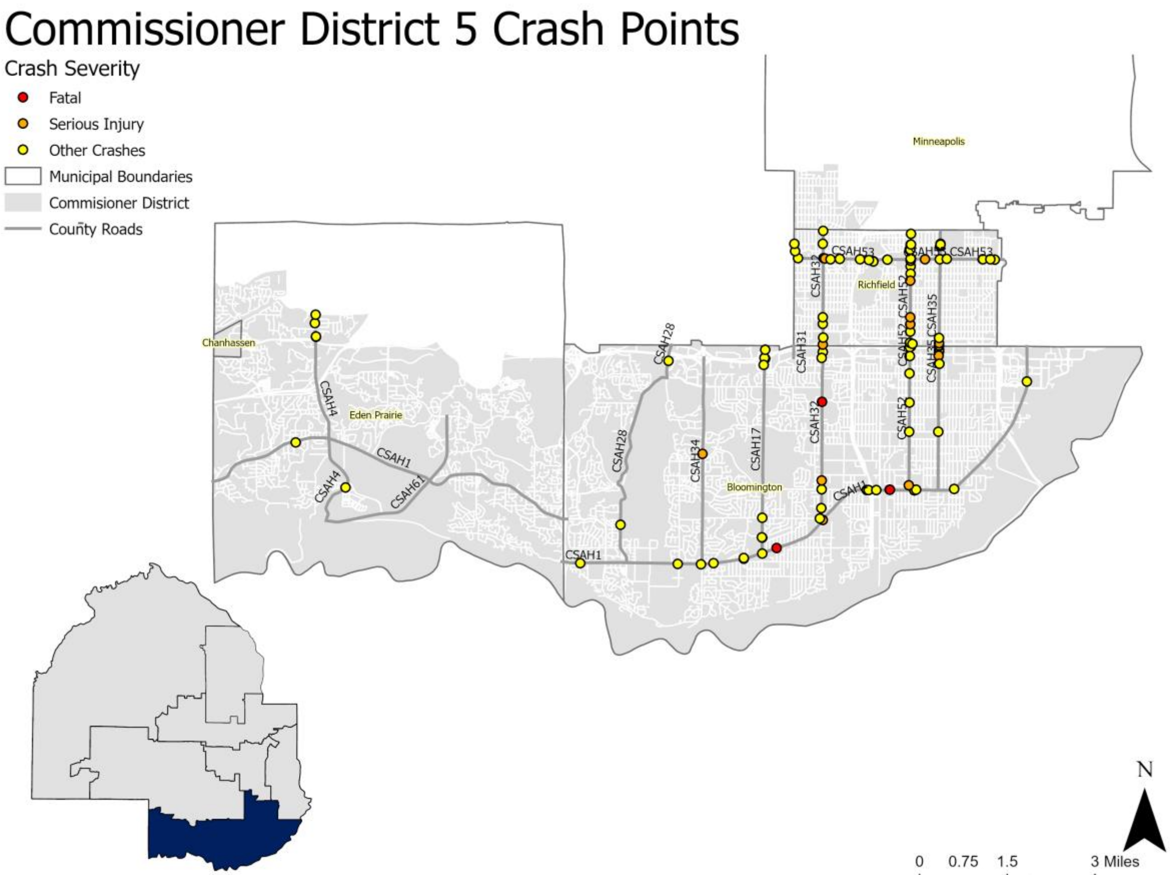
Commissioner District 2 Crash Points



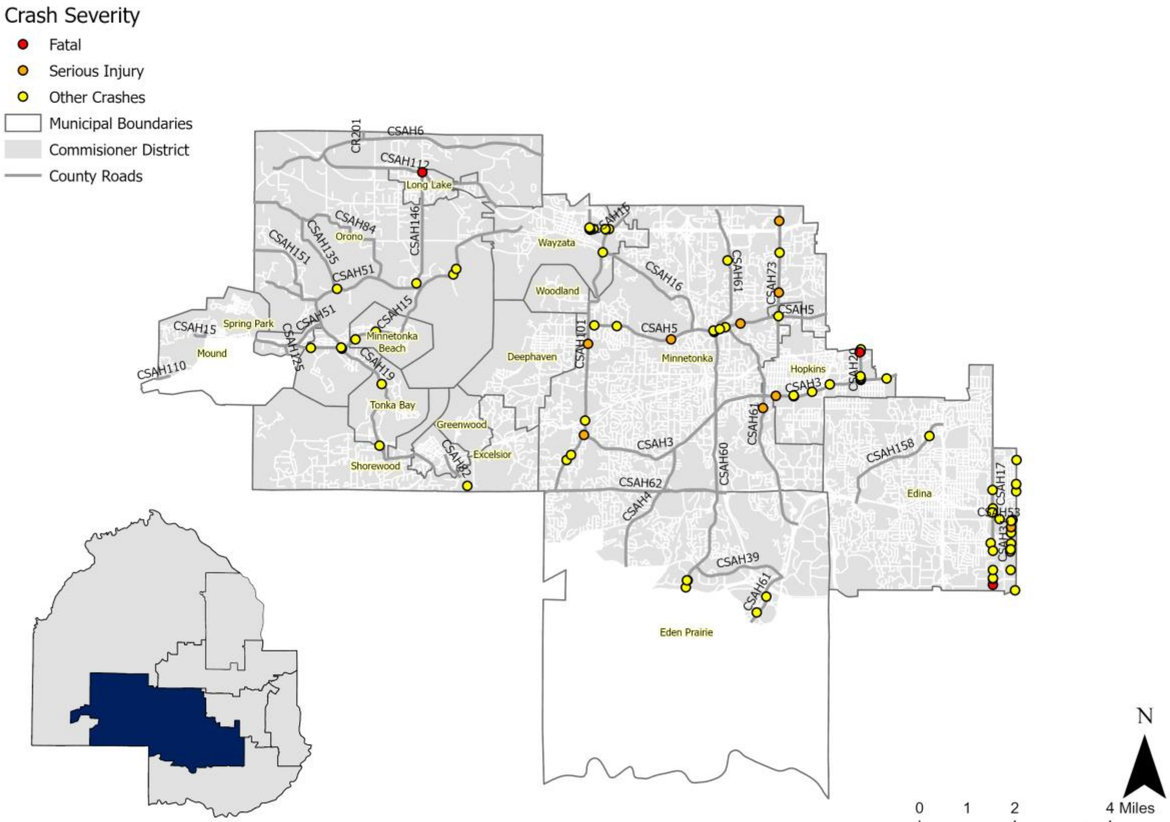
Commissioner District 3 Crash Points



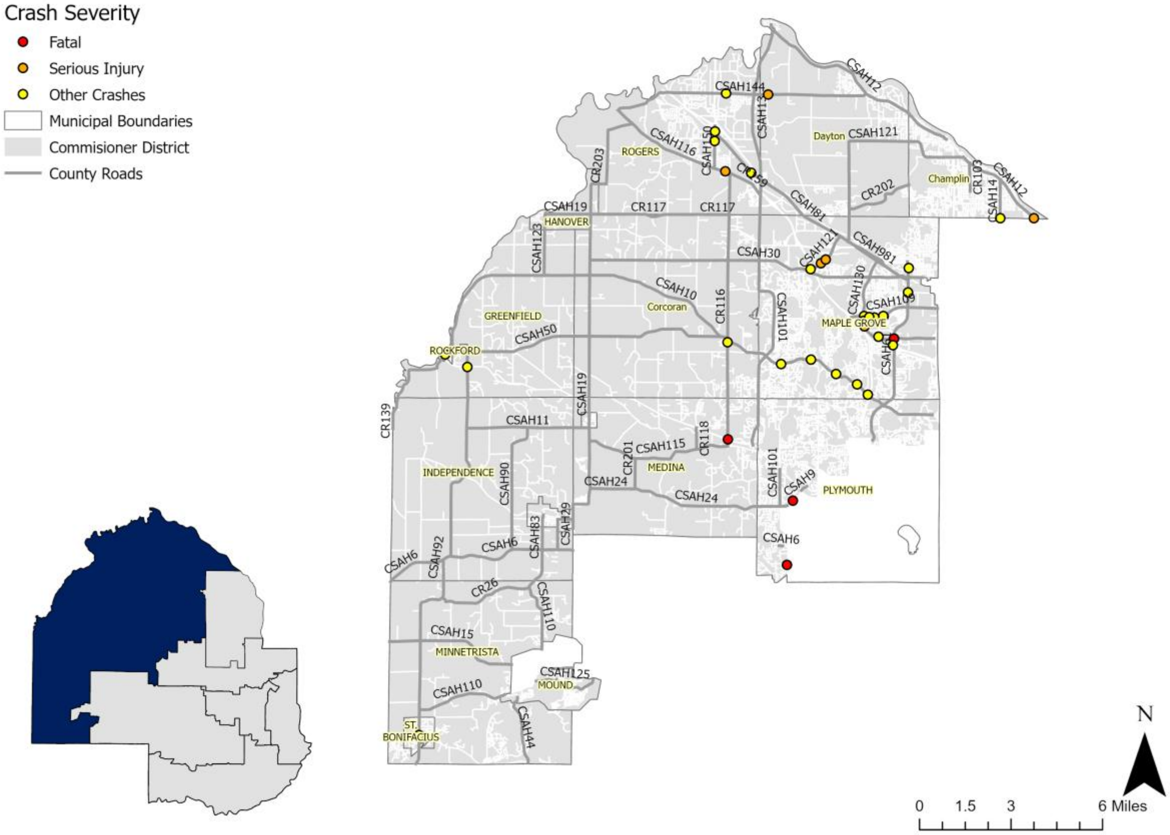

Commissioner District 4 Crash Points
Crash Severity
Fatal
Serious Injury
Other Crashes
Municipal Boundaries
Commisioner District
County Roads
CSAH88
CSAH52
CSAH952
CSAH27
CSAH36
CSAH122
CSAH5
CSAH3
CSAH109
Minneapolis
CSAH48
CSAH152
CSAH42
CSAH46
CSAH46
CR205
CSAH204
Fort Snelling
(unorg.)
N
0 0.5 1 2 Miles


Commissioner District 5 Crash Points
Crash Severity
Fatal
Serious Injury
Other Crashes
Municipal Boundaries
Commisioner District
County Roads
Minneapolis
Richfield
Chanhassen
Eden Prairie
Bloomington
CSAH53
CSAH52
CSAH35
CSAH32
CSAH31
CSAH28
CSAH34
CSAH17
CSAH1
CSAH4
CSAH61
N
0 0.75 1.5 3 Miles

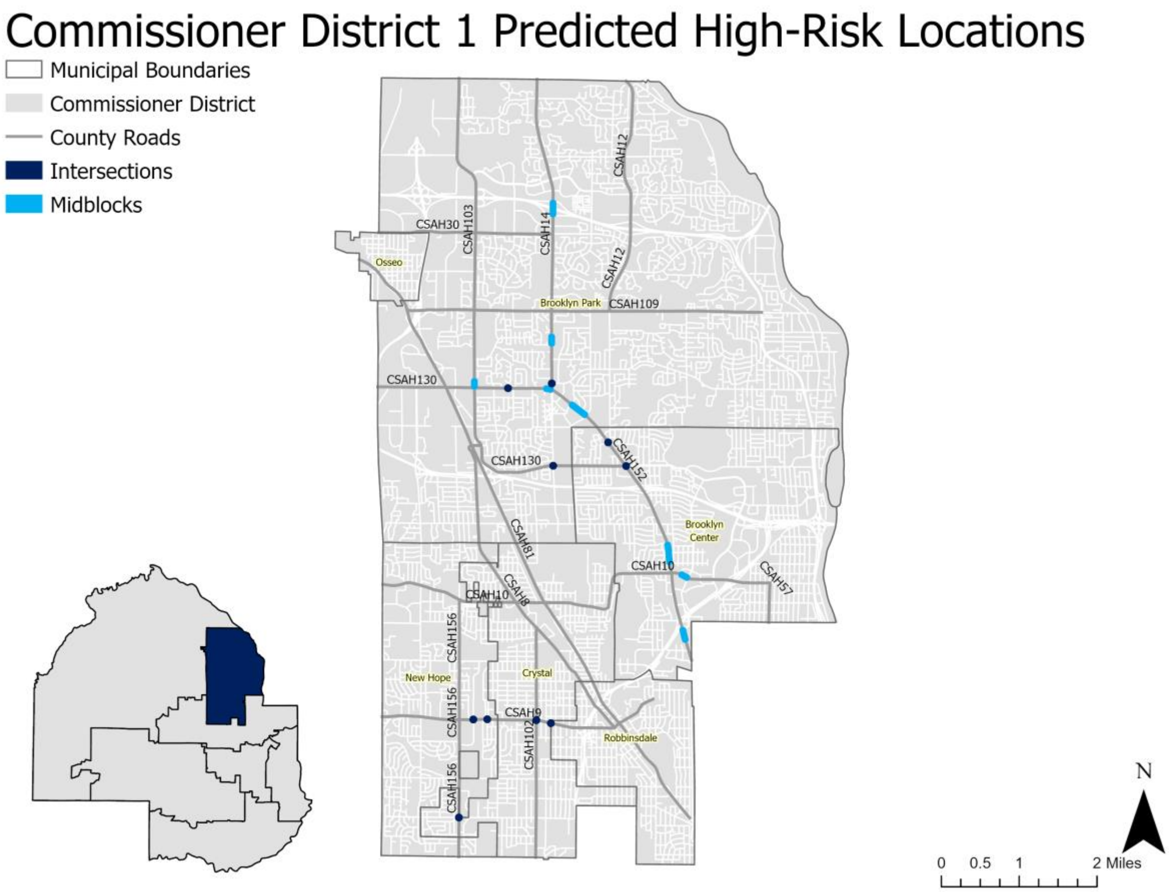
Commissioner District 6 Crash Points

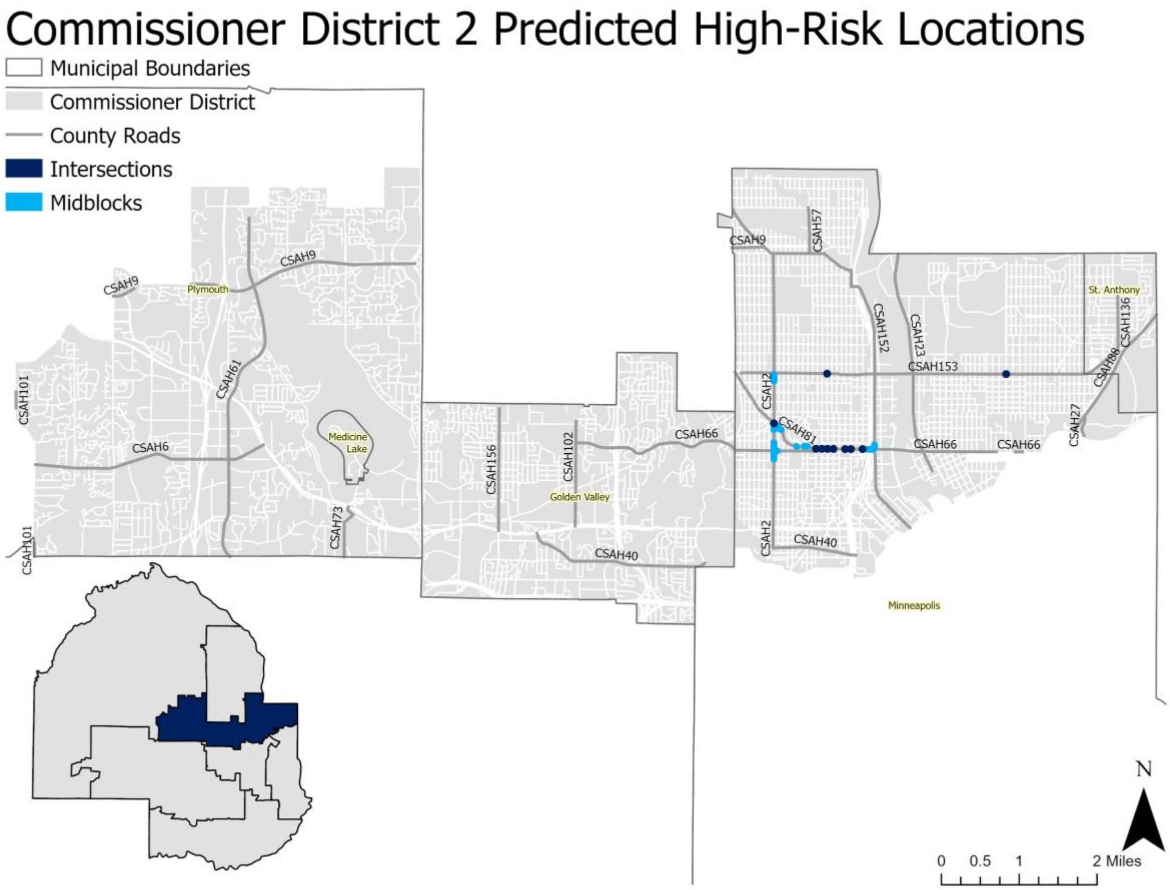


Commissioner District 7 Crash Points

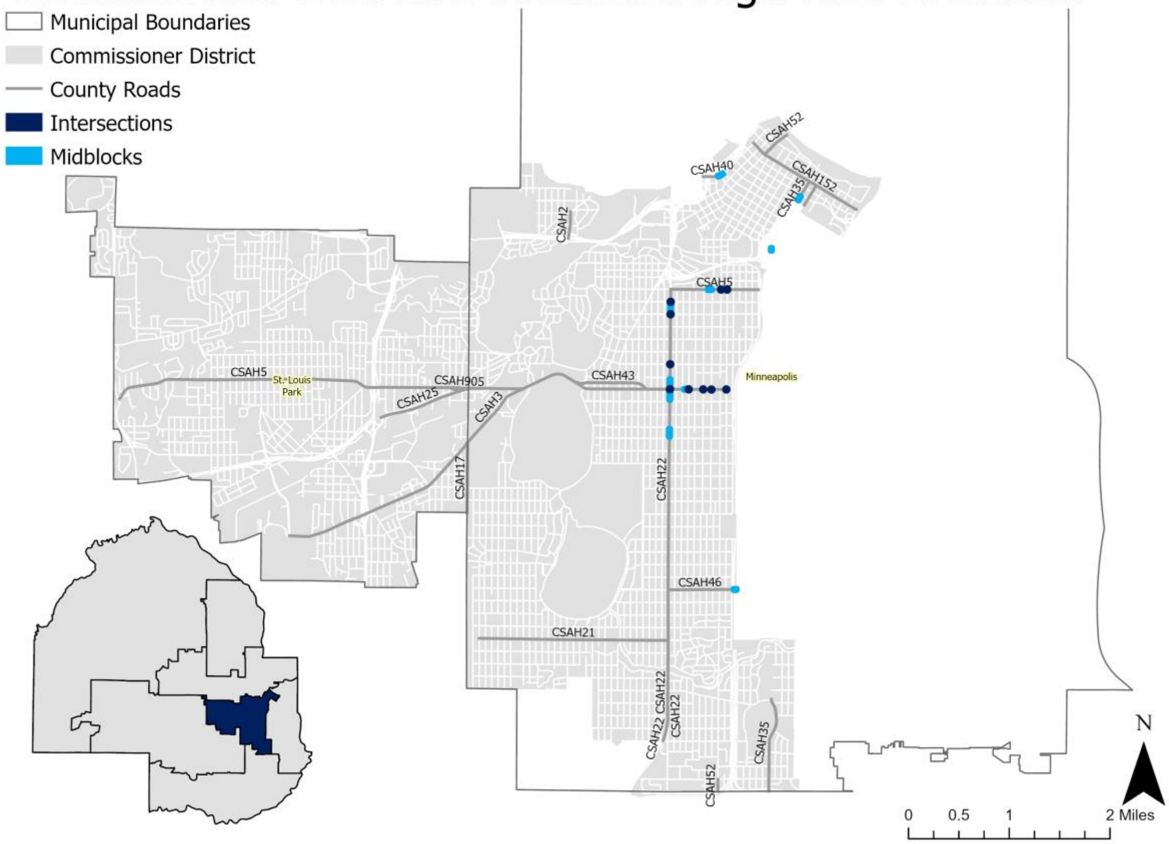


Appendix B: Predicted High-Risk Locations by Commissioner District

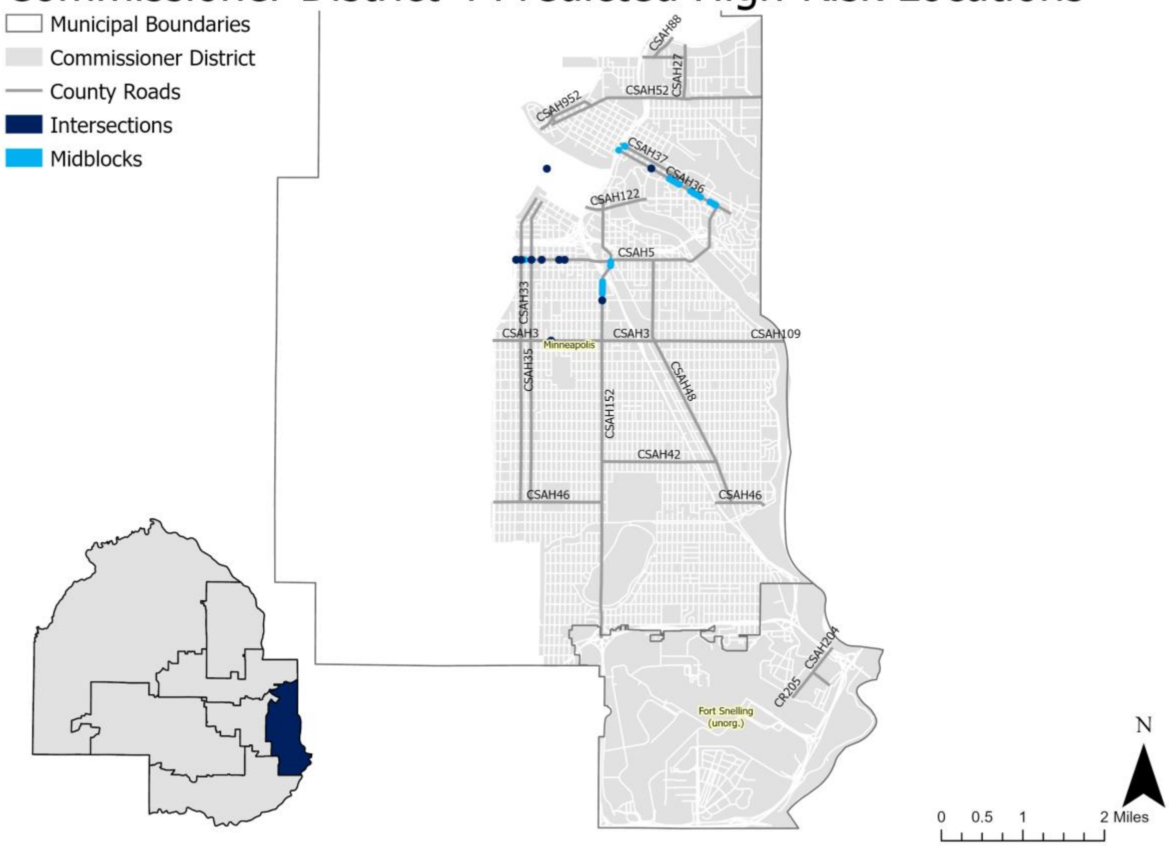


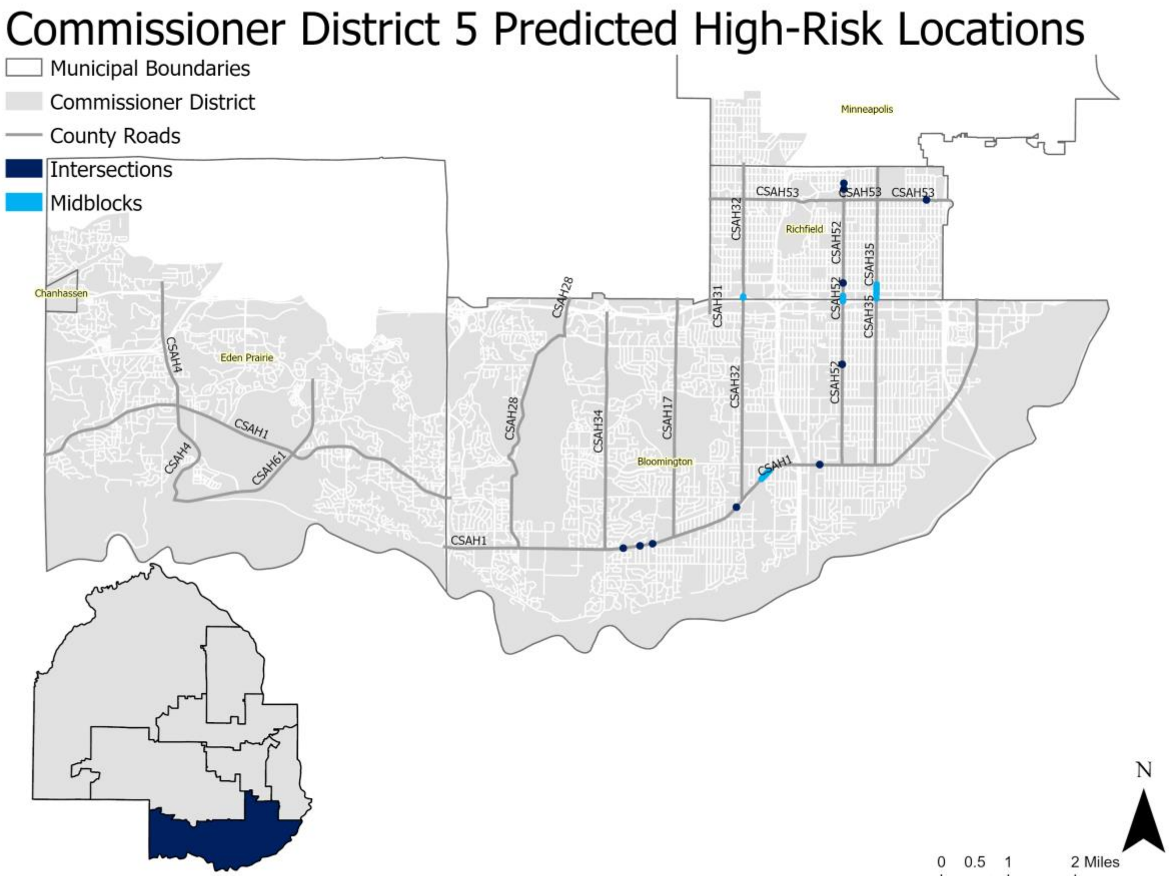

Commissioner District 2 Predicted High-Risk Locations
Municipal Boundaries
Commissioner District
County Roads
Intersections
Midblocks
CSAH9
Plymouth
CSAH61
CSAH101
CSAH6
Medicine Lake
CSAH73
CSAH156
CSAH102
Golden Valley
CSAH66
CSAH40
CSAH57
CSAH2
CSAH81
CSAH152
CSAH23
CSAH153
CSAH27
CSAH88
CSAH136
St. Anthony
Minneapolis
N
0 0.5 1 2 Miles

Commissioner District 3 Predicted High-Risk Locations

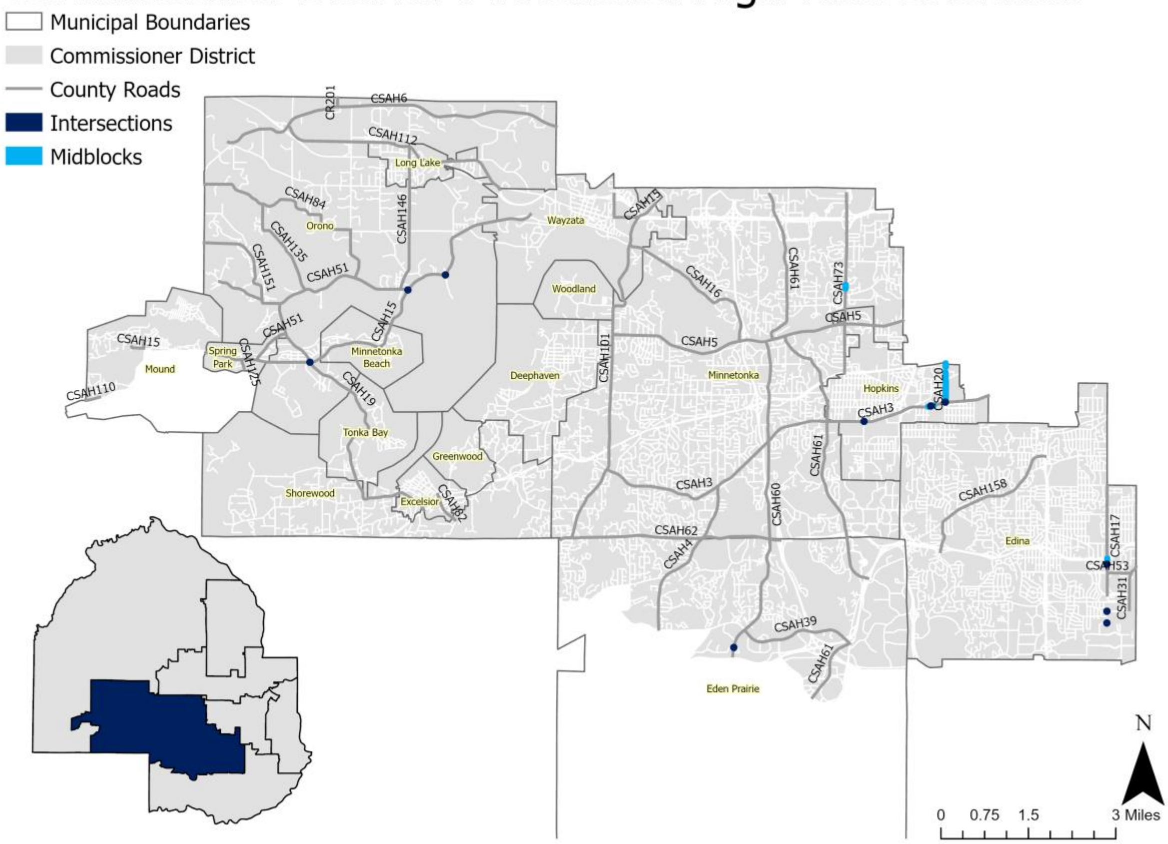


Commissioner District 4 Predicted High-Risk Locations

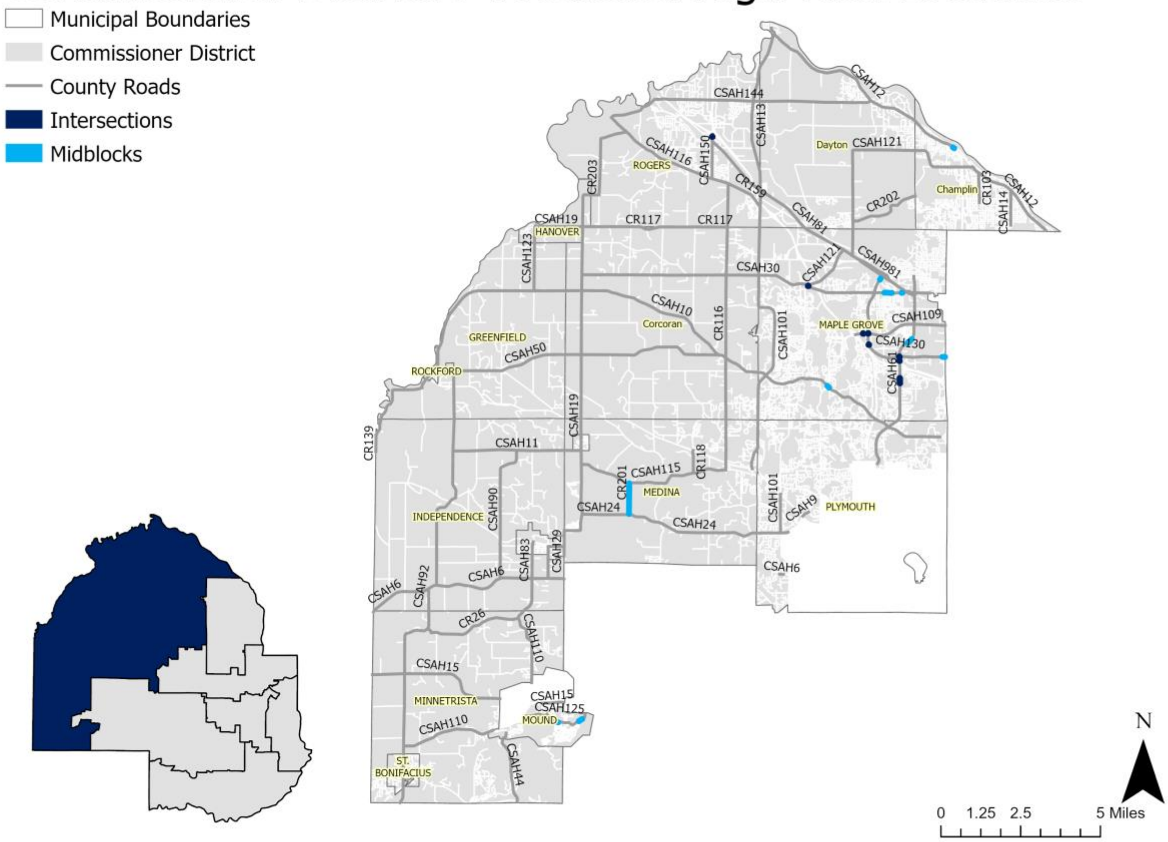



Commissioner District 5 Predicted High-Risk Locations
Municipal Boundaries
Commissioner District
County Roads
Intersections
Midblocks
Minneapolis
Richfield
Chanhassen
Eden Prairie
Bloomington
CSAH53
CSAH32
CSAH52
CSAH35
CSAH31
CSAH28
CSAH4
CSAH1
CSAH61
CSAH34
CSAH17
N
0 0.5 1 2 Miles

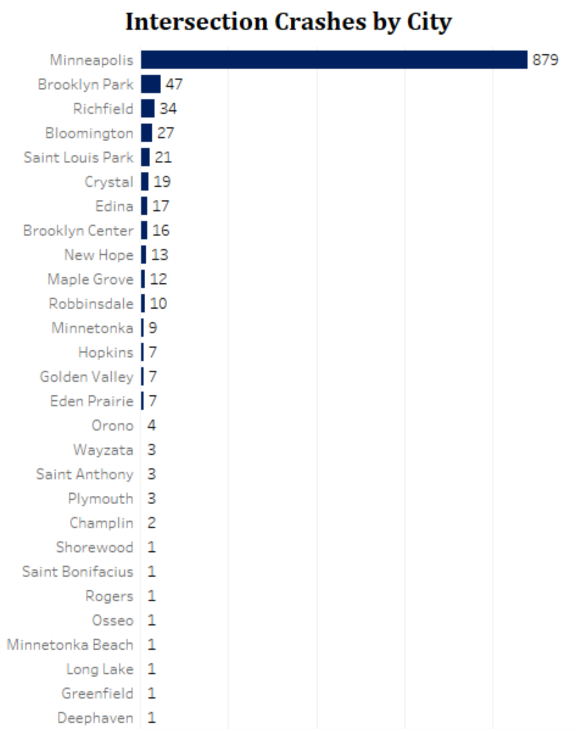
Commissioner District 6 Predicted High-Risk Locations

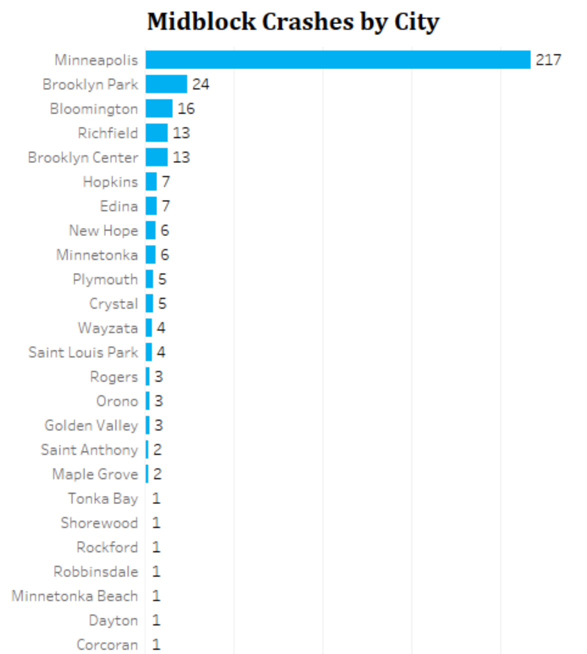


Commissioner District 7 Predicted High-Risk Locations



Appendix C: Intersection & Midblock Crashes by City





Appendix D: Intersection & Midblock Crashes by City per 10,000 People