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Statewide Analysis of Bicycle Crashes

Prepared for:

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DISCLAIMER

METRIC CONVERSION TABLE

U.S. UNITS TO SI* (MODERN METRIC) UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.400	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.610	kilometers	km
mm	millimeters	0.039	inches	in
m	meters	3.280	feet	ft
m	meters	1.090	yards	yd
km	kilometers	0.621	miles	mi

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		AREA		
in^2	square inches	645.200	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.590	square kilometers	km^2
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.470	acres	ac
km^2	square kilometers	0.386	square miles	mi^2

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		VOLUME		
fl oz	fluid ounces	29.570	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
NOTE: volumes greater than 1,000 L shall be shown in m^3.				

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.

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16. Abstract

Bicycle crashes are a major traffic safety concern in Florida. In 2014, Florida led the nation with 139 bicyclist fatalities, representing approximately 20% of the nation's total. This project aims to improve bicycle safety on Florida's state roads by conducting a comprehensive study focusing on both statewide and site-specific analyses. The specific project objectives include: (1) review and summarize existing literature on bicycle safety; (2) identify specific contributing causes and patterns of bicycle crashes; (3) identify and analyze bicycle hot spots for crash causes and potential countermeasures; and (4) develop Florida-specific Crash Modification Factors (CMFs) to assess the safety effects of common engineering treatments on bicycle safety.

In this study, an extensive literature review focusing on the methods to identify bicycle hot spots and findings on bicycle crash causes, crash contributing factors, and potential countermeasures was first conducted. A descriptive trend analysis was then conducted based on a total of 26,036 bicycle crashes that occurred during 2011-2014. The top five bicycle crash hot spots in each Florida Department of Transportation (FDOT) district were then identified using spatial analysis in ArcGIS. These hot spots experienced a total of 2,954 bicycle crashes during the four-year analysis period. Police reports of these crashes were reviewed in detail to identify specific bicycle crash types. Crash contributing factors related to each crash type along with specific countermeasures were then identified. Macroscopic spatial analysis was conducted to model the relation between demographic, socio-economic, roadway, traffic, and bicycle activity data at the census block group level and bicycle crash frequencies in Florida. Finally, cross-sectional analysis was conducted to develop Florida-specific CMFs for bicycle crashes for different roadway segment and intersection facility types.

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EXECUTIVE SUMMARY

This report describes a comprehensive study that aims to identify ways to reduce the frequency and severity of bicycle crashes in Florida. The objective is achieved through a detailed analysis of the roadway, behavioral, and spatial factors associated with bicycle crashes. An extensive literature review was first conducted. The review focuses on the methods to identify bicycle hot spots and findings on bicycle crash causes, crash contributing factors, and potential countermeasures. A descriptive trend analysis was then performed based on a total of 26,036 bicycle crashes that occurred during 2011-2014. A spatial analysis using ArcGIS was then performed to identify the top five bicycle crash hot spots in each Florida Department of Transportation (FDOT) district. These hot spots together experienced a total of 2,954 bicycle crashes during the four-year analysis period. Police reports of these bicycle crashes were reviewed in detail to identify specific bicycle crash types, their crash contributing factors and potential countermeasures. Macroscopic spatial analysis was performed to model the relation between demographic, socio-economic, roadway, traffic, and bicycle activity data at the census block group level and bicycle crash frequencies in Florida. Finally, a cross-sectional analysis was performed to develop Florida-specific Crash Modification Factors (CMFs) for bicycle crashes for different roadway segment and intersection facility types.

Literature Review

The review summarized existing studies in the following four areas: (1) risk factors that affect the frequency and severity of bicycle crashes; (2) bicycle crash causes, patterns, and contributing factors; (3) network screening methods used to identify and prioritize bicycle hot spots; and (4) safety performance of the most commonly implemented engineering countermeasures.

Researchers preferred to differentiate the risk factors affecting bicycle safety for intersections and mid-block locations due to the obvious variability in the operational characteristics. Roadway traffic, geometric, and socio-economic variables were investigated to determine their impact on bicycle crash frequency and severity. Spatial analysis, especially the use of ArcGIS, has evolved as an effective tool to better understand and model bicycle crash frequencies. Moreover, spatial analysis using ArcGIS was found to be the most commonly used network screening approach. Several studies, however, used a combination of different methods to identify and rank bicycle high crash locations.

In addition to the typical bicycle infrastructure such as bicycle lanes and bicycle slots, researchers have investigated the impact of several other roadway characteristics, including shared path width and separation, shoulder type, shoulder width, etc., on bicycle safety. One of the main challenges observed in improving bicycle safety is the lack of bicycle exposure data. Unlike traffic volumes, bicycle volumes are scarcely available, if at all. Researchers addressed this limitation by using surrogate measures of bicycle exposure such as number of transit stops in a region, population, etc.

Statewide Bicycle Crash Causes and Patterns

Statewide bicycle crash patterns and causes were identified based on a total of 26,036 bicycle crashes that occurred during 2011-2014. The descriptive trend analysis was based on temporal, environmental, bicyclist-related, crash location-related, and vehicle-related factors. The effect of roadway geometric features on the frequency and severity of bicycle crashes was also studied using data from 9,884.3 miles of non-limited-access state roads in Florida, which experienced a total of 10,546 bicycle crashes during the four-year analysis period. Some of the key findings include:

- Bicycle fatal crashes accounted for 5.6% of all traffic fatal crashes, while they constituted only 1.9% of total crashes.
- The majority of bicycle crashes occurred on urban roadways; only 1.2% of all crashes that occurred on state roads occurred in rural areas. In terms of crash severity, 16.9% of all bicycle crashes that occurred on rural facilities resulted in fatalities while only 2.5% of those that occurred on urban facilities resulted in fatalities.
- Nighttime bicycle crashes resulted in more fatalities compared to daytime crashes.
- Crashes involving elder bicyclists (≥ 65 years) resulted in more fatalities compared to crashes involving younger bicyclists (< 65 years).
- Crashes involving male bicyclists resulted in more fatalities compared to crashes involving female bicyclists.
- Over 10% of all bicyclists involved in crashes who were under the influence of alcohol were killed, and a high 27.6% of all bicyclists involved in crashes who were under the influence of drugs were killed.
- Crashes involving bicyclists using helmets or protective pads were less severe compared to those involving bicyclists using reflective clothing or lighting.
- Although bicyclists were frequently hit while cycling on the sidewalk, these crashes resulted in very few fatalities.
- Crashes involving bicyclists cycling along the roadway against traffic were found to be more severe compared to those involving bicyclists cycling along the roadway with traffic.
- In terms of bicyclist's action at the time of the crash, failure to yield right-of-way was the most frequent contributing cause, resulting in about 15% of total crashes.
- Among all types of vehicles, passenger cars were found to result in relatively less severe crashes. Medium and heavy trucks resulted in more severe crashes; a relatively high 14.5% of all crashes involving medium and heavy trucks were fatal.

Bicycle Crash Patterns at Hot Spots

A spatial analysis using ArcGIS was performed to identify the top five bicycle hot spots in each FDOT district. Police reports of all the 2,954 bicycle crashes that occurred at these hotspots were reviewed in detail to identify specific bicycle crash types and patterns. Some of the key findings from the police report review include:

- Drivers were at-fault in 45.7% of the crashes, while bicyclists were at-fault in 30.2% of the crashes.
- Crashes involving at-fault bicyclists resulted in a greater percentage of fatal crashes compared to those involving at-fault drivers.
- Signalized intersections experienced a greater proportion of bicycle crashes compared to unsignalized locations.
- Locations with bicycle lanes experienced a smaller proportion of fatal crashes compared to locations without bicycle lanes.

- Crossing the street was found to result in a greater proportion of fatal crashes compared to riding along the roadway.
- Crashes involving bicyclists riding along the roadway facing traffic resulted in a greater proportion of fatal crashes compared to crashes involving bicyclists riding along with vehicles.
- Crosswalk locations, although experienced a high frequency of bicycle crashes, experienced a relatively low proportion of fatal crashes.

The crash pattern analysis identified the following four major bicycle crash types:

- Motorist turns right while bicyclist is crossing the street
- Motorist turns left facing bicyclist
- Bicyclist rides out at intersection
- Motorist drives out at stop sign

In addition to these crash types, the following bicycle crash contributing factors and scenarios were also observed frequently:

- Inadequate street lighting
- Unconventional intersection geometry
- Traffic violations by motorists and bicyclists
- Bicyclists sideswipe vehicles
- Driveways near intersections
- U-turn maneuvers by bicyclists and motorists
- Bicyclists hit the door of parked vehicle
- Bicyclists ride opposite to the traffic

Several engineering and education countermeasures were recommended for these crash types and scenarios. Engineering countermeasures, including signal optimization, turn restrictions, and sign and pavement marking improvements, could improve the overall safety situation for bicyclists. Agency-wide education campaigns on the laws pertaining to bicyclists and extensive driver education campaigns that focus on driver compliance with bicyclist right-of-way laws and stricter enforcement could improve bicycle safety.

Macroscopic Analysis of Bicycle Crashes

Bicycle crash trends are quite distinctive and are dependent on land use, existing bicycle infrastructure, socio-economic factors, etc. The impact of these factors on bicycle crash frequencies was therefore studied using spatial analysis. A macro-level spatial analysis was performed to determine the relation between bicycle crashes and independent variables, including demographic and socio-economic factors, roadway and traffic characteristics, and bicycle activity, while accounting for the effect of spatial correlation among census block groups. Separate models were developed for total and F+S bicycle crashes.

Table E-1 provides an overview of the impact of different demographic and socio-economic, roadway and traffic, and bicycle activity data on the total and F+S bicycle crash models.

Table E-1: Impact of Variables on Bicycle Crash Models at Census Block Group Level

Variable Description	Total Crash Model	F+S Crash Model
Demographic and Socio-economic Characteristics		
Log of total population	⇧	⇧
Proportion of households with no automobile	⇧	⇧
Proportion of households with one automobile	⇧	⇧
Proportion of male population	NC	⇧
Proportion of Black or African American population	⇧	NC
Proportion of Hispanic or Latino population	⇧	NC
Proportion of population aged 18 - 29 years	⇧	NC
Proportion of population aged 30 - 39 years	⇧	NC
Proportion of population aged 40 - 49 years	NC	⇧
Proportion of population aged 50 - 64 years	⇧	NC
Proportion of population 25 years and above having high school diploma only	⇩	⇩
Proportion of population 25 years and above having Associate's degree or attended some college with no degree achieved	⇩	⇩
Proportion of population 25 years and above having Associate's degree or attended some college with no degree achieved	⇩	⇩
Proportion of population 25 years and above having Bachelor's degree or higher	⇩	⇩
Roadway and Traffic Characteristics		
Density of rural collector roads per sq. mi. of area	⇩	⇩
Density of rural local roads per sq. mi. of area	⇩	⇩
Length of urban principal arterials per sq. mi. of area	⇧	⇧
Length of urban collector roads per sq. mi. of area	⇧	NC
Length of urban local roads per sq. mi. of area	⇧	NC
Density of bicycle lane and bicycle slot per sq. mi. of area	⇧	⇧
Log of daily vehicle miles traveled (DVMT) in thousands	⇧	⇧
Log of number of bicycle commuters	⇧	NC
Truck percentage	⇩	⇩
Strava Users' Ride Characteristics		
Bicycle trip miles: Medium	⇧	NC
Bicycle trip miles: High	⇧	⇧
Bicycle trip intensity: Medium	⇧	⇧
Bicycle trip intensity: High	⇧	⇧

Note: ⇧ indicates credible and increasing effect; ⇩ indicates credible and decreasing effect; NC is not credible.

Florida-Specific CMFs

A cross-sectional analysis was performed to develop Florida-specific CMFs for bicycle crashes. Relevant multivariate regression models were developed using a generalized linear model (GLM) approach with negative binomial (NB) distribution. Only the variables that were significant at the 80% confidence interval in the initial model were used to develop the final models. Finally, the CMFs were estimated based on these final models. For each facility type, the data and model coefficients were reviewed closely to identify reliable CMFs. Tables E-2 and E-3 provide the Florida-specific CMFs developed for total bicycle crashes for different roadway segment and intersection facility types, respectively. Similarly, Tables E-4 and E-5 list the Florida-specific CMFs developed for F+S bicycle crashes for different roadway segment and intersection facility types, respectively.

Table E-2: Florida-Specific CMFs for Total Bicycle Crashes for Segment Facility Types

Variable	Urban				Rural
	Divided			Undivided	Divided
	2L[a]	4L[b]	6L[c]	4L2[d]	2L[e]
Median Width	--	0.99	0.99	NA	0.84
Presence of Bicycle Lane	1.69	0.86	--	2.24	--
Presence of Shared Path	--	--	0.75	--	--
Presence of Sidewalk	--	1.78	1.87	--	--
Presence of Sidewalk Barrier	2.18	--	1.99	0.33	--
Type of Parking (One Side)[f]	--	--	--	--	--
Type of Parking (Both Sides)[f]	2.65	--	0.48	--	--
Lane Width	0.64	0.77	0.75	--	--
Type of Median (Raised Traffic Separator)[g]	2.65	1.22	--	NA	--
Type of Median (Vegetation)[g]	--	0.62	0.49		--
Type of Median (Curb & Vegetation)[g]	2.43	0.85	0.80		--
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[h]	0.51	--	0.89	--	--
High Bicycle Activity (Annual Trips > 10,000)[h]	0.73	--	0.73	--	--

-- Not significant; NA is not applicable.
[a] Urban 2-Lane Divided Two-way Road; [b] Urban 4-Lane Divided Two-way Road;
[c] Urban 6-Lane Divided Two-way Road; [d] Urban 4-Lane Undivided Two-way Road;
[e] Rural 2-Lane Divided Two-way Road.
[f] The base condition for type of parking is no parking allowed.
[g] The base condition for type of median is paved.
[h] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

Table E-3: Florida-Specific CMFs for Total Bicycle Crashes for Intersection Facility Types

Variables	Urban 4-Leg Signalized	Urban 3-Leg Stop-controlled
1-2 Bus Stops within Intersection Influence Area[a]	--	×
≥ 3 Bus Stops within Intersection Influence Area[a]	1.90	×
1-8 Alcohol Sales within Intersection Influence Area[b]	1.53	×
≥ 9 Alcohol Sales within Intersection Influence Area[b]	--	×
Presence of Bicycle Facilities	1.27	1.36

-- Not significant; × Excluded from modeling.
[a] The base condition for bus stops is absence of bus stops within intersection influence area.
[b] The base condition for alcohol sales establishments is absence of alcohol sales establishments within intersection influence area.

Table E-4: Florida-Specific CMFs for F+S Bicycle Crashes for Segment Facility Types

Variable	Urban					
	Divided			Undivided		
	2L[a]	4L[b]	6L[c]	2L2[d]	3L1[e]	4L2[f]
Median Width	--	0.98	--	NA	NA	NA
Presence of Sidewalk	0.41	--	2.71	--	--	--
Presence of Sidewalk Barrier	4.20	--	--	3.96	--	0.36
Type of Parking (One Side)[g]	--	--	--	--	--	--
Type of Parking (Both Sides)[g]	4.62	--	--	--	--	--
Lane Width	0.52	--	0.79	0.42	0.24	--
Type of Median (Raised Traffic Separator)[h]	5.9	--	--			
Type of Median (Vegetation)[h]	--	--	0.45	NA	NA	NA
Type of Median (Curb & Vegetation)[h]	--	0.97	--			
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[i]	0.47	1.63	--	--	--	--
High Bicycle Activity (Annual Trips > 10,000)[i]	--	1.43	0.76	--	--	--

-- Not significant; NA is not applicable.
[a] Urban 2-Lane Divided Two-way Road; [b] Urban 4-Lane Divided Two-way Road;
[c] Urban 6-Lane Divided Two-way Road; [d] Urban 2-Lane Undivided Two-way Road;
[e] Urban 3-Lane Undivided One-way Road; [f] Urban 4-Lane Undivided Two-way Road.
[g] The base condition for type of parking is no parking allowed.
[h] The base condition for type of median is paved.
[i] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

Table E-5: Florida-Specific CMFs for F+S Bicycle Crashes for Intersection Facility Types

Variable	Urban 4-Leg Signalized Intersection
Number of Approaches with Right-Turn Lanes	0.82
Presence of Bicycle Facilities	1.71

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS/ABBREVIATIONS

AADT	Annual Average Daily Traffic
ACS	American Community Survey
ANCOVA	Analysis of covariance
Caltrans	California Department of Transportation
CARS	Crash Analysis Reporting System
CI	Confidence Interval
CMF	Crash Modification Factor
CRF	Crash Reduction Factor
DHSMV	Department of Highway Safety and Motor Vehicles
DVMT	Daily Vehicle Miles Traveled
EB	Empirical Bayes
EPDO	Equivalent Property Damage Only
ESDA	Exploratory Spatial Data Analysis
F+S	Fatal and Serious Injury
FDOT	Florida Department of Transportation
FGDL	Florida Geographic Data Library
FHWA	Federal Highway Administration
GES	General Estimates System
GIS	Geographic Information System
GLM	Generalized Linear Model
HSIP	Highway Safety Improvement Program
HSIS	Highway Safety Information System
HSM	Highway Safety Manual
LRS	Linear Referencing System
MCE	Multi-Criteria Evaluation
MORPC	Mid-Ohio Regional Planning Commission
MRF	Markov Random Field
NB	Negative Binomial
NHTS	National Household Travel Survey
ODOT	Oregon Department of Transportation
PCRRS	Police Crash Report Review System
PDO	Property Damage Only
RCI	Roadway Characteristics Inventory
RoCIS	Road Casualty Information Database System
RTOR	Right-Turn-On-Red
SHS	State Highway System
SPF	Safety Performance Function
TAZ	Traffic Analysis Zone
TDOS	Tennessee Department of Safety
TDOT	Tennessee Department of Transportation
TRADS	Traffic Accident Database System
UBR	Unified Basemap Repository

CHAPTER 1
INTRODUCTION

1.1 Background

Bicyclists are vulnerable road users who are at greater risk for fatal or serious injury when involved in a crash with a motor vehicle. While bicycling accounts for only 1% of all trips taken in the United States (Pucher et al., 2011), bicycle fatalities constitute over 2% of all traffic fatalities. In 2014, Florida led the nation with 139 bicyclist fatalities, representing approximately 20% of the nation's total. From 2011 to 2014, the number of fatal and serious injury crashes involving a bicyclist increased by 30%, and reported crashes increased by 44%.

Improving bicycle safety is a different challenge compared to improving the safety and mobility of motorized vehicular traffic because of the following reasons: bicycle crashes are rare and often severe; bicycle exposure is different from vehicle exposure and is difficult to quantify; and bicycle crash trends are quite distinctive and are dependent on land use, existing bicycle infrastructure, socio-economic factors, etc. A thorough analysis of the roadway, behavioral, and spatial factors associated with bicycle crashes is therefore required to improve bicycle safety.

1.2 Project Goal and Objectives

The goal of this research project is to conduct a comprehensive study to improve bicycle safety in Florida. This study considers a combination of analysis techniques, including descriptive trend analyses, area-wide spatial analyses, site-specific analyses, and statistical modeling. Descriptive statistics provide insights on bicycle crash patterns and causes. Spatial analyses provide the necessary tools to identify and rank bicycle hot spots and to investigate the contributing effects of socio-economic and demographic, roadway environment and infrastructure, bicycle activity, and traffic characteristics on bicycle crash frequency. Analysis of collision-condition diagrams and detailed review of police crash reports provide additional details on bicycle crashes and contributing factors that are not usually available in crash summary records. Lastly, statistical models help quantify the impact of different roadway characteristics and countermeasures on the frequency and severity of bicycle crashes.

The specific project objectives include:

1. Review and summarize existing literature on bicycle safety, including methods to identify bicycle hot spots and findings on bicycle crash causes, crash contributing factors, and potential countermeasures.

2. Identify specific contributing causes and patterns of bicycle crashes.

3. Identify and analyze bicycle hot spots for crash causes and potential countermeasures.

4. Develop Florida-specific Crash Modification Factors (CMFs) to assess the safety effects of common engineering treatments on bicycle safety.

1.3 Report Organization

The rest of this report is organized as follows:

- Chapter 2 provides a review of existing literature on bicycle safety. It focuses on the risk factors affecting the frequency and severity of bicycle crashes; bicycle crash causes, patterns, and contributing factors; the network screening methods used to identify and prioritize bicycle hot spots; and safety performance of the most commonly implemented engineering-related bicycle crash countermeasures.

- Chapter 3 discusses the overall statewide bicycle crash patterns and trends in Florida. The descriptive trend analysis is based on temporal, environmental, bicyclist-related, crash location-related, and vehicle-related factors. It also documents the effect of roadway geometric features on the frequency and severity of bicycle crashes.

- Chapter 4 focuses on analyzing bicycle crashes using spatial applications. It identifies the top five bicycle crash hot spots in each Florida Department of Transportation (FDOT) district. It also includes collision-condition diagrams of locations with bicycle crash clusters in Florida. The chapter further discusses bicycle crash contributing factors and potential countermeasures.

- Chapter 5 discusses the relation between demographic, socio-economic, roadway, and traffic variables at the census block group level and bicycle crash frequencies in Florida.

- Chapter 6 presents the bicycle crash modification factors for total bicycle crashes and fatal and severe injury (F+S) bicycle crashes for different roadway segment and intersection facility types.

- Chapter 7 provides a summary of this project effort and the relevant findings and conclusions.

CHAPTER 2
LITERATURE REVIEW

This chapter presents a brief review of the literature on bicycle safety. The chapter is divided into three major sections. The first section focuses on the risk factors affecting the frequency and severity of bicycle crashes. It also includes a brief discussion on bicycle crash causes, patterns, and contributing factors. The second section discusses the network screening methods used to identify and prioritize bicycle hot spots. Finally, the third section focuses on the safety performance of the most commonly implemented engineering-related bicycle crash countermeasures such as bicycle lanes, bicycle tracks, and raised bicycle crossings.

2.1 Risk Factors Affecting Bicycle Safety

This section includes a review of recent literature on different risk factors affecting bicycle crashes. It also includes studies that focus on the causes, patterns, and contributing factors associated with bicycle crashes. Researchers have used several statistical and spatial models to evaluate bicycle safety. This section is therefore organized according to the analytical methods applied in the reviewed literature.

2.1.1 Statistical Methods

In this section, studies that have applied statistical models including logit models, probit models, odds models, multivariate Poisson-lognormal models, and regression models are discussed.

Logit Models

Klassen et al. (2014) analyzed the severity of bicycle crashes using spatial mixed logit model for Edmonton. A total of 424 intersection-related and 147 mid-block-related bicycle crashes that occurred during 2006-2009 were investigated. Corridor design, human, temporal, and environmental factors were considered as covariate categories. The authors did not identify any common factor contributing to bicycle crash severity at intersections or mid-block locations. However, the interaction between roadway and approach-control type, the existence of partial crosswalks and bicycle signs, and the bicyclist's gender and age were identified as significant factors for bicycle crash severities at intersections. On the contrary, roadway classification, on-street parking, and driver's age were found significant for mid-block bicycle crash severities.

Moore et al. (2011) also differentiated the factors for intersection and non-intersection bicycle crashes. A total of 10,029 bicycle-related crashes that occurred from 2002-2008 in Ohio were considered for the study. Standard multinomial logit and mixed logit models were developed to estimate the injury severity factors. Roadway geometry (i.e., horizontal curve and vertical grade), vehicle type (i.e., van, heavy truck, etc.), bicyclist safety devices (i.e., helmet), drug and alcohol usage, and driver insurance played a significant role in determining the injury severity of bicycle crashes at intersections and mid-block sections.

Zahabi et al. (2011) used an ordered logit model to investigate the effects of crash location, roadway type, vehicle movement, vehicle type, environmental conditions, population density, road connectivity, and land use mix on injury severity of pedestrians and bicyclists involved in collision with motor vehicles in the City of Montreal. Crashes at signalized intersections were found to be more dangerous for bicyclists. Straight (i.e., through) movement of vehicles was found to have significant associations with sustaining an injury, i.e., increased the bicyclist's injury severity in bicycle crashes. Transit access and median income were not statistically significant. The authors did not find population density and lighting to be significant factors in bicycle crashes. This result is contradictory to the result from a later study by Hamann et al. (2014) which considered these factors to be significant.

Eluru et al. (2008) applied a mixed generalized ordered response logit model to analyze pedestrian and bicyclist injury severity using data from the 2004 General Estimates System (GES). Age (the elderly are more injury-prone), speed limit (higher speed limits lead to more severe injuries), crash location (crashes at signalized intersections are less severe compared to those that occurred elsewhere), and time-of-day (dark conditions experienced more severe injuries) were identified as influential variables affecting the non-motorist injury severity.

Kim et al. (2007) used a multinomial logit model to identify the factors leading to the four injury severity levels in bicyclists (i.e., fatal injury, incapacitating injury, non-incapacitating injury, and possible or no injury). The authors used crash data from 1997-2002 from North Carolina. Inclement weather, no streetlights, morning peak hour (06:00 AM to 09:59 AM), head-on crashes, speeding involving vehicle speeds over 48.3 kmph (30 mph), truck involvement, drunk driver, bicyclist age 55 or over, and drunk bicyclist were found to double the probability of a fatal injury in a bicycle crash. An estimated pre-crash speed of vehicles of more than 80.5 kmph (50 mph) was found to increase the bicyclist's probability of a fatal injury by more than 16 times. Compared to the bicycle crashes involving at-fault drivers, those involving at-fault bicyclists were identified to be more closely correlated with bicyclist injury severity.

Probit Models

Klop and Khattak (1999) examined the impacts of physical and environmental factors on the bicyclist injury severity in bicycle crashes. North Carolina Highway Safety Information System (HSIS) crash and inventory data from 1990-1993 for state-controlled, two-lane, undivided roadways were analyzed. Using the KABCO scale of injury severity distribution, two ordered probit models, one with all crashes and the other one restricted to only those in rural areas were estimated. Roadway characteristics such as speed limit, straight grades, and curved grades; driver- and bicyclist-related factors including impaired braking, acceleration, and maneuverability; environmental factors including fog and dark unlighted conditions showed increased severity trend, most probably due to their effect on driver reaction time and speed differentials at the time of impact. Average annual daily traffic (AADT), interaction between shoulder width and speed limit, and street lighting were found to be associated with decreased injury severity. Marginal effects of each factor on the likelihood of each injury severity class were identified. They highlighted the fact that in addition to vehicular traffic and scenery, decision makers should also review the frequency of straight grades and curved grades on roadway segments, the presence of a shoulder, and the presence of foggy conditions in selecting State Bicycle Routes. Reducing grades and curves in new two-lane roadway construction might have additional benefits in terms of reduced bicycle crash severity.

Odds Models

Wang et al. (2015) investigated the factors associated with the severity of injuries sustained by bicyclists in bicycle crashes at unsignalized intersections. The study objective was to improve bicycle safety through site-specific countermeasures and interventions. Bicycle crash data were extracted from Kentucky State Police's Kentucky Collision Database for the period 2002-2012. The authors employed a partial proportional odds model. Stop-controlled intersections, one-lane approaches, helmet usage, and lower speed limits were found to be associated with decreased injury severity. On the other hand, uncontrolled intersections, older drivers and bicyclists (age > 55 years), child bicyclists (age < 16 years), foggy and rainy weather, inadequate use of lights in dark conditions, and wet road surfaces were found to be the triggering factors for increased injury severity.

Multivariate Poisson-Lognormal Models

Kaplan and Prato (2015) utilized a multivariate Poisson-lognormal model to analyze land use and network effects on frequency and severity of bicycle crashes in the Copenhagen region. A total of 5,349 bicycle crashes from 2000-2013 were extracted for analysis from the National Crash Database compiled by the Danish Road Directorate. Traffic exposure of non-motorized and motorized transport modes was controlled for the model. The effect of infrastructure (e.g., the presence of bicycle lanes or paths, the presence of different types of intersections) and land use (e.g., the characteristics of the area where the roads were located and their interactions with the aforementioned infrastructure) was evaluated, and heterogeneity and spatial correlation across links was accounted in the model framework. The model resulted in reduced crash rates as bicycle traffic increased and this happened more for fatal and severe injury bicycle crashes.

The study revealed that crash rates decreased with increasing traffic volume, and particularly severe crash rates reduced more with increasing level of congestion. Fatal and severe injury crashes were related to the presence of more heavy vehicles on the road. Bicycle lanes and segregated bicycle paths reduced the number of severe injury crashes, and the effects were more pronounced in suburban areas. Possible injury or no injury crashes were more concentrated at the Copenhagen city center; whereas, fatal and severe injury crashes were more associated with industrial zones. One-way streets were correlated with decreased number of crashes, although this relationship was found to be reversed for the city center. The model identified intersections to be more problematic than mid-block sections, and the difference was even more pronounced when located in suburban areas. Roundabouts were found to be the most problematic type of intersections. Giving the right-of-way, crossing a traffic signal, and crossing a roundabout triggered more bicycle crashes (Kaplan and Prato, 2015).

Regression Models

Boufous et al. (2012) examined the risk factors associated with the injury severity of bicyclists involved in traffic crashes in Victoria, Australia during 2004-2008. A logistic regression was used to ascertain the predictors of serious injury and fatal crashes. About 34% of 6,432 police-reported bicycle crashes resulted in severe injury. The multivariate analysis identified age (50 years and above), not wearing helmet, dark unlit roadway conditions, 70 kmph or above speed zones (43.5

mph), curved roadway sections, rural locations, head-on collisions, run-off-road crashes due to loss of control, striking the door of a parked vehicle on paths as the main factors increasing the severity of injuries.

Schepers et al. (2011) also investigated the safety of bicyclists at unsignalized intersections within built-up areas in Netherlands using crash data from 2005-2008. The study focused on the association between intersection design characteristics and bicycle crashes. The authors classified bicycle crashes into two types based on the movements of the involved motorists and bicyclists: type I - through bicycle-related crashes where the bicyclist had the right-of-way, i.e., bicycle on the priority road; and type II - through motor vehicle-related crashes where the motorist had the right-of-way, i.e., motorist on the priority road. Negative Binomial (NB) method was employed for the study. The probability of each crash type was found related to its relative flows and independent variables. Type I crashes were found to occur more at intersections with two-way bicycle tracks, well-marked, and reddish colored bicycle crossings; and these crashes are negatively related to raised bicycle crossings, i.e., speed humps and other speed-reducing measures. The intersections where the bicycle track approaches were 2-5 m away from the main carriageway were found to have lower crash probability. Roadway geometric factors such as raised medians did not have any significant impact on type II crashes. However, bicycle crashes were found to be less severe at intersections with speed-reducing devices.

Bíl et al. (2010) evaluated the critical factors in fatal crashes involving adult bicyclists (over 17 years) using multivariate regression analysis. The authors analyzed 1995-2007 crash data from the Traffic Police of Czech Republic. Inappropriate driving speeds, head-on collisions, and unlit roadways were identified as significant factors. Bicycle crashes were found to be more serious when associated with the consequence of bicyclist's denial of right-of-way on crossroads. Male bicyclists were found to be more prone to fatal injuries compared to female bicyclists. The most vulnerable age group was found to be 65 years and older. The authors also found that more crashes where bicyclists were at-fault resulted in a fatal injury compared to those where drivers were at-fault (598 vs. 370).

Oh et al. (2008) developed bicycle crash prediction models for urban signalized intersections. The authors conducted field surveys at 151 intersections in Inchon, Korea to identify the potential variables affecting bicycle crashes. The study revealed Poisson regression model to be most suitable for predicting bicycle crashes. The primary and alternative models identified the following factors (and their direction of association) to be the most critical for bicycle crashes at urban signalized intersections: average daily traffic volume (+), presence of bus stops (-), sidewalk widths (-), number of driveways (+), presence of speed restriction devices (-), presence of crosswalks (+), and industrial land use (+). In addition, the study emphasized the need to incorporate driver characteristics, roadway geometric design, and operational features in the analysis.

2.1.2 Spatial Frameworks

A number of studies have spatially integrated and analyzed roadway characteristics, crash, and traffic data in Geographic Information System (GIS). Moreover, researchers have traditionally been using spatial analysis to study the influence of socio-economic and demographic factors such as population, median household income, vehicle ownership, etc. on bicycle crashes. This section presents the newer studies that have analyzed bicycle safety spatially in ArcGIS. More specifically, studies focusing on the spatial analysis of bicyclist injury severity trends, bicycle crash clusters, and the spatial correlation between bicycle safety and several engineering, socio-economic and demographic factors are reviewed and summarized.

Lawrence et al. (2015) conducted a geospatial analysis of bicyclist injury trends in Melbourne, Australia. The objective was to identify reduced bicyclist injury density areas. The study examined crash characteristics and cycling environment to better understand the factors associated with bicycle safety. Two methods were employed: (a) cycling injury severity was calculated using a kernel density estimation method for the period 2000-2011 to study patterns in injury density across Melbourne over an extended time period; and (b) the absolute change in injury density was calculated between 2005 and 2011, which helped identify a geographic area which experienced a relatively more significant reduction in injury density. Figure 2-1 displays the spatial analysis results. The crash characteristics were then analyzed to identify the changes to the cycling environment that were associated with reduced injury rate. As shown in Figure 2-1, a geographical area to the southeast of Melbourne was found to have experienced a significant reduction in injury rate. It appeared that a combination of behavior and road infrastructure change might be the contributing factors for such a reduction. However, the lack of cycling exposure data prevented more conclusive statements.

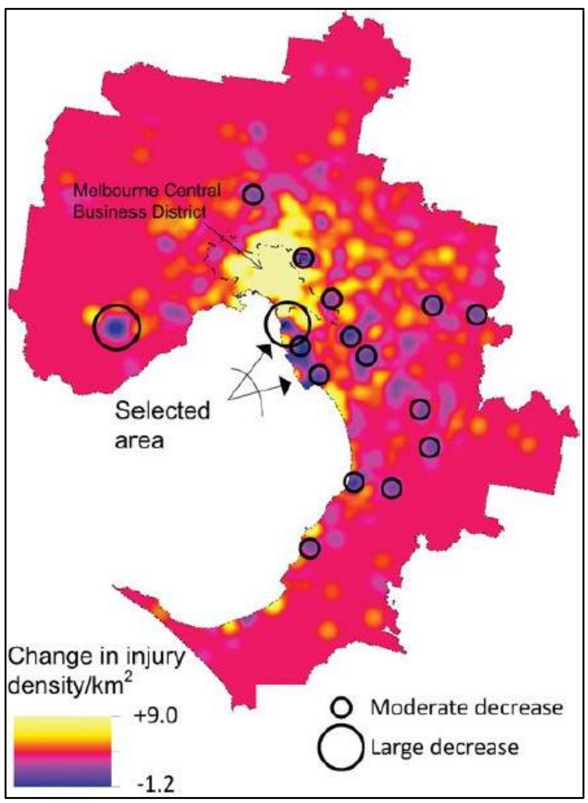


Figure 2-1: Geographic Region in Melbourne, Australia, Selected for Detailed Case Study Based on Spatial Analysis (Source: Lawrence et al., 2015)

Chimba et al. (2014) also used GIS to geo-locate and cluster the pedestrian and bicycle crash locations on the roadway network in Tennessee. The study objective was to investigate demographic, socio-economic, roadway geometric, traffic, and land use characteristics affecting pedestrian and bicycle crash frequency. NB regression was employed to model the relationship between contributing factors and crashes. The findings were used to identify patterns of pedestrian and bicycle high crash locations in Tennessee. Population distribution by race, age group, mean household income, percentage in the labor force, poverty level, vehicle ownership, land use, number of lanes crossed by pedestrians or bicyclists, posted speed limit, and the presence of special speed zones were found to significantly influence the frequency of pedestrian and bicycle crashes.

Siddiqui et al. (2012) applied a Bayesian spatial framework to model bicycle crashes to investigate the spatial correlation at Traffic Analysis Zones (TAZs) level in Hillsborough and Pinellas counties in Florida. Roadway characteristics, environmental, demographic and socio-economic variables associated with bicycle crashes were used to develop the aggregate (i.e., macroscopic) models. The Bayesian models were compared with the traditional NB models to assess the effect of spatial correlation. Two Bayesian models were developed, one with only the random effects which did not account for the spatial correlation, and the other with both the random effects and spatial correlation to compare the results and explicitly identify the effect of spatial correlation. A Heuristic approach, Bayesian Poisson-lognormal, was used along with the traditional forward and backward methods for variable selection while developing the non-Bayesian models. FDOT District Seven's bicycle crash data for 2005-2006 was analyzed. It was found that variations contributed by spatial correlations are about 79% for bicycle crashes in the TAZs; thus, Bayesian models controlled for spatial correlation resulted in a better fit.

The authors considered the following eleven significant variables for the non-Bayesian NB model: (1) the total length of roadways with 15 mph posted speed limit, (2) total length of roadways with 35 mph posted speed limit, (3) total number of intersections per TAZ, (4) median household income per TAZ, (5) total number of dwelling units, (6) log of population per square mile of a TAZ, (7) percentage of households with non-retired workers but zero auto, (8) percentage of households with non-retired workers and one auto, (9) urban flag for a TAZ, (10) number of kindergarten through 12th grade enrollment, and (11) log of total employment number in a TAZ. The Bayesian model which did not account for spatial correlation identified similar variables as significant; whereas, median household income per TAZ, urban flag for a TAZ, and number of kindergarten through 12th grade enrollments were found statistically insignificant when spatial correlation was considered in the Bayesian model. Neighborhood-related variables did not reveal any significant difference in the two models.

A similar conclusion was drawn by Kim et al. (2007) except for institutional areas (i.e., schools) which were found to be associated with higher possibilities of incapacitating injuries. Moran's I statistics identified the spatial orientation of kindergarten through 12th grade school enrollment as 'random' which explained the reason why it was not found significant in the model addressing the spatial relation by Siddiqui et al. (2012). Total roadway length with 15 mph posted speed limit was found as the only variable negatively associated with bicycle crashes. On the contrary, total roadway length with 35 mph posted speed limit was found to have positive association. A similar positive association between 30 mph and 40 mph was recognized by Kim et al. (2007). The number of intersections was also found to be highly associated with bicycle crashes. A study by Carter and

Council (2007) identified the similar relationship that about 48% of bicycle crashes are intersection-related in urban areas. The estimates for percent of households with non-retired workers with zero autos was found to be twice than that of non-retired workers with one auto in the model with spatial correlation, implying the latter is less critical than the former variable while other variables being controlled. Population density and total employment, the two possible surrogate measures for bicycle exposure, were also found to be positively associated with bicycle crashes. Siddiqui et al. (2012) concluded that Bayesian Poisson-lognormal models with spatial correlation to be the better one compared to other models that did not account for spatial correlation among TAZs. Quddus (2008) acknowledged the Bayesian framework as a more capable platform to account for spatial correlation and uncontrolled heterogeneity present in macro-level crash data.

Loo and Tsui (2010) conducted a spatial, circumstantial, and epidemiological study on bicycle crashes in Hong Kong, where bicycle is a minor mode of transport. The Traffic Accident Database System (TRADS) of Hong Kong police from 2005-2007 and a hospital based Road Casualty Information Database (RoCIS) were used. Spatial and statistical tools including buffer analysis, chi-square tests, analysis-of-variance and binary logistic regression were used to analyze bicycle crashes. It was found that large proportion of crashes occurred on public roads near cycle tracks which triggered the careful consideration of fully integrated cycle tracks in the new territories and sufficient safe road network connecting the new cycle tracks. Majority of the bicycle crashes were found to have taken place on relatively simple road environment which highlighted the lack of sufficient training and practice. The bicycle safety problem was found to be more serious on roads outside the cycle tracks as these locations experienced bicycle crashes often resulting in serious and fatal injuries. These bicyclists were mainly middle-aged males (> 45 years) riding bicycles on public roads and were using bicycles as their mode of transport for daily trips. Proper education for all bicyclists focusing on the use of helmets and protective gears was stressed in the study.

2.1.3 Descriptive Data Analysis

Descriptive data analysis is one of the oldest and the most common techniques in crash data analyses. It provides an overall understanding about the safety situation and helps to identify the most probable predictors that affect crash frequency and severity. This section discusses several recent studies that have used the descriptive data analysis techniques to improve bicycle safety.

Johnson et al. (2013) studied the crash characteristics and risk factors associated with bicyclists and open vehicle doors in Victoria, Australia. Three complementary data sources were used for the study: a total of 1,247 police-reported bicycle crashes from 2000-2011, a total of 401 hospitals' emergency department presentations for the period 2000-2010, and a sample of video footage from a naturalistic study of commuter bicyclists in Melbourne during 2009-2010. Bicyclist-open vehicle door crashes accounted about 8.4% of the police-reported crashes, and 3.1% of the hospital-recorded crashes. Male population (police report: 67.1%; hospital record: 65.8%) comprised the higher portion of the injured bicyclists. Adults aged 18 years or older (police report: 97.5%; hospital record: 96.3%) were found to be the most vulnerable age group for bicyclists. A high percentage (93.1%) of crashes took place within 60 kmph (37.3 mph) speed zones. The study identified 13 door-related events with a rate of 0.59 events per trip from the naturalistic cycling study data; most drivers were found to not look in the direction of the bicyclist before opening their vehicle doors.

Schepers and Wolt (2012) investigated the single-bicycle crash types and their characteristics using a questionnaire survey conducted in the Netherlands. The survey targeted bicycle crash victims treated at an Emergency Care Department. The questionnaire had two types of questions: open-ended questions about the crash, and closed-ended questions focusing on possible direct causes, crash characteristics, and circumstances. About half of all single-bicycle crashes were found to be related to infrastructure: collision with an obstacle, run-off-road, bicycle skidding due to slippery road surface, the bicyclist was unable to stabilize the bicycle or stay on the bicycle because of an uneven road surface. Loss of control at low speed, forcing on the front wheel, poor or risky riding behavior, bicycle defects, and gust of wind were the other main contributing factors.

2.1.4 Combination of Methods

This section focuses on recent studies that have applied a combination of spatial methods and regression techniques in analyzing crash frequency and severity, and identifying crash causes, patterns, and contributing factors.

Hamann et al. (2014) examined bicycle crashes at intersections and non-intersections in Iowa for the period 2001-2011 to identify the influence of person, crash, environment, and population characteristics. The study employed descriptive statistics, GIS mapping, and multivariable logistic regression to examine factors associated with crash risk and crash location. These variables were identified as independent predictors of the crash location (i.e., intersection or non-intersection). It was found that young bicyclists (< 10 years old) were more prone to non-intersection bicycle crashes. Obscured vision was found to be a triggering factor for non-intersection crashes. Non-intersection crashes were found to take place outside the city limits, i.e., in rural areas, probably due to variation in exposure or with reduced lighting. Failing to yield right-of-way was a less associated factor for non-intersection crashes. Densely populated, low income, and low education areas were found to be more crash prone; however, crash location did not make any difference on the crash statistics in these areas. Evans and Kantrowitz (2002) attributed bicycle crash issues to more traffic and/or poorer maintenance of these areas. On the other hand, Edwards et al. (2008) and Morency et al. (2012) recognized the socio-economic disparity inclusive of behavioral aspects as greater risk-taking likelihood for these bicycle crashes.

As mentioned earlier in Section 2.1.2, Chimba et al. (2014) investigated demographic, socio-economic, roadway geometric, traffic, and land use characteristics affecting pedestrian and bicycle crash frequency in Tennessee. In this study, GIS was used to geo-locate and cluster the crash locations, and NB regression was employed to model the relationship between contributing factors and crashes. Pedestrian and bicycle crash data for the period 2003-2009 from Tennessee Department of Transportation (TDOT) and Tennessee Department of Safety (TDOS) databases were used in the study. The crash data contained 5,360 pedestrian crashes and 2,558 bicycle crashes. TDOT’s geospatial data and U.S. census website’s demographic and socio-economic data at census tract level were also used for the GIS analysis. Population distribution by race, age group, mean household income, percentage in the labor force, poverty level, vehicle ownership, land use, number of lanes crossed by pedestrians or bicyclists, posted speed limit, and the presence of special speed zones were found to significantly influence the frequency of pedestrian and bicycle crashes. The findings were used to identify patterns of pedestrian and bicycle high crash locations in Tennessee. Emaasit (2013) recommended the similar approach to identify bicycle and pedestrian hot spots and identify the contributing factors for such crashes.

Rodgers (1997) evaluated the crash risk factors associated with adult bicyclists by comparing information on the characteristics and travel patterns of bicyclists who had crashed with those who had not. The logistics regression technique was used for the analysis. The analysis was based on data from a national survey of over 3,000 bicyclists of 18 years of age and older. The survey had the information on the characteristics and use patterns of the bicyclists and whether they had crashed or fallen from their bicycles during the preceding year. The crash risk was found higher for males than for females and was lower for bicyclists in the 25-64 year age group than it was for bicyclists younger than 25 years and older than 64 years. Risk was found to be directly proportional to the miles traveled. Furthermore, risk was found to be substantially higher for off-road bicyclists compared to on-road bicyclists; for those who race; for all-terrain style bicycles as opposed to general-purpose bicycles; and for Pacific Coast states compared to eastern, midwestern, southern, and mountain states. Hands-on training geared toward adults, improvement of riding environment through bicycle paths and bicycle lanes, use of helmets, and further research were emphasized as injury reduction strategies.

2.2 Network Screening Methods

This section includes a review of literature on the existing network screening methods to identify and prioritize bicycle hot spots. GIS was found to be the most commonly used network screening tool. Furthermore, several studies have used a combination of different methods to rank bicycle high crash locations.

2.2.1 Traditional and Risk-Based Safety Planning Method

Kittelson & Associates, Inc., (2014) developed a combination of two network screening methods to prioritize pedestrian and bicycle hot spots for Oregon Department of Transportation (ODOT). The first network screening method is based on 'traditional' metrics, i.e., reported crash frequency and severity to prioritize locations for safety improvement. This method used the most recent five years of crash data to identify locations across the state with frequent and/or severe crashes. The second method is based on a risk-based systemic safety planning process consistent with Federal Highway Administration (FHWA) guidance. The process identifies safety risk based on roadway characteristics that have contributed to pedestrian and bicycle crashes over the study period. This method is proactive in the sense that it may identify locations where crashes have not been reported. In this method, crash history is not excluded, but considered as one of many risk factors used to prioritize locations. Risk factors include a range of roadway or location characteristics such as road geometry (e.g., presence or absence of turn lanes, number of intersection legs, etc.); intersection traffic control (e.g., signalized, unsignalized, all-way stop control, etc.); and segment characteristics (e.g., number of access points per mile, presence of sidewalk or bicycle lane, presence of illumination, etc.). The two network screening methods resulted in a list of potential safety improvement projects for pedestrians and bicyclists within each ODOT region.

2.2.2 Crash Reduction Factor-based Approach

Ragland et al. (2011) developed a stand-alone tool based on an approach that used Crash Reduction Factors (CRFs). The tool can be applied in a differential manner to the various crashes occurring at a site, a set of sites, a corridor, or a zone to identify locations that have a potential for reduction in bicyclist and pedestrian injuries. The tool used standard formulae for benefit-cost calculations from the Highway Safety Improvement Program (HSIP) guide and linked to extensive HSIP safety resources. The study was based on the principle that sites with the most potential for injury reduction are the sites where the most injuries can be prevented per dollar spent. These sites would result in highest expected number of injuries if nothing is done and everything else being the same. The study was funded by the California Department of Transportation (Caltrans). A 16.5-mile section of San Pablo Ave (SR 123) in the San Francisco East Bay was used as the study area. Crash data from 1998-2007 was analyzed. the following approaches were evaluated and compared to develop stable statistical estimates: extend the number years for both the baseline and follow-up periods, expand the size of the target sites considered, and apply Bayesian methods to include a modeled estimate of risk in the calculation. Finally, the authors discussed the strengths and weaknesses of each approach using the data from the study area. Table 2-1 summarizes these strengths and weaknesses.

Table 2-1: Comparison of Strengths and Weaknesses of Different Site Selection Approaches (Source: Ragland et al., 2011)

Approach	Description	Strengths	Weaknesses	Comment
A. Choose Specific Sites using Past History	Calculate benefit-cost for individual sites and rank.	Intuitive, methods exist to identify sites.	Instability of estimates of expected injuries, especially if injury rates are low.	Traditional approach followed by many current jurisdictions and funding programs.
B. Increasing Time Horizon for Events, either Years of History and/or Follow-up	Same as Approach Abut increase years of history and/or years of follow-up.	Gain numbers and therefore increase stability of estimates of expected injuries.	Potential bias if changes take place over time (i.e., greater chance of change with increasing time).	Very effective in increasing stability of estimates if no reason to suspect historical change in conditions.
C. Increasing Geographic Scale (from specific sites to corridors, zones, or entire network)	Same as Approach A but increase scale of sites in order to increase numbers.	Gain numbers and therefore increase stability of estimates of expected injuries.	Need to spread countermeasures over a greater area or number of sites.	Very effective if treatment costs per unit of area or number of sites can be kept low.
D. Combining Sites with Similar Characteristics	For example, combine mid-block crossings.	Gain numbers and therefore increase stability of estimates of expected injuries. The same countermeasures installed at all locations, possible economy of scale.	Need to spread countermeasures over a greater distance or number of sites.	Very effective if treatment costs per unit of area or number of sites can be kept low and there can be an advantage of consolidating engineering analyses.
E. Creating Estimates Using the Bayesian Method	Create model of the network and apply combined modeled estimate of injuries with history of injuries.	Increase stability of estimates of expected injuries.	Need for network database with relevant variables.	Can be combined with any of the above if data is available.

2.2.3 GIS Crash Mapping

Mid-Ohio Regional Planning Commission (MORPC) used GIS to identify bicycle and pedestrian hot spots. After importing the crash data into ArcGIS, *Spatial Analyst* tool was employed to identify and calculate the relative magnitude (or density) of pedestrian and bicycle crashes. First, a ten square foot grid was overlaid on top of the crash locations, and then a score was assigned to each grid based on the number of crashes within 500 feet of the corresponding grid cell. *Spatial Join* process was then employed to calculate the number of crashes within each of the highest-crash clusters. Only bicycle and pedestrian crashes occurring within the clusters were counted. A list and a map were generated with bicycle or pedestrian crash clusters. The *Kernel Density* tool was next used to convert crash locations into high resolution raster images identifying high-crash clusters, which were then converted into polygon shapes. Because of the lower frequency of pedestrian and bicycle crashes, the analysis considered five years of crash data, instead of three years which is often used in identifying the top locations for all crash types (MORPC, 2015). Chimba et al. (2014) also utilized GIS to geo-locate and cluster the pedestrian and bicycle crash locations on the roadway network. Emaasit (2013) also recommended a similar approach to identify bicycle and pedestrian hot spots.

Rybarczyk and Wu (2010) proposed a multi-criteria evaluation (MCE) analysis along with the use of GIS for bicycle facility planning. The MCE analysis facilitated incorporating variables from supply as well as demand side of bicycle planning models. Analysis was performed at two geographic levels: network level and neighborhood level. Network-level analysis addressed site specific issues and provided detailed information for further improvements. On the other hand, neighborhood-level analysis provided a strategic view of bicycle facilities, and facilitated policy development and implementations. A GIS-based Exploratory Spatial Data Analysis (ESDA) method was applied to explore the spatial patterns of bicycle facilities at the neighborhood level. This model was applied to Milwaukee City, Wisconsin. The researchers concluded that a combination of GIS and MCE analyses could serve as a better alternative to plan for optimal bicycle facilities, highlighting inadequacies of typical supply-side measures, and could meet multiple planning objectives of government agencies, planners, and bicyclists.

Bejleri et al. (2007) presented a new crash mapping method that located bicycle and pedestrian crashes based on street intersections and offset distance using GIS. The authors developed a customized GIS crash mapping application. This application filled the gap of the standard GIS geocoding software. The application was able to map both property addresses and street intersections; and was also generic and flexible. The application resulted in accurate and high matching rates. The application utilized the standard geocoding method for matching the street addresses and employed a location-referencing system for the address with a distance from an intersection. The location-referencing system of the application did not require any pre-processed data as it applied street names as a reference to identify the intersection location. This process overcame the limitations of the node reference system used by Palm Beach County, Florida. The application was able to compare street names on a crash record with street names on a street map to identify an intersection without the node number. Crash analysis methodologies were applied to mapped crashes at different geographical levels. Cluster, trend, and proximity analyses were employed to understand the general spatial and temporal crashes patterns. Linear and area density indices were used to identify crash concentration areas at both intersection and mid-block levels. Figure 2-2 provides the study results.

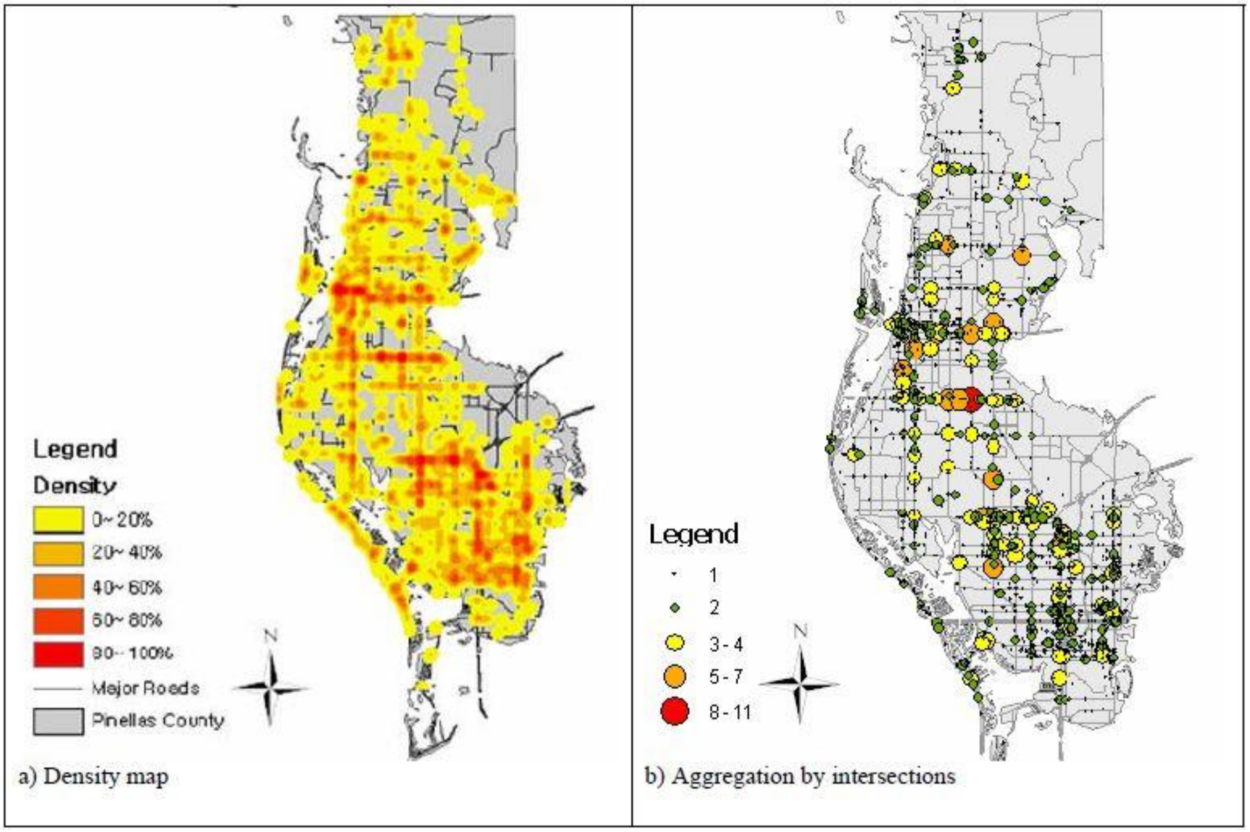


Figure 2-2: Pedestrian and Bicycle Crash Distribution in Pinellas County, FL (Source: Bejleri et al., 2007)

2.2.4 Logistic Model

Allen-Munley et al. (2004) developed a logistic model for rating urban bicycle routes based on safety. The safety rating model was based on injury severity; and the rating was based on the principle that safe routes would produce less-severe crashes than unsafe routes. The modeled rating of bicycle routes' relative safety was defined as the expected value of the predicted injury severity. Bicycle crash data from Jersey City, New Jersey from 1997-2000 was used to develop the model with a logistic transformation. Key operational and physical variables such as AADT, lane width, population density, highway functional classification, presence of vertical grades, one-way streets, and truck routes were evaluated, and the resulting model met a 90% confidence level. Urban adult commuting bicyclist was the focus group for this study because of this group's predominant peak-hour nondiscretionary trips during the highest hours of congestion, and thus had the greatest potential to reduce air pollution.

2.3 Bicycle Crash Countermeasures

This section includes a review of literature on the safety performance of the existing engineering-related bicycle crash countermeasures. Particularly, the following countermeasures are discussed:

- bicycle lanes,

- bicycle tracks,
- bicycle boulevards,
- wide curb lanes,
- traffic calming measures such as speed humps and road diets (i.e., lane reductions),
- roadway and intersection geometry related countermeasures such as raised medians,
- crosswalks,
- roadway lighting, and
- on-street parking treatments.

2.3.1 Bicycle Lanes

Bicycle lanes are defined as a portion of the roadway designated for the preferential or exclusive use of bicyclists and are separated from motor vehicle traffic through the use of pavement markings (Mead et al., 2014). Figure 2-3 shows an example of bicycle lanes in Chicago, IL.

Figure 2-3: Bicycle Lanes in Chicago, IL (Source: NACTO, 2012; Photo: CDOT)

Park et al. (2015) determined the relationships between the safety effects of adding a bicycle lane and the roadway characteristics on urban arterial facilities in Florida. The authors used observational before-and-after with empirical Bayes (EB) and cross-sectional methods to develop the crash modification factors (CMFs). Adding a bicycle lane on urban arterials had positive safety effect (i.e., CMF < 1.0) for all crashes, and was more effective in reducing bicycle crashes (CMF of 0.439 with EB method and 0.422 with cross-sectional method). The CMFs were found to be varying across the sites with different roadway characteristics. AADT, number of lanes, AADT per lane, median width, bicycle lane width, and lane width were found to be the significant characteristics that affect the variation in safety effects for adding a bicycle lane. Socio-economic characteristics such as bicycle commuter rate and population density were also found to have significant effect on the CMFs variation. Full crash modification functions showed better model fit than simple crash modification functions since they account for the heterogeneous effects of multiple roadway and socio-economic characteristics.

Chen et al. (2012) evaluated the safety effects of bicycle lanes installed prior to 2007 in New York City on total crashes, bicycle crashes, pedestrian crashes, multi-vehicle crashes, and injury or fatal crashes. The impact of bicycle lane installation in a treatment group and a comparison group was studied using generalized estimation equation methodology. The study revealed that the number of bicyclists increased after the installation of bicycle lanes; however, the lanes did not increase bicycle crash frequency, most likely due to reduced vehicular speeds and fewer vehicle-bicycle conflicts.

Nosal and Miranda-Moreno (2012) studied the bicyclist injury risk on bicycle lanes in Montreal using relative risk ratios. Most bicycle lanes were found to exhibit lower bicyclist injury rates than the corresponding control streets. Operation way, visibility, physical separation, presence and location of parking, vehicular traffic, and the direction of vehicular traffic were identified as the prominent factors affecting the bicyclist injury risk.

Turner et al. (2011) analyzed three main safety studies undertaken in New Zealand and Adelaide, Australia. The authors applied generalized linear modeling and before-and-after, control-impact methods. Crash, traffic, and bicycle volumes and layout data were collected for urban road links, traffic signals, and roundabouts. A safety-in-numbers effect, i.e., crash risk per bicyclist, was shown to be lower as bicycle volumes increased was demonstrated by the flow-only models. Before-and-after analysis was employed to identify the presence of biasness toward the sites with bicycle facilities. The research findings on the impact of bicycle facilities on safety were mixed. The safety performance factor value with bicycle lane was 1.21, indicating a 21% increase in bicycle crashes after the bicycle lanes were constructed. However, a before-and-after study using the EB method showed a 10% reduction in bicycle crashes at treatment sites, which indicated bias in the sites that were selected for treatment. Colored bicycle lanes decreased bicycle crashes by 39% in the before-and-after studies, and resulted in safety performance factors of less than 0.5 for most crash types. Thus, well-designed bicycle lane facilities with adequate width and color pavement appeared to perform best.

Hunter et al. (2009) examined bicycle counts and speeds associated with the installation of bicycle lanes in St. Petersburg, Florida. The study showed a total of 17.1% increase in bicycle usage per day after installation of the bicycle lanes; however, one of the streets experienced almost no change in bicycle usage. The average bicycle speeds remained the same (approximately 11-12 mph) both prior to and after the construction of bicycle lanes. The study highlighted the fact that the addition of bicycle lanes alone on a street could not guarantee an immediate increase in bicycle volume and/or speed; rather other factors such as adjacent land use, convenient origins and destinations, and connectivity of bicycle lanes to other bicycle facilities within the street system were critical in encouraging bicycling.

Hunter et al. (2008) studied the impact of green colored pavement and accompanying signing in a bicycle lane weaving area (Figure 2-4), where motor vehicles cross the bicycle lane near intersection on bicyclist's and motorist's behavior. The study was conducted in St. Petersburg, Florida. The authors compared the operational behavior of the bicyclists and motorists at selected locations using video footage recorded before and after the green pavement and signing treatments were installed. The authors found that 11.8% more motorists yielded to bicyclists, and 4% more motorists signaled their intention to turn right in the after-period. Overall, 6% more bicyclists scanned for proximate vehicles in the after-period; while the percentage of conflicts (i.e., sudden changes in speed and/or direction) was lower in the after-period, the differences were not statistically significant. The significant increase in yielding behavior by motorists was similar to the study findings by Hunter et al. (2000) in Portland, Oregon.

Figure 2-4: Green-colored Pavement and Accompanying Signing in a Bicycle Lane Weaving Area in St. Petersburg, FL (Source: Hunter et al., 2008)

Jensen (2008) conducted an observational before-and-after study to evaluate the safety performance of bicycle lanes in Copenhagen, Denmark. A general comparison group in the observational study was incorporated to address the changes in traffic volumes and crash frequency and crash severity trends through correction factors. Bicycle lanes in the study resulted in a 5% increase in crashes and a 15% increase in injuries for urban areas. Thus, the study revealed that safety for bicyclist's worsened at locations where bicycle lanes were constructed and safety was found to be the worst for bicyclists and moped riders with a 49% increase in injuries. The study findings are quite dissimilar to the findings from several other studies including Rodegerdts et al (2004), Chen et al. (2012), Nosal and Miranda-Moreno (2012), and Park et al. (2015). Rodegerdts et al. (2004) concluded that bicycle lanes reduced fatal, serious, and minor injury bicycle crashes by 35%, i.e., the study resulted in a CMF of 0.65 for bicycle lanes.

2.3.2 Bicycle Tracks

Bicycle track is a bicycle facility which is designated for the exclusive use of bicyclists. These are physically separated from the sidewalk and the roadway by curbs. Parked vehicles between the moving traffic and the bicycle track may offer an additional buffer from roadway traffic (Mead et al., 2014). Figure 2-5 depicts a schematic diagram of a bicycle track and a bicyclist using such a track in Copenhagen, Denmark.

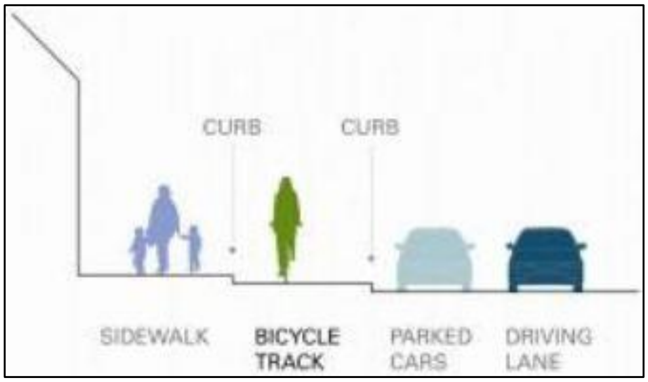


Figure 2-5: Bicycle Track (Source: Mead et al., 2014)
(Photo Courtesy: Lars Gemzøe and Gehl Architects, Member of the Cycling Embassy of Denmark)

Nosal and Miranda-Moreno (2012) studied the bicyclist injury risk on bicycle lanes and also the effect of bicycle tracks in Montreal using relative risk ratios. The performance of bicycle track was found to be similar to the performance of bicycle lanes. Most bicycle tracks were found to result in lower bicyclist injury rates than the corresponding control streets. Similar to the bicycle lanes, direction of traffic operation (i.e., bidirectional or not), visibility, physical separation, presence and location of on-street parking, vehicular traffic, and the direction of vehicular traffic were identified as the prominent factors affecting the bicyclist injury risk on bicycle tracks.

Schepers et al. (2011) also investigated the safety effects of bicyclists at intersections with two-way bicycle tracks, well-marked, and reddish colored bicycle crossings in Netherlands. Bicycle crashes where the bicyclist had the right-of-way (i.e., bicyclist on the priority road) were found to be more prone to occur at these sites than where the motorist had the right-of-way (i.e., motorist on the priority road). Intersections where bicycle track approaches were 2-5 meters away from the main travel way were found to have decreased crash probability, with a CMF of 0.55. Similarly, bicycle tracks that were over 5 meters away from the main travel way also resulted in a decreased crash probability with a CMF of 0.93. However, the crash probability was found to be almost the same for bicycle lanes and bicycle paths when the distance between the bicycle track and the side of the main road is less than 2 meters. The red color and high quality markings did not improve the safety for bicyclists, and resulted in a CMF of 1.47 for red color, a CMF of 1.74 for high quality markings, and a CMF of 2.53 for the presence of both red color and high quality markings at bicycle crossings.

Jensen (2008) conducted an observational before-and-after study to evaluate the safety performance of bicycle tracks in Copenhagen, Denmark. A general comparison group in the observational study was incorporated to address the changes in traffic volumes and crash and injury trends through correction factors. Bicycle tracks increased crashes and injuries by 10% in urban areas. Thus, the study revealed that safety for bicyclists worsened at locations with bicycle tracks. However, bicycle tracks resulted in a 20% increase in bicycle/moped traffic mileage and a 10% decrease in AADT. The author calculated a CMF of 1.05 for all crash types and for all crash severities. The study also calculated the CMFs for different combinations of crash types and crash severities.

2.3.3 Bicycle Boulevards

Bicycle boulevards are defined as traffic-calmed side streets signed and improved for bicyclists to provide a safer alternative to riding on arterials. Figure 2-6 gives an example of a bicycle boulevard. Minikel (2012) studied bicyclist safety on bicycle boulevards and parallel arterial routes in Berkeley, California. Police-reported bicycle crashes and manually collected bicyclist count data from bicycle boulevards and parallel arterial routes in Berkeley, California from 2003 to 2010 were analyzed. The study identified that crash rates on Berkeley's bicycle boulevards are two to eight times lower than those on parallel, adjacent arterial routes, and resulted in a CMF of 0.37.

Figure 2-6: Bicycle Boulevard (Source: Williams, 2014)

2.3.4 Wide Curb Lanes

An alternative to the installation of a five-foot bicycle lane is to design the curb lane wide enough so that it can accommodate bicyclists. It is a good provision when there is right-of-way limitation. The wide curb lanes are often enhanced with shared lane markings to increase awareness of the presence and position of bicyclists. Figure 2-7 gives an example of a wide curb lane in Virginia.

Sando et al. (2011) studied the motorists' behavior when passing bicyclists on wide curb lanes. The authors video recorded 956 passing events at 10 sites in Tallahassee, St. Petersburg, and Brandon, Florida at peak traffic hours. A multivariate regression model was developed to identify and understand the significant variables influencing the passing behavior. The authors concluded that motorist passing distance is influenced by environmental factors, such as lane width; contextual factors, such as the presence or absence of vehicles in adjacent lanes; and bicyclist characteristics, such as gender.

Hunter et al. (1999) conducted a comparative study of bicycle lanes versus wide curb lanes in Santa Barbara, California; Gainesville, Florida; and Austin, Texas. They video recorded motor vehicle-bicyclist interactions at 48 study sites and documented 276 conflicts between motor vehicles and bicyclists. It was found that while passing bicyclists on the left, a significantly higher percentage of vehicles encroached into the adjacent traffic lane at locations with wide curb lanes (17%) than at locations with bicycle lanes (7%). Lane encroachments hardly caused any conflict with motor vehicles using the other lane. Where the bicycle lane width was 5.2 feet or less, the average bicyclist distance from the curb was less than for wide curb lanes; however, at locations where the bicycle lane width was greater than 5.2 feet, the average bicyclist distance from the curb was greater than for wide curb lanes. The authors concluded that bicycle lanes and wide curb lanes were both effective in improving bicyclist safety; however, they recommended the installation of bicycle lanes if right-of-way permits.

Figure 2-7: Wide Curb Lane (Source: Mead et al., 2014)
(Photo Courtesy: James and Gilbert, 2012)

Harkey and Stewart (1997) examined motorist and bicyclist behavior on roadway segments with a bicycle lane, a wide curb lane, and a paved shoulder. The study revealed that motorists passed at a distance of approximately six feet irrespective of the facility type. Motorists tended to move about one foot laterally while passing a bicyclist in a bicycle lane, regardless of the width of the bicycle lane; whereas, motorists kept an additional 1.3 feet when passing bicyclists in a wide curb lane compared to bicycle lanes and paved shoulders. Moreover, bicyclists were more likely to ride further from the curb in a bicycle lane or paved shoulder than in a wide curb lane. The authors conducted an observational study and concluded that bicycle lanes and paved shoulders offered a safety advantage over wide curb lanes.

2.3.5 Traffic Calming Measures

Traffic calming consists of modifications to the roadway design and signing to slow down and/or reduce traffic, and to improve safety. Several traffic calming measures including speed-reducing measures (e.g., speed humps) and road diets (i.e., lane reductions) are proven to be effective in improving bicycle safety.

Speed-reducing Measures

Schepers et al. (2011) studied the impacts of speed-reducing measures such as raised bicycle crossings and speed humps on bicycle safety. Similar to the findings of Gårder et al. (1998), Schepers et al. (2011) revealed that speed-reducing measures for drivers leaving or entering the main road (e.g., a raised bicycle path and/or exit construction) effectively improved safety and resulted in a CMF of 0.49. The authors stated that speed-reducing measures on the minor road are suitable for most cases as they do not require additional right-of-way, in contrast to the construction of a bicycle path or a bicycle track. However, for through motorized vehicles on the main road where the motorists had the right-of-way, installation of speed-reducing measures such as a raised bicycle crossing resulted in a CMF of 1.28. Elvik and Vaa (2004) also recognized such negative effect of a raised bicycle crossing in reducing bicycle crashes and serious and minor injuries. Their study resulted in a 9% increase in bicycle crashes after the construction of raised bicycle crossings. Oh et al. (2008) concluded that the presence of speed restriction devices such as speed bumps and red light cameras improved bicycle safety (CMF of 0.28).

Lane Reduction

Chen et al. (2013) evaluated the effectiveness of lane reduction at intersections on bicycle safety. The researchers applied a pretest-posttest methodology to compare crash statistics after the implementation of lane reduction at 324 intersections in New York City. Five-year crash data before the lane reduction strategy implementation and two-year crash data after the implementation were analyzed. Analysis of covariance (ANCOVA) was used to control for potential regression-to-the-mean effects. The study identified that bicyclist crash incidence increased by 5.9% at treatment intersections compared to a 25.6% reduction at comparison intersection sites. Thus, an ANCOVA adjusted increase of 21% bicyclist crashes at intersections was calculated; however, the results were not significant at the 5% significance level. The authors could not make a conclusive decision due to lack of bicycle volume data.

Hamann & Peek-Asa (2013) examined the link between on-road bicycle facilities and bicycle crashes in Iowa during 2007-2010. A total of 147 crash sites were matched with 147 non-crash control sites, and conditional multivariate logistic regression was employed. It was found that for every 10-foot increase in the total roadway width, the odds of the roadway being the site of a bicycle crash increased by 38%. However, the researchers were not able to specify whether crashes took place when bicyclists were crossing the roadway or riding along the roadway. The results indicated that reducing the roadway width may be associated with a decreased crash risk for bicyclists.

2.3.6 Roadway and Intersection Geometry

Schepers et al. (2011) studied the effect of number of lanes and intersection geometry on bicycle safety. The authors did not identify any statistically significant relation for bicycle crashes involving through motor vehicles where motorists had the right-of-way (i.e., motorist on the priority road). However, the results were not conclusive because of the study’s limited scope.

Räsäsen and Summala (1998) found that the provision of raised middle islands at intersections that enclosed a left-turn section for both vehicles and bicyclists on roadways with more than two lanes resulted in a CMF of 0.96; on the other hand, raised middle islands at intersections on roadways with two lanes resulted in a reduction in safety, with a CMF of 1.48. The authors found that enabling bicyclists to cross in two phases might lower the demands and increase safety on roadways with more than two lanes.

Miranda-Moreno et al. (2011) concluded that the presence of medians produced a positive safety effect on bicycle crashes (CMF of 0.97), while a CMF of 1.67 was estimated for locations without the raised medians (Räsäsen and Summala, 1998).

Turner et al. (2011) analyzed the effect of left-turn lanes at signalized intersections in Christchurch, New Zealand and Adelaide, Australia. In New Zealand, intersections with exclusive left-turn lanes resulted in a CMF of 0.97, and the intersections with shared left turn and through lanes resulted in a CMF of 0.60. However, bicycle safety worsened in Adelaide, Australia; intersections with exclusive left-turn lanes resulted in a CMF of 1.36, and those with shared left turn and through lanes resulted in a CMF of 1.40. Schepers et al. (2011) in their study observed a similar result. In their study, left-turn lane or left-turn section on the main road where bicyclists have right-of-way at the intersections in Netherlands resulted in a CMF of 1.12.

Schepers et al. (2011) concluded that restricted visibility of vehicles on a minor road to approaching bicyclists at intersections with bicyclist priority worsened the safety condition. The study resulted in a CMF of 1.37. Surprisingly, the authors found that very poor visibility improved the safety situation and resulted in a CMF of 0.54 for the same scenario. The same study identified that three-legged intersections are more bicyclist friendly (CMF 0.83) than four-legged intersections (CMF 1.28). Miranda-Moreno et al. (2011) also supported this observation, the authors calculated a CMF of 0.86 for three-legged intersections in Montreal, Canada.

Daniels et al. (2009) investigated the effect of converting intersections into roundabouts on bicycle safety. The study assumed that the effectiveness of roundabouts depend on the types of bicycles, bicycle facilities, and other geometric factors. Regression analyses on effectiveness-indices resulting from a before-and-after study of bicyclist injury crashes at 90 roundabouts in Flanders, Belgium were performed. Roundabouts with bicycle lanes performed significantly worse compared to three other design types (mixed traffic, separate bicycle paths, and grade-separated bicycle paths) for all injury crashes involving bicyclists. Conversion of traditional intersections into roundabouts with bicycle lanes resulted in a CMF of 1.93 for all injury crashes and a CMF of 1.37 for fatal and severe injury crashes. Conversion of traditional intersections into roundabouts with separated bicycle paths however improved the overall bicycle safety (CMF 0.83); however, degraded the fatal and severe bicycle crash scenario (CMF 1.42). Conversion of traditional intersections into roundabouts with grade separated bicycle paths also improved safety with a CMF of 0.56 for all crash severities, and a CMF of 1.31 for fatal and severe injury crashes. Elvik and Vaa (2004) also recognized the negative effect of raised intersections in reducing crashes. Their study resulted in a 5% increase in serious and minor injury crashes and a 13% increase in property damage only (PDO) crashes.

2.3.7 Crosswalks

Oh et al. (2008) concluded that the presence of crosswalks is crucial in the prevention of bicycle crash probability at intersections. Their study for Korea indicated bicyclists might have a conflict with pedestrians and vehicles making a right turn when crossing an intersection. Permitting a RTOR (Right-Turn-On-Red) signal at signalized intersections increased the probability of crashes between pedestrians and bicyclists. Signs prohibiting a RTOR signal during certain hours could be more effective. The study also identified presence of bus stops as very favorable (CMF 0.18) in reducing bicycle crashes at intersections.

2.3.8 Roadway Lighting

Kim et al. (2007) investigated the factors that increase the probability of a severe or fatal injury in a bicycle crash using a multinomial logit model. The analysis was based on police-reported crash data from 1997-2002 from North Carolina. It was found that lack of street lights at night was associated with a 111% increase in the probability of a fatal injury. The researchers emphasized that lighting not only affected bicyclist visibility but also decreased the probability of a driver taking evasive action that would reduce injury severity. However, the study did not account for the presence or absence of illumination equipment on bicycles.

Wanvik (2009) examined the safety effect of roadway lighting on crashes in darkness on Dutch roads. The author analyzed two decades of crash data. The study concluded that roadway lighting was associated with nearly 60% reduction in bicyclist injury crashes in dark conditions on rural roads. The observed safety effect was found to be significantly greater for bicyclists compared to vehicles.

2.3.9 Parking Treatments

The City of Toronto Transportation Services Division (2003) reported running into open car doors as the third most frequent type of bicycle crashes. The analysis was based on police-reported bicycle crashes that occurred from 1997-1998. The authors found that these crashes accounted for 11.9% of the 2,574 reported crashes, and resulted in more severe injuries compared to other types of bicycle crashes.

Duthie et al. (2010) studied the effects of on-street bicycle facility configuration on bicyclist and motorist behavior. Observational studies were conducted at 48 sites in three large Texas cities, Austin, Houston, and San Antonio. Bicyclist and motorist lateral position and motorist encroachment on an adjacent lane were observed. Two multivariate regression models were developed based on these observations. It was found that bicycle lanes created a safer and more predictable riding environment compared to wide outside lanes, and the provision of a buffer between parked vehicles and bicycle lanes was found to result in fewer conflicts between bicyclists and open car doors. Furthermore, the lateral position of bicyclists was found to be safer when riding next to a row of parked vehicles than riding next to only a few parked vehicles.

Teschke et al. (2012) examined the route infrastructure on injury risk to bicyclists. A total of 690 bicycle crashes in Toronto and Vancouver, Canada were analyzed, and the infrastructure of the injury occurrence location was compared to a randomly selected control site from the same trip. A case-crossover methodology was adopted in this research. It was found that bicycle riding on a major street route without parked vehicles and with bicycle infrastructure decreased injury risk by 37% when compared to the same type of road with on-street parking. Vancouver route preference survey also indicated a public preference for major streets without on-street parking and with shared lanes or bicycle lanes.

2.4 Summary

This chapter presented a review of recent bicycle safety literature. Specifically, studies in the following four areas are summarized: (1) risk factors that affect the frequency and severity of bicycle crashes; (2) bicycle crash causes, patterns, and contributing factors; (3) network screening methods used to identify and prioritize bicycle hot spots; and (4) safety performance of the most commonly implemented engineering countermeasures. The literature review revealed that researchers have used a number of different approaches to analyze bicycle crashes, depending on the study objectives and data availability.

CHAPTER 3
STATEWIDE BICYCLE CRASH PATTERNS AND TRENDS

This chapter focuses on identifying the overall statewide bicycle crash patterns and trends in Florida. Particularly, the general trends in bicycle crash data and roadway characteristics data are identified. The chapter is divided into four major sections. The first section focuses on the data preparation efforts. The second and third sections discuss the bicycle crash and roadway geometric characteristics, respectively. Finally, the fourth section summarizes the analysis results.

3.1 Data

The analysis was based on four years of crash and traffic data from 2011 to 2014 and the Roadway Characteristics Inventory (RCI) data from 2014. The following subsections discuss these data in detail.

3.1.1 Crash Data

The law enforcement agencies in Florida document traffic crash incidents using either a long-form or a short-form Florida Traffic Crash Report. The long-form report includes all the crash-specific information, and a narrative and a diagram, and is used during the following conditions:

- a crash resulting in death of, personal injury to, or any indication of complaints of pain or discomfort by any of the parties or passengers involved in the crash;
- a crash involving a driver leaving the scene involving damage to attended vehicles or property;
- a crash involving a driver under the influence of alcohol and/or drugs;
- a crash rendering a vehicle inoperable to a degree that required a wrecker to remove it from the scene of the crash; or
- a crash involving a commercial motor vehicle.

The short-form report is used to report other types of traffic crashes and usually does not include narratives and diagrams. The law enforcement agencies are required to report crashes recorded in both the long-form and the short-form reports to the Florida Department of Highway Safety and Motor Vehicles (DHSMV) within 10 days of investigation. The FDOT State Safety Office receives the long-form crash data from the DHSMV and uploads them into the Crash Analysis Reporting (CAR) database.

The following CAR databases were used to identify bicycle crash patterns and trends:

- Crash level data file
- Non-motorist level data file
- Vehicle, driver, and passenger level data file

Non-motorist level data file was used to identify bicycle crashes based on the non-motorist type code (NON_MOTR_TYP_CD) 3 (bicyclist) or 4 (other cyclist). From 2011-2014, a total of 26,036 crashes were identified as bicycle crashes. These crashes involved 26,462 bicyclists. Table 3-1 lists the crash data variables used in the analysis. It also provides the databases which include these variables. Note that all bicycle crashes were analyzed to identify crash-specific patterns, while only those that occurred on non-limited-access state roads were analyzed to study the effect of roadway characteristics on bicycle crashes.

Table 3-1: Bicycle Crash Data Variables Used in the Analysis

Variable Name	Variable Description	Database
CRSH_NUM	Crash Number	• Crash • Non-motorist • Vehicle, driver, and passenger
CAL_YR	Calendar Year	Non-motorist
EVNT_CRSH_ TM	Event Crash Time	Crash
EVNT_CRSH_DT	Event Crash Date	Crash
DAYOWEEK	Day Of Week	Crash
WRK_ZONE_REL_CD	Work Zone Related	Crash
LGHT_COND_CD	Lighting Condition	Crash
EVNT_WTHR_COND_CD	Event Weather Condition	Crash
AGE3	Non-motorist Age	Non-motorist
PERS_SEX_CD	Non-motorist Gender	Non-motorist
INJSEVER	Non-motorist Injury Severity	Non-motorist
NON_MOTR_TYP_CD	Non-motorist Type	Non-motorist
NON_MOTR_LOC_CD	Non-motorist Location	Non-motorist
ACTN_BFR_CRSH_CD	Non-motorist Action Before Crash	Non-motorist
FRST_SAF_EQUIP_CD	Non-motorist First Safety Equipment	Non-motorist
NONMOTR_ACTN_01_CD	First Non-Motorist Action	Non-motorist
SUSP_ALC_USE_CD	Non-motorist Suspected Alcohol Use	Non-motorist
SUSP_DRUG_USE_CD	Non-motorist Suspected Drug Use	Non-motorist
VHCL_BDY_TYPE_CD	Vehicle Body Type	Vehicle, driver, and passenger
VHCL_MOVE_CD	Vehicle Movement Code	Vehicle, driver, and passenger
HAR_CD	Hit and Run	Vehicle, driver, and passenger

3.1.2 Roadway Characteristics Data

The RCI database maintained by FDOT is the primary source of roadway geometric data. It is a comprehensive roadway inventory database which includes segments that are part of the state highway system (SHS), segments that are currently being constructed and yet to be added as part of the SHS, segments that are no longer maintained by the FDOT, historic roads, local roads, exclusive roads (ramps, frontages roads etc.), etc. Segments that are currently not part of the SHS do not have complete roadway traffic, geometric, and crash data. Therefore, only those segments that are part of the SHS were included in the analysis. FDOT's State Roads GIS shapefile was used to identify the state road network in Florida. A total of 12,118.6 miles of roadways were identified as state roads in Florida.

The following data variables were extracted from the RCI database (the name in the parentheses gives the description of the variable). Note that AADT data were extracted for the years 2011 through 2014 while data for all the other roadway features were extracted for the year 2014. The RCI data were reported to be current as of December 31 of each year (i.e., 2011 through 2014).

- FUNCLASS (functional classification)
- NOLANES (number of lanes)
- MAXSPEED (posted speed limit)
- BIKELANE (presence of bicycle lane)
- AADT (annual average daily traffic)

The crash summary records in the CAR system have crash location information including the roadway ID and the milepost at which the crash occurred. This information was used to identify crashes that occurred on state roads.

3.2 Descriptive Trend Analysis – Crash Characteristics

The descriptive trend analysis focused on the following factors:

- *Temporal Factors*
    - Annual trend
    - Monthly trend
    - Day of week
    - Time of day

- *Environmental Factors*
    - Lighting conditions
    - Weather conditions

- *Bicyclist-related Factors*
    - Age
    - Gender
    - Impairment
    - Safety equipment
    - Action prior to the crash
    - Action at the time of the crash
    - Location at the time of the crash

- *Crash Location-related Factors*
    - County
    - Work zone

- *Vehicle-related Factors*
    - Vehicle type
    - Vehicle maneuver action
    - Hit and run

3.2.1 Temporal Factors

Annual and Monthly Trend

Table 3-2 provides annual bicycle crash frequency by crash severity for the years 2011-2014. Overall, during the four-year analysis period, a total of 503 fatal crashes and 22,146 injury crashes involved bicyclists. Bicycle fatal crashes accounted for 5.6% of all traffic fatal crashes, while they constituted only 1.9% of total crashes. These statistics prove that bicycle crashes are often severe. Table 3-3 gives the annual bicyclist fatality and injury rates based on population. On average, the annual bicyclist fatality and injury rates were 6.48 fatalities and 287.14 injuries per million population.

Table 3-2: Annual Bicycle Crash Statistics by Crash Severity

Year	Bicycle Crashes			All Crash Types			Percent of Bicycle Crashes		
	Fatal	Injury	All	Fatal	Injury	All	Fatal	Injury	All
2011	120	4,587	5,702	2,214	117,802	297,997	5.4%	3.9%	1.9%
2012	117	5,961	6,857	2,238	128,794	345,957	5.2%	4.6%	2.0%
2013	134	6,377	7,410	2,223	138,169	400,419	6.0%	4.6%	1.9%
2014	132	5,221	6,067	2,289	113,817	362,964	5.8%	4.6%	1.7%
Total	**503**	**22,146**	**26,036**	**8,964**	**498,582**	**1,407,337**	**5.6%**	**4.4%**	**1.9%**
Average	**126**	**5,537**	**6,509**	**2,241**	**124,646**	**351,834**	**5.6%**	**4.4%**	**1.9%**

Table 3-3: Annual Bicyclist Fatality and Injury Rates

Year	Population (in Thousands)	Bicyclist Fatalities	Bicyclist Fatality Rate per Million Population	Bicyclist Injuries	Bicyclist Injury Rate per Million Population
2011	19,106	120	6.28	4,631	242.38
2012	19,352	118	6.10	6,026	311.39
2013	19,595	135	6.89	6,441	328.71
2014	19,906	132	6.63	5,287	265.60
Average	**19,490**	**126**	**6.48**	**5,596**	**287.14**

Source: (U.S. Census Bureau, n.d.)

Table 3-4 provides the monthly bicycle crash frequencies. It can be inferred that bicycle crash frequencies were relatively higher in the months of March to May and October to December.

Day of Week

Table 3-5 gives the bicycle crash statistics by day of week and crash severity. The percentage in parentheses gives the proportion of crashes by severity that occurred on each day of the week. It can be inferred from the table that fatal crashes were more frequent on Friday and Saturday.

Table 3-4: Monthly Bicycle Crash Statistics

Month	2011	2012	2013	2014	Average
January	343	517	688	442	497.5
February	369	555	611	517	513.0
March	497	653	604	545	574.8
April	539	575	628	616	589.5
May	509	545	606	549	552.3
June	450	475	550	437	478.0
July	444	517	572	440	493.3
August	481	553	605	478	529.3
September	516	573	621	474	546.0
October	510	668	691	592	615.3
November	508	603	579	466	539.0
December	536	623	655	511	581.3
Total	**5,702**	**6,857**	**7,410**	**6,067**	**6,509.0**

Table 3-5: Statistics by Day of Week

Day of Week	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Monday	57 (11.3%)	3,350 (15.1%)	415 (14.3%)	3,897 (15.0%)
Tuesday	69 (13.7%)	3,524 (15.9%)	480 (16.5%)	4,145 (15.9%)
Wednesday	65 (12.9%)	3,599 (16.3%)	457 (15.7%)	4,197 (16.1%)
Thursday	52 (10.3%)	3,360 (15.2%)	511 (17.6%)	3,994 (15.3%)
Friday	93 (18.5%)	3,440 (15.5%)	447 (15.4%)	4,075 (15.7%)
Saturday	91 (18.1%)	2,726 (12.3%)	332 (11.4%)	3,205 (12.3%)
Sunday	76 (15.1%)	2,147 (9.7%)	260 (9.0%)	2,523 (9.7%)
Total	**503 (100%)**	**22,146 (100%)**	**2,902 (100%)**	**26,036 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

Time of Day

Table 3-6 gives the bicycle crash statistics by time of day (divided into three-hour intervals) and crash severity. About one-quarter of all bicycle crashes (i.e., 23.9%) occurred from 3:00 PM to 5:59 PM, while 20.3% of fatal crashes occurred from 6:00 PM to 8:59 PM.

Table 3-6: Statistics by Time of Day

Time of Day	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Midnight - 2:59 AM	45 (8.9%)	1,561 (7.0%)	174 (6.0%)	1,788 (6.9%)
3:00 AM - 5:59 AM	27 (5.4%)	321 (1.4%)	38 (1.3%)	391 (1.5%)
6:00 AM - 8:59 AM	67 (13.3%)	2,695 (12.2%)	328 (11.3%)	3,156 (12.1%)
9:00 AM - 11:59AM	56 (11.1%)	3,313 (15.0%)	383 (13.2%)	3,835 (14.7%)
Noon - 2:59 PM	46 (9.1%)	4,015 (18.1%)	578 (19.9%)	4,739 (18.2%)
3:00 PM - 5:59 PM	69 (13.7%)	5,316 (24.0%)	722 (24.9%)	6,233 (23.9%)
6:00 PM - 8:59 PM	102 (20.3%)	3,548 (16.0%)	493 (17.0%)	4,217 (16.2%)
9:00 PM - 11:59 PM	91 (18.1%)	1,377 (6.2%)	186 (6.4%)	1,677 (6.4%)
Total	**503 (100%)**	**22,146 (100%)**	**2,902 (100%)**	**26,036 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

3.2.2 Environmental Factors

Environmental factors such as lighting condition and weather condition were examined to study the effect of these conditions on bicycle crash frequencies and severities.

Lighting Condition

Table 3-7 summarizes the bicycle crash statistics by lighting condition. Table 3-8 provides daytime and nighttime bicycle crash statistics. Although a majority of crashes occurred during daylight (75.2%), they resulted in a lower percentage of fatal crashes; only 1.1% of all bicycle crashes that occurred during daylight resulted in fatalities. Crashes at night were found to result in a disproportionately high percentage of fatal crashes. For example, 8.5% of all bicycle crashes that occurred during dark with no street light condition resulted in fatalities. The *Z*-test for proportions was used to compare the proportion of fatal crashes that occurred during daytime and nighttime. The following equation was used to calculate the Z-test statistic:

$$Z\text{- test statistic}= \frac{(\widehat{P}_1 - \widehat{P}_2)}{\sqrt{\left(\widehat{P}\left(1-\widehat{P}\right) \times \left(\frac{1}{N_1}+\frac{1}{N_2}\right)\right)}} ;\ \widehat{P}= \frac{x_1+x_2}{N_1+N_2} \tag{3-1}$$

where,

$\hat{P}_1$ and $\hat{P}_2$ = proportion of fatal crashes that occurred during daytime and nighttime, respectively;

N_1 and N_2 = total number of crashes that occurred during daytime and nighttime, respectively; and

x_1 and x_2 = number of fatal crashes that occurred during daytime and nighttime, respectively.

At a 5% significance level, there is sufficient evidence to conclude that there is a significant difference in the proportion of fatal crashes that occurred during daytime and nighttime. Additionally, at a 5% significance level, there is sufficient evidence to conclude that there is a significant difference in the proportion of fatal crashes that occurred during dark with street light and dark with no street light conditions.

Table 3-7: Statistics by Lighting Condition

Lighting Condition	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Daylight	219 (1.1%)	16,764 (85.7%)	2,201 (11.2%)	19,571 (100%)
Dusk	18 (1.8%)	824 (83.9%)	121 (12.3%)	982 (100%)
Dawn	17 (4.1%)	350 (84.7%)	37 (9.0%)	413 (100%)
Dark with Street Light	128 (3.6%)	3,001 (83.3%)	417 (11.6%)	3,604 (100%)
Dark with No Street Light	115 (8.5%)	1,104 (82.0%)	117 (8.7%)	1,346 (100%)
Dark with Unknown Light	5 (8.3%)	50 (83.3%)	4 (6.7%)	60 (100%)
Unknown	1 (1.7%)	53 (88.3%)	5 (8.3%)	60 (100%)
Total	**503 (1.9%)**	**22,146 (85.1%)**	**2,902 (11.1%)**	**26,036 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

Table 3-8: Daytime and Nighttime Bicycle Crash Statistics

Lighting Condition	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Daytime	219 (1.1%)	16,764 (85.7%)	2,201 (11.2%)	19,571 (100%)
Nighttime[2]	283 (4.4%)	5329 (83.2%)	696 (10.9%)	6,405 (100%)
Unknown	1 (1.7%)	53 (88.3%)	5 (8.3%)	60 (100%)
Total	**503 (1.9%)**	**22,146 (85.1%)**	**2,902 (11.1%)**	**26,036 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

[2] Nighttime crashes include dusk, dawn, dark with street light, dark with no street light, and dark with unknown light condition.

Weather Condition

Table 3-9 provides bicycle crash statistics by weather condition. As expected, a majority of bicycle crashes occurred in clear weather condition. Only a very small proportion of fatal crashes occurred in adverse weather conditions. It can be inferred from the table that fog, smog, and smoke condition resulted in a high proportion of fatal crashes.

Table 3-9: Statistics by Weather Condition

Weather Condition	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Clear	394 (1.9%)	17,843 (84.8%)	2,427 (11.5%)	21,053 (100%)
Cloudy	89 (2.4%)	3,236 (86.5%)	346 (9.2%)	3,742 (100%)
Rainy	14 (1.2%)	970 (86.5%)	115 (10.3%)	1,121 (100%)
Fog, Smog, Smoke	5 (8.8%)	41 (71.9%)	8 (14.0%)	57 (100%)
Severe Crosswinds	0 (0.0%)	1 (100%)	0 (0.0%)	1 (100%)
Other	1 (1.7%)	53 (88.3%)	6 (10.0%)	60 (100%)
Unknown	0 (0.0%)	2 (100%)	0 (0.0%)	2 (100%)
Total	**503 (1.9%)**	**22,146 (85.1%)**	**2,902 (11.1%)**	**26,036 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

3.2.3 Bicyclist-related Factors

This section identifies the general trends based on the following bicyclist-related factors:

- Age
- Gender
- Impairment
- Safety equipment
- Action prior to the crash
- Action at the time of the crash
- Location at the time of the crash

Age

Since bicyclist exposure data (e.g., bicycle volumes) are not readily available and is expensive to collect, researchers often rely on surrogate measures to estimate bicyclist exposure, such as population or population density. In this study, bicycle crashes in each age group were normalized by population (i.e., crashes per million population). The 2009 travel survey data extracted from the National Household Travel Survey (NHTS) database were used to estimate population by age group.

Table 3-10 gives the summary statistics of bicycle crashes by age group, population, and crash severity. The average age of bicyclists killed in crashes with motor vehicles was 43 years, while the average age of bicyclists involved in traffic crashes was 33.8 years. Among the different age groups, bicyclists between 45 and 54 years of age experienced the highest fatality rate of 19.76 fatalities per year per million population, and those in 65-74 year age group experienced the highest injury rate of 875.43 injuries per year per million population. Note that the results from this table have to be interpreted with caution because the statistics are based on population, and they might not reflect the actual bicyclist exposure.

The *Z*-test for proportions was used to compare the fatality rate of elder bicyclists (≥ 65 years) with the fatality rate of younger bicyclists (< 65 years). Based on the *Z*-test statistic, at a 5% significance level, there is sufficient evidence to conclude that there is a significant difference in the proportion of fatal crashes involving elder bicyclists compared to those involving younger bicyclists.

Table 3-10: Statistics by Age Group

Bicyclist Age Group (years)	Population (in Thousands)[1]	Bicyclist Fatalities	Bicyclist Fatality Rate per Year per Million Population	Bicyclist Injuries	Bicyclist Injury Rate per Year per Million Population
< 5	1,078	2	0.5	72	16.7
5-9	1,106	3	0.7	590	133.4
10-15	1,369	12	2.2	2,035	371.6
16-20	1,198	43	9.0	2,615	545.7
21-24	1,060	21	5.0	1,949	459.7
25-34	2,440	57	5.8	3,322	340.4
35-44	2,414	59	6.1	2,647	274.1
45-54	2,748	113	10.3	3,762	342.2
55-64	2,497	96	9.6	2,537	254.0
65-74	1,935	39	5.0	4,055	523.9
75-84	1,148	20	4.4	337	73.4
85+	495	8	4.0	75	37.9
Unknown	--	32	--	1,389	--
Total	**19,488**	**505**	**6.5**	**22,385**	**287.2**

Source: (U.S. Census Bureau, n.d.)
[1]Average population from 2011 to 2014.

Gender

Table 3-11 provides bicycle crash statistics by gender. Table 3-12 gives the summary statistics of bicycle crashes by gender, population, and crash severity. It is clear from these tables that crashes involving male bicyclists were more frequent and more severe compared to those involving female bicyclists. Again, *Z*-test for proportions was used to compare the proportion of fatal crashes that involved male and female bicyclists. Based on the *Z*-test statistic, at a 5% significance level, there is sufficient evidence to conclude that there is a significant difference in the proportion of fatal crashes involving male bicyclists compared to those involving female bicyclists.

Table 3-11: Statistics by Gender and Severity

Bicyclist Gender	Bicyclist Fatalities	Bicyclist Injuries	Uninjured Bicyclists	Total Bicyclists[1]
Male	427 (84.6%)	16,794 (75.0%)	2,295 (74.5%)	19,881 (75.1%)
Female	48 (9.5%)	4,426 (19.8%)	496 (16.1%)	5,058 (19.1%)
Unknown	30 (5.9%)	1,165 (5.2%)	288 (9.4%)	1,523 (5.8%)
Total	**505 (100%)**	**22,385 (100%)**	**3,079 (100%)**	**26,462 (100%)**

[1] Total bicyclists include bicyclists with unknown severity and non-traffic fatalities.

Table 3-12: Statistics by Gender and Population

Bicyclist Gender	Population (in Thousands)[1]	Bicyclist Fatalities	Bicyclist Fatality Rate per Year per Million Population	Bicyclist Injuries	Bicyclist Injury Rate per Year per Million Population
Male	9,526	427	11.2	16,794	440.7
Female	9,963	48	1.2	4,426	111.1
Unknown	---	30	---	1,165	--
Total	**19,489**	**505**	**6.5**	**22,385**	**287.1**

Source: (U.S. Census Bureau, n.d.)

[1]Average population from 2011 to 2014.

Impairment

Table 3-13 provides statistics on impaired bicyclists. The table includes separate statistics for bicyclists influenced by alcohol and drugs. As can be inferred from the table, 3.3% of all bicyclists involved in crashes were under the influence of alcohol, and 0.4% of all bicyclists involved in crashes were under the influence of drugs. Over 10% of all bicyclists involved in crashes who were under the influence of alcohol were killed, and a high 27.6% of all bicyclists involved in crashes who were under the influence of drugs were killed. These proportions were found to be statistically significant at a 5% significance level.

Table 3-13: Statistics on Impaired Bicyclists

Impairment	Bicyclist Fatalities	Bicyclist Injuries	Uninjured Bicyclists	Total Bicyclists[1]
		Alcohol		
Yes	89 (10.2%)	690 (79.4%)	70 (8.1%)	869 (100%)
No	228 (1.0%)	20,332 (86.0%)	2,636 (11.2%)	23,633 (100%)
Unknown	188 (9.6%)	1,363 (69.5%)	373 (19.0%)	1,960 (100%)
Total	**505 (1.9%)**	**22,385 (84.6%)**	**3,079 (11.6%)**	**26,462 (100%)**
		Drugs		
Yes	29 (27.6%)	64 (61.0%)	10 (9.5%)	105 (100%)
No	264 (1.1%)	20,633 (86.0%)	2,650 (11.0%)	23,993 (100%)
Unknown	212 (9.0%)	1,688 (71.4%)	419 (17.7%)	2,364 (100%)
Total	**505 (1.9%)**	**22,385 (84.6%)**	**3,079 (11.6%)**	**26,462 (100%)**

[1] Total bicyclists include bicyclists with unknown severity and non-traffic fatalities.

Safety Equipment

Safety equipment plays a crucial role in reducing the frequency and severity of bicycle crashes. Safety equipment such as helmets, protective pads, etc., protect the bicyclists involved in a crash; while other equipment such as reflective clothing, lighting on bicycles, etc., make bicyclists more visible to the drivers. Table 3-14 provides bicycle crash statistics based on the safety equipment used by the bicyclists at the time of the crash. The *Z*-test for proportions was used to compare the proportion of fatal crashes that involved bicyclists using safety equipment versus bicyclists not using any type of safety equipment. Based on the *Z*-test statistic, at a 5% significance level, there is sufficient evidence to conclude that there is no significant difference in the proportion of fatal crashes involving bicyclists using safety equipment compared to those involving bicyclists without using any type of safety equipment.

Table 3-14: Statistics by Safety Equipment Used

Safety Equipment	Bicyclist Fatalities	Bicyclist Injuries	Uninjured Bicyclists	Total Bicyclists[1]
None	404 (1.9%)	18,292 (84.9%)	2,457 (11.4%)	21,549 (100%)
Helmet	52 (1.7%)	2,665 (86.7%)	293 (9.5%)	3073 (100%)
Protective Pads Used[2]	2 (5.3%)	31 (81.6%)	4 (10.5%)	38 (100%)
Reflective Clothing[3]	5 (4.5%)	95 (85.6%)	9 (8.1%)	111 (100%)
Lighting	31 (5.0%)	507 (82.2%)	71 (11.5%)	617 (100%)
Not Applicable	1 (1.0%)	78 (78.8%)	16 (16.2%)	99 (100%)
Other	1 (0.9%)	103 (88.0%)	9 (7.7%)	117 (100%)
Unknown	9 (1.0%)	614 (71.6%)	220 (25.6%)	858 (100%)
Total	**505 (1.9%)**	**22,385 (84.6%)**	**3,079 (11.6%)**	**26,462 (100%)**

[1] Total bicyclists include bicyclists with unknown severity and non-traffic fatalities.
[2] E.g., elbows, knees, etc.; [3] e.g., jacket, backpack, etc.

Since the type of safety equipment impacts the severity of crashes, *Z*-test for proportions was again used to compare the proportion of fatal crashes that involved bicyclists using either helmets or protective pads and those using reflective clothing or lighting on bicycles. At a 5% significance level, there is sufficient evidence to conclude that there is a significant difference in the proportion of fatal crashes involving bicyclists using helmets or protective pads compared to those involving bicyclists using reflective clothing or lighting.

Bicyclist's Action Prior to the Crash

Table 3-15 provides statistics based on bicyclist's action prior to the crash. Over one-third of bicyclists (35.2%) were hit while crossing the road, 2.2% of these crashes resulted in fatalities. It is worth noting that although bicyclists were frequently hit while cycling on the sidewalk, these crashes resulted in very few fatalities; only 0.4% of all crashes involving bicyclists cycling on sidewalk resulted in fatalities.

The *Z*-test for proportions was used to compare the proportion of fatal crashes that involved bicyclists crossing the roadway and those cycling along the roadway. At a 5% significance level, there is sufficient evidence to conclude that there is no statistically significant difference in the proportion of fatal crashes involving bicyclists crossing the roadway compared to those involving bicyclists cycling along the roadway. The *Z*-test for proportions was again used to compare the proportion of fatal crashes that involved bicyclists cycling along the roadway with traffic and those cycling along the roadway against traffic. At a 5% significance level, there is sufficient evidence to conclude that the proportion of fatal crashes involving bicyclists cycling along the roadway with traffic is significantly greater than those involving bicyclists cycling along the roadway against traffic.

Table 3-15: Statistics by Bicyclist's Action Prior to the Crash

Action Prior to the Crash	Bicyclist Fatalities	Bicyclist Injuries	Uninjured Bicyclists	Total Bicyclists[1]	Proportion of Total Bicyclists
Crossing Roadway	209	7,845	1,055	9,303	35.2%
Waiting to Cross Roadway	7	274	54	343	1.3%
Cycling Along Roadway with Traffic	153	4,277	427	4,930	18.6%
Cycling Along Roadway against Traffic	35	1,887	263	2,214	8.4%
Cycling on Sidewalk	24	5,034	693	5,857	22.1%
In Roadway (working, playing, etc.)	20	474	63	573	2.2%
Adjacent to Roadway	15	300	43	367	1.4%
Going to or from School	0	143	22	168	0.6%
Working in Traffic Way	0	1	1	2	0.0%
None	5	233	32	275	1.0%
Other	23	1,485	277	1,831	6.9%
Unknown	14	432	149	599	2.3%
Total	**505**	**22,385**	**3,079**	**26,462**	**100.0%**

[1] Total bicyclists include bicyclists with unknown severity and non-traffic fatalities.

Bicyclist's Location at the Time of the Crash

Table 3-16 gives bicyclist crash statistics by location at the time of the crash and crash severity. At a 5% significance level, there is sufficient evidence to conclude that there is a significant difference in the proportion of fatal crashes that occurred on segments compared to those that occurred at intersections.

Bicyclist's Action and Location at the Time of the Crash

Table 3-17 gives statistics based on bicyclist's action at the time of the crash. Note that no improper action was identified in 46% of crashes. Failure to yield right-of-way was found to be the most frequent contributing cause, resulting in about 15% of total crashes.

Table 3-16: Statistics by Bicyclist's Location at the Time of the Crash

Bicyclist's Location at the Time of the Crash	Bicyclist Fatalities	Bicyclist Injuries	Uninjured Bicyclists	Total Bicyclists[1]
Intersection[2]	137 (1.2%)	9,882 (85.5%)	1,321 (11.4%)	11,563 (100%)
Segment[3]	305 (2.8%)	9,260 (84.9%)	1,198 (11.0%)	10,910 (100%)
Driveway/Access	4 (0.3%)	1,184 (83.9%)	163 (11.5%)	1,412 (100%)
Shared-use Path or Trail	2 (1.9%)	91 (85.8%)	8 (7.5%)	106 (100%)
Non-traffic Way Area	1 (1.6%)	46 (74.2%)	13 (21.0%)	62 (100%)
Other	44 (2.4%)	1,515 (81.5%)	252 (13.6%)	1,859 (100%)
Unknown	12 (2.2%)	407 (74.0%)	124 (22.5%)	550 (100%)
Total	**505 (1.9%)**	**22,385 (84.6%)**	**3,079 (11.6%)**	**26,462 (100%)**

[1] Total bicyclists include bicyclists with unknown severity and non-traffic fatalities.

[2] Intersection location includes crashes that occurred at intersection-marked crosswalk, intersection-unmarked crosswalk, intersection-other locations.

[3] Segment location includes crashes that occurred at midblock-marked crosswalk, travel lane-other location, bicycle lane, shoulder/roadside, sidewalk, and median/crossing island.

Table 3-17: Statistics by Bicyclist's Action at the Time of the Crash

Bicyclist's Action at the Time of the Crash	Bicyclist Fatalities	Bicyclist Injuries	Uninjured Bicyclists	Total Bicyclists[1]	Proportion of Total Bicyclists
No Improper Action					
No Improper Action	124	10,436	1,417	12,180	46.0%
Any Improper Action					
Dart/Dash	33	1,239	139	1,444	5.5%
Failure to Yield Right-of-way	127	3,347	409	3,950	14.9%
Failure to Obey Traffic Signs, Signals	33	1,180	140	1,388	5.2%
In Roadway[2]	29	416	47	504	1.9%
Disabled Vehicle Related[3]	0	14	0	14	0.1%
Entering/Exiting Parked/Standing Vehicle	0	42	14	58	0.2%
Inattentive[4]	1	221	33	260	1.0%
Not Visible[5]	36	621	68	733	2.8%
Improper Turn/Merge	8	181	18	215	0.8%
Improper Passing	2	85	14	105	0.4%
Wrong Way, Riding	18	1,447	192	1,709	6.5%
Other	55	2,162	375	2,640	10.0%
Any Improper Action[6]	**342**	**10,955**	**1,449**	**13,020**	**49.2%**
Unknown Action					
Unknown	39	994	213	1,262	4.8%
Total					
Total	**505**	**22,385**	**3,079**	**26,462**	**100.0%**

[1] Total bicyclists include bicyclists with unknown severity and non-traffic fatalities.

[2] E.g., standing, lying, working, etc.; [3] e.g., working on, pushing, leaving/approaching, etc.;

[4] e.g., talking, eating, etc.; [5] e.g., dark clothing, no lighting, etc.

[6] Any improper action includes dart/dash, failure to yield right-of-way, failure to obey traffic signs and signals, in roadway, disabled vehicle-related, entering/exiting parked/standing vehicle, inattentive, not visible, improper turn/merge, improper passing, wrong way, riding, and other.

3.2.4 Crash Location-related Factors

County

Table 3-18 lists the ten counties in Florida with the highest number of bicycle crashes during the years 2011-2014. Miami Dade County, followed by Broward County experienced the highest number of bicycle crashes. However, Pinellas and Brevard counties experienced a high 10.0 bicyclist fatalities per year per million population.

Table 3-18: Statistics in Top Ten Counties in Florida

County	Total Bicycle Crashes (2011-2014)	Population (in Thousands)[1]	Bicyclist Fatalities (2011-2014)	Bicyclist Fatality Rate[2]	Bicyclist Injuries (2011-2014)	Bicyclist Injury Rate[2]
Miami-Dade	3,589	2,626	40	3.8	2,897	275.8
Broward	3,202	1,830	52	7.1	2,631	359.4
Pinellas	2,082	927	37	10.0	1,762	475.2
Palm Beach	2,066	1,368	30	5.5	1,814	331.5
Orange	1,875	1,214	33	6.8	1,621	333.8
Hillsborough	1,840	1,291	40	7.7	1,668	323.0
Duval	1,108	885	21	5.9	937	264.7
Volusia	782	500	16	8.0	672	336.0
Brevard	765	550	22	10.0	649	295.0
Lee	715	654	19	7.3	629	240.4
Total	**18,024**	**11,845**	**310**	**6.5**	**15,280**	**322.5**

Source: (U.S. Census Bureau, n.d.); [1] Average population from 2011 to 2014; [2] rate is per year per million population.

Presence of Work Zone

Of the 26,036 bicycle crashes that occurred during 2011-2014, 205 crashes (0.8%) were identified as work zone-related. Table 3-19 provides these statistics. The proportion of fatalities in work zone-related crashes was found to be slightly lower than the proportion of fatalities in non-work zone-related crashes. Note that this difference was not statistically significant. Statistics of work zone-related crashes by year revealed that the total bicyclists involved in work zone-related crashes reduced from 65 in 2013 to 39 in 2014. Moreover, work zone-related crashes were found to be more frequent during daytime (157 of 205) compared to nighttime (43 of 205).

Table 3-19: Work Zone-related Crash Statistics

Work Zone-related	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
No	497 (1.9%)	21,898 (85.0%)	2,874 (11.2%)	25,752 (100%)
Yes	3 (1.5%)	184 (89.8%)	16 (7.8%)	205 (100%)
Unknown	3 (3.8%)	64 (81.0%)	12 (15.2%)	79 (100%)
Total	**503 (1.9%)**	**22,146 (85.1%)**	**2,902 (11.1%)**	**26,036 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

3.2.5 Vehicle-related Factors

Vehicle Type

Table 3-20 provides bicycle crash statistics by vehicle type and crash severity. Overall, a total of 26,766 vehicles were involved in bicycle crashes. As can be observed from the table, among all types of vehicles, passenger cars were found to result in relatively less severe crashes. Medium and heavy trucks resulted in more severe crashes; a relatively high 14.5% of all crashes involving medium and heavy trucks resulted in fatalities. The 214 bicycle crashes involving medium and heavy trucks were further analyzed to determine the reasons for high bicyclist fatality rate involving these vehicles. Analysis based on average vehicle speed, first harmful event, vehicle maneuver action, driver and bicyclist action at the time of the crash, bicyclist safety equipment, etc. was conducted. The average vehicle speed in all the bicycle crashes was found to be 12.4 mph, while the speed of medium and heavy trucks was found to be 14.1 mph. High speeds of these vehicles might have contributed to a higher proportion of fatal crashes compared to crashes involving other vehicles. Besides the average vehicle speed, no other obvious patterns that could potentially result in more severe crashes were identified.

Table 3-20: Statistics by Vehicle Type

Vehicle Type	Vehicles Involved in			
	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Passenger Car	248 (1.7%)	12,706 (84.6%)	1,798 (12.0%)	15,027 (100%)
Sport Utility Vehicle	88 (2.2%)	3,394 (86.6%)	360 (9.2%)	3,917 (100%)
Pickup Truck	85 (2.9%)	2,585 (86.7%)	260 (8.7%)	2,981 (100%)
Passenger Van	46 (3.0%)	1,317 (85.9%)	151 (9.8%)	1,533 (100%)
Light Truck[2]	12 (3.3%)	300 (82.2%)	39 (10.7%)	365 (100%)
Medium/Heavy Trucks	31 (14.5%)	156 (72.9%)	20 (9.3%)	214 (100%)
Bus	5 (2.5%)	160 (79.2%)	32 (15.8%)	202 (100%)
Motorcycle	5 (2.7%)	144 (77.8%)	31 (16.8%)	185 (100%)
Moped	0 (0.0%)	36 (78.3%)	10 (21.7%)	46 (100%)
Motor Home	0 (0.0%)	21 (95.5%)	1 (4.5%)	22 (100%)
Others[3]	13 (1.9%)	526 (78.9%)	98 (14.7%)	667 (100%)
Unknown	25 (1.6%)	1,326 (82.5%)	235 (14.6%)	1,607 (100%)
Total	**558 (2.1%)**	**22,671 (84.7%)**	**3,035 (11.3%)**	**26,766 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.
[2] Light trucks include cargo van.
[3] Others include all-terrain vehicle, farm labor vehicle, low speed vehicle, motor coach, and "other" category.

Vehicle Maneuver Action

Table 3-21 provides statistics by vehicle maneuver action and crash severity. Overall, about 45% of all vehicles were traveling straight ahead at the time of the crash. Most severe crashes involved vehicles leaving traffic lane, followed by vehicles changing lanes and negotiating a curve.

Hit-and-run Crashes

Table 3-22 gives statistics of Hit-and-Run crashes. From 2011-2014, a total of 4,157 bicycle crashes were identified as Hit-and-Run. These constitute 16.0% of total bicycle crashes. In general, the severity of crashes involving hit and run vehicles was found to be similar to the severity of all bicycle crashes. In other words, involvement of hit and run drivers did not affect crash severity.

Table 3-21: Statistics by Vehicle Maneuver Action

Vehicle Maneuver Action	Vehicles Involved in			
	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Straight Ahead	442 (3.7%)	10,114 (84.0%)	1,248 (10.4%)	12,038 (100%)
Turning Right	33 (0.4%)	6,648 (86.2%)	892 (11.6%)	7,712 (100%)
Turning Left	23 (0.8%)	2,538 (87.8%)	282 (9.8%)	2,890 (100%)
Stopped in Traffic	2 (0.3%)	481 (80.0%)	112 (18.6%)	601 (100%)
Backing	0 (0.0%)	303 (88.1%)	37 (10.8%)	344 (100%)
Entering Traffic Lane	0 (0.0%)	296 (86.0%)	36 (10.5%)	344 (100%)
Slowing	2 (0.7%)	239 (80.5%)	46 (15.5%)	297 (100%)
Parked	1 (0.4%)	184 (74.5%)	60 (24.3%)	247 (100%)
Overtaking/Passing	4 (2.2%)	159 (88.8%)	14 (7.8%)	179 (100%)
Changing Lanes	10 (7.9%)	102 (80.3%)	14 (11.0%)	127 (100%)
Negotiating a Curve	5 (5.2%)	84 (86.6%)	7 (7.2%)	97 (100%)
Making U-turn	0 (0.0%)	59 (85.5%)	6 (8.7%)	69 (100%)
Leaving Traffic Lane	5 (9.6%)	42 (80.8%)	3 (5.8%)	52 (100%)
Other	9 (1.6%)	457 (79.2%)	90 (15.6%)	577 (100%)
Unknown	22 (1.8%)	965 (81.0%)	188 (15.8%)	1,192 (100%)
Total	**558 (2.1%)**	**22,671 (84.7%)**	**3,035 (11.3%)**	**26,766 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

Table 3-22: Hit-and-Run Crash Statistics

Hit-and-Run Involvement	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Hit and Run	80 (1.9%)	3,286 (79.0%)	735 (17.7%)	4,157 (100%)
Not Hit and Run	420 (2.0%)	18,429 (86.3%)	2,086 (9.8%)	21,352 (100%)
Unknown	3 (0.6%)	431 (81.8%)	81 (15.4%)	527 (100%)
Total	**503 (1.9%)**	**22,146 (85.1%)**	**2,902 (11.1%)**	**26,036 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

3.3 Descriptive Trend Analysis – Roadway Characteristics

This section presents statewide bicycle crash characteristics based on the following roadway-related factors:

- functional classification
- number of lanes
- posted speed limit
- presence of bicycle lane
- traffic volume (i.e., AADT)

During the analysis years 2011-2014, of the total 26,036 bicycle crashes, 10,580 crashes occurred on state roads, which include both limited-access facilities and non-limited-access facilities. Although bicycles are prohibited on limited-access facilities, 34 bicycle crashes were found to have occurred on these facilities. These 34 crashes were excluded from further analysis. The statistics by number of lanes, posted speed limit, crash location, presence of bicycle lane, and traffic volume were provided for non-limited-access facilities which constitute 9,884.3 miles of state road network, and experienced 10,546 bicycle crashes from 2011 through 2014.

Functional Classification

Table 3-23 provides bicycle crash statistics by functional classification of the road network and crash severity. The majority of bicycle crashes occurred on urban roadways; only 1.2% of all crashes that occurred on state roads occurred in rural areas. This is expected since traffic volumes and bicyclists are usually higher on urban roads as compared to rural roads. In terms of crash severity, 16.9% of all bicycle crashes that occurred on rural facilities resulted in fatalities while only 2.5% of those that occurred on urban facilities resulted in fatalities.

Table 3-23: Statistics by Functional Class

Functional Classification		Miles	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]	Total Crashes per Mile per Year
Rural Facilities	Rural Principal Arterial – Interstate	717.3	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0.00
	Rural Principal Arterial – Freeways and Expressways	175.0	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0.00
	Rural Principal Arterial – Other	2,586.0	17 (15.6%)	79 (72.5%)	12 (11.0%)	109 (100%)	0.01
	Rural Minor Arterial	1,761.2	5 (25.0%)	12 (60.0%)	3 (15.0%)	20 (100%)	0.00
	Rural Major Collector	404.9	0 (0.0%)	1 (100%)	0 (0.0%)	1 (100%)	0.00
	Rural Minor Collector	0.0	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	--
	Rural Local	0.3	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0.00
	Total Rural Facilities	**5,644.7**	**22 (16.9%)**	**92 (70.8%)**	**15 (11.5%)**	**130 (100%)**	**0.01**
Urban Facilities	Urban Principal Arterial – Interstate	778.0	1 (12.5%)	6 (75.0%)	1 (12.5%)	8 (100%)	0.00
	Urban Principal Arterial – Freeways and Expressways	562.3	2 (7.7%)	22 (84.6%)	2 (7.7%)	26 (100%)	0.01
	Urban Principal Arterial – Other	3,466.9	211 (2.8%)	6237 (84.2%)	803 (10.8%)	7,404 (100%)	0.53
	Urban Minor Arterial	1,499.4	48 (1.7%)	2356 (85.1%)	298 (10.8%)	2,768 (100%)	0.46
	Urban Major Collector	158.0	2 (0.8%)	208 (87.4%)	23 (9.7%)	238 (100%)	0.38
	Urban Minor Collector	3.7	0 (0.0%)	2 (100%)	0 (0.0%)	2 (100%)	0.14
	Urban Local	3.9	0 (0.0%)	3 (75.0%)	1 (25.0%)	4 (100%)	0.26
	Total Urban Facilities	**6,472.2**	**264 (2.5%)**	**8,834 (84.5%)**	**1,128 (10.8%)**	**10,450 (100%)**	**0.40**
Total		**12,118.6[2]**	**286 (2.7%)**	**8,926 (84.4%)**	**1,143 (10.8%)**	**10,580 (100%)**	**0.22**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.
[2] Total miles include 1.7 miles of unknown facility type.

In particular, urban principal arterials excluding interstates, freeways, and expressways and urban minor arterials experienced over 95% of total bicycle crashes. The urban principle arterial other category experienced the highest bicycle crash rate of 0.53 bicycle crashes per mile per year. This was followed by urban minor arterials with 0.45 bicycle crashes per mile per year. Based on these statistics, it can be concluded that urban principal arterials other than interstates, freeways, and expressways and urban minor arterials experience a high frequency of bicycle crashes.

Number of Lanes

Table 3-24 provides bicycle crash statistics by number of lanes and crash severity. A majority of bicycle crashes occurred on either four-lane or six-lane facilities; these two facilities experienced more than 80% of all bicycle crashes. The six-lane facilities experienced the highest crash rate of 0.97 bicycle crashes per mile per year, followed by facilities with more than six lanes and five lanes, respectively. On the other hand, the two-lane facilities experienced the highest proportion of fatal crashes; 4.4% of all bicycle crashes at two-lane facilities resulted in fatalities while 2.7% of crashes on all non-limited-access facilities were fatal.

Table 3-24: Statistics by Number of Lanes

Number of Lanes	Miles	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]	Total Crashes per Mile per Year
1	11.8	0 (0.0%)	5 (83.3%)	1 (16.7%)	6 (100%)	0.13
2	5,002.6	41 (4.4%)	781 (84.3%)	93 (10.0%)	927 (100%)	0.05
3	151.7	1 (0.3%)	242 (84.6%)	41 (14.3%)	286 (100%)	0.47
4	3,394.1	129 (3.0%)	3,654 (83.9%)	488 (11.2%)	4,355 (100%)	0.32
5	88.9	4 (1.7%)	189 (79.7%)	37 (15.6%)	237 (100%)	0.67
6	1,142.1	99 (2.2%)	3,771 (85.0%)	451 (10.2%)	4,436 (100%)	0.97
≥ 7	91.4	9 (3.0%)	256 (85.6%)	29 (9.7%)	299 (100%)	0.82
Unknown	1.7	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0.00
Total	**9,884.3**	**283 (2.7%)**	**8,898 (84.4%)**	**1,140 (10.8%)**	**10,546 (100%)**	**0.27**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

Posted Speed Limit

Table 3-25 gives bicycle crash statistics by posted speed limit and crash severity. Overall, roadways with 40 mph posted speed limit experienced the highest bicycle crash rate of 0.86 crashes per mile per year. As expected, more severe crashes occurred on high-speed facilities. For example, a high 12.5% of all crashes that occurred on roadways with speed limit ≥ 55 mph resulted in fatalities, while on average, only 2.7% of all bicycle crashes on non-limited-access facilities were fatal. It can be inferred from the table that low-speed facilities experienced a greater number of bicycle crashes while high-speed facilities experienced a greater proportion of fatal crashes.

Table 3-25: Statistics by Posted Speed Limit

Posted Speed Limit	Miles	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]	Total Crashes per Mile per Year
≤ 35 mph	921.4	28 (1.0%)	2,353 (82.6%)	392 (13.8%)	2,850 (100%)	0.77
40 mph	621.3	46 (2.1%)	1,819 (85.0%)	237 (11.1%)	2,140 (100%)	0.86
45 mph	2,193.8	117 (2.6%)	3,844 (85.6%)	427 (9.5%)	4,491 (100%)	0.51
50 mph	583.1	30 (5.6%)	454 (84.5%)	50 (9.3%)	537 (100%)	0.23
≥ 55 mph	5,508.1	62 (12.5%)	397 (80.0%)	33 (6.7%)	496 (100%)	0.02
Unknown	56.6	0 (0.0%)	31 (96.9%)	1 (3.1%)	32 (100%)	0.14
Total	**9,884.3**	**283 (2.7%)**	**8,898 (84.4%)**	**1,140 (10.8%)**	**10,546 (100%)**	**0.27**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

Crash Location

Table 3-26 gives the bicycle crash statistics by crash location. A total of 48.2% all bicycle crashes occurred at non-intersections, followed by 37.5% at intersections, and 10.3% at driveways. A greater proportion of crashes at non-intersections (i.e., segments) were found to result in fatalities compared to the crashes at intersections, and this difference was found to be statistically significant at a 5% significance level.

Table 3-26: Statistics by Crash Location

Location	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]
Non-intersection	178 (3.5%)	4,169 (82.0%)	574 (11.3%)	5,085 (100%)
Intersection	85 (2.1%)	3,425 (86.6%)	408 (10.3%)	3,956 (100%)
Driveway	7 (0.6%)	970 (89.3%)	93 (8.6%)	1,086 (100%)
Railway Grade Crossing	0 (0.0%)	2 (100.0%)	0 (0.0%)	2 (100%)
Entrance/Exit Ramp	0 (0.0%)	32 (88.9%)	4 (11.1%)	36 (100%)
Crossover related	2 (10.5%)	12 (63.2%)	5 (26.3%)	19 (100%)
Shared-use Path or Trail	1 (5.0%)	14 (70.0%)	4 (20%)	20 (100%)
Through Roadway	4 (14.8%)	16 (59.3%)	4 (14.8%)	27 (100%)
Other	5 (3.5%)	118 (82.5%)	18 (12.6%)	143 (100%)
Unknown	1 (0.6%)	140 (81.4%)	30 (17.4%)	172 (100%)
Total	**283 (2.7%)**	**8,898 (84.4%)**	**1,140 (10.8%)**	**10,546 (100%)**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

Presence of Bicycle Lane

Table 3-27 presents the bicycle crash statistics by the presence or absence of bicycle lanes. Of the entire 9,884.3 miles of the non-limited-access facilities on the state road network in Florida, only 1,160.9 miles (i.e., 11.7%) were found to have bicycle lanes. Facilities with bicycle lanes experienced 0.48 crashes per mile per year while those without bicycle lanes experienced 0.24 crashes per mile per year. These statistics need to be interpreted with caution since bicycle exposure (e.g., bicycle volumes) is not taken into consideration. It is fair to assume that the facilities with bicycle lanes have higher exposure, and hence, could result in more crashes compared to the facilities without bicycle lanes. Bicycle crash severities at locations with and without bicycle lanes were found to be similar. In other words, crash severity was not affected by the presence of bicycle lanes. However, more in-depth analysis is required to understand the effect of bicycle lanes on the frequency and severity of bicycle crashes.

Table 3-27: Statistics by Presence of Bicycle Lane

Presence of Bicycle Lane	Miles	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]	Total Crashes per Mile per Year
Yes	1,160.9	58 (2.6%)	1,901 (84.8%)	213 (9.5%)	2,241 (100%)	0.48
No	8,723.4	225 (2.7%)	6,997 (84.3%)	927 (11.2%)	8,305 (100%)	0.24
Total	**9,884.3**	**283 (2.7%)**	**8,898 (84.4%)**	**1,140 (10.8%)**	**10,546 (100%)**	**0.27**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

Traffic Volume

Table 3-28 presents the bicycle crash statistics for different AADT ranges. As expected, low-volume roads (i.e., with AADT ≤ 10,000 veh/day) experienced the lowest number of bicycle crashes per mile per year. However, a greater proportion of these crashes resulted in fatalities. The highest bicycle crash rate of 1.05 bicycle crashes per mile per year was observed on high volume roads (AADT > 50,000 veh/day).

Table 3-28: Statistics by Traffic Volume

AADT (veh/day)	Miles	Fatal Crashes	Injury Crashes	PDO Crashes	Total Crashes[1]	Total Crashes per Mile per Year
≤ 10,000	4,916.2	31 (6.6%)	379 (80.6%)	55 (11.7%)	470 (100%)	0.02
10,001-20,000	2,116.9	49 (2.9%)	1,448 (84.6%)	180 (10.5%)	1,712 (100%)	0.20
20,001-30,000	1,153.2	65 (2.7%)	1,993 (83.6%)	275 (11.5%)	2,384 (100%)	0.52
30,001-40,000	851.6	55 (2.1%)	2,282 (86.0%)	262 (9.9%)	2,652 (100%)	0.78
40,001-50,000	443.5	46 (2.7%)	1,469 (85.1%)	174 (10.1%)	1,726 (100%)	0.97
> 50,000	380.5	37 (2.3%)	1,325 (82.8%)	194 (12.1%)	1,600 (100%)	1.05
Unknown	22.4	0 (0.0%)	2 (0.0%)	0 (0.0%)	2 (100%)	0.02
Total	**9,884.3**	**283 (2.7%)**	**8,898 (84.4%)**	**1,140 (10.8%)**	**10,546 (100%)**	**0.27**

[1] Total crashes include crashes of unknown severity and crashes that resulted in a non-traffic fatality.

3.4 Summary

This chapter focused on identifying the overall statewide bicycle crash patterns in Florida. The general trends in bicycle crash data and roadway characteristics data were identified, and are summarized in the following sections.

3.4.1 Crash Characteristics

The descriptive trend analysis was based on temporal, environmental, bicyclist-related, crash location-related, and vehicle-related factors. The analysis was based on a total of 26,036 bicycle crashes that occurred during 2011-2014. Some of the key findings include:

- From 2011-2014, a total of 503 fatal crashes and 22,146 injury crashes involved bicyclists.
- Bicycle fatal crashes accounted for 5.6% of all traffic fatal crashes, while they constituted only 1.9% of total crashes.
- Nighttime bicycle crashes resulted in more fatalities compared to daytime crashes.
- The majority of bicycle crashes occurred in clear weather condition. Additionally, only a very small proportion of fatal crashes occurred in adverse weather conditions.
- The average age of bicyclists killed in traffic crashes was 43 years, while the average age of bicyclists involved in traffic crashes was 33.8 years.
- Crashes involving elder bicyclists (≥ 65 years) resulted in more fatalities compared to crashes involving younger bicyclists (< 65 years).
- Crashes involving male bicyclists resulted in more fatalities compared to crashes involving female bicyclists.
- Over 10% of all bicyclists involved in crashes who were under the influence of alcohol were killed, and a high 27.6% of all bicyclists involved in crashes who were under the influence of drugs were killed.
- Crashes involving bicyclists using helmets or protective pads were less severe compared to those involving bicyclists using reflective clothing or lighting.
- Although bicyclists were frequently hit while cycling on the sidewalk, these crashes resulted in very few fatalities.
- Crashes involving bicyclists cycling along the roadway against traffic were found to be more severe compared to those involving bicyclists cycling along the roadway with traffic.
- In terms of bicyclist's action at the time of the crash, failure to yield right-of-way was the most frequent contributing cause, resulting in about 15% of total crashes.
- Miami Dade and Broward counties experienced the highest number of bicycle crashes in Florida.
- Of the 26,036 bicycle crashes that occurred during 2011-2014, 205 crashes (0.8%) were identified as work zone-related. The proportion of fatalities in work zone-related crashes was slightly lower than the proportion of fatalities in non-work zone-related crashes.
- Among all types of vehicles, passenger cars were found to result in relatively less severe crashes. Medium and heavy trucks resulted in more severe crashes; a relatively high 14.5% of all crashes involving medium and heavy trucks were fatal. The average vehicle speed of medium/heavy trucks was found to be 14.1 mph, while the average speed of all vehicles involved in bicycle crashes was found to be 12.4 mph. High speeds of these vehicles might have contributed to more fatal crashes compared to other vehicles.
- In terms of vehicle maneuver action, a high proportion of severe crashes involved vehicles leaving traffic lane, followed by vehicles changing lanes and negotiating a curve.
- About 16.0% of total bicycle crashes constituted hit and run crashes. However, involvement of hit and run drivers did not affect crash severity.

3.4.2 Roadway Characteristics

The effect of roadway geometric features on the frequency and severity of bicycle crashes was studied using data from 9,884.3 miles of non-limited-access state roads in Florida, which experienced a total of 10,546 bicycle crashes during the four-year analysis period. Some of the key findings include:

- The majority of bicycle crashes occurred on urban roadways; only 1.2% of all crashes that occurred on state roads occurred in rural areas. In terms of crash severity, 16.9% of all bicycle crashes that occurred on rural facilities resulted in fatalities while only 2.5% of those that occurred on urban facilities resulted in fatalities.
- Urban principal arterials other than interstates, freeways, and expressways and urban minor arterials experienced a high frequency of bicycle crashes.
- Six-lane facilities experienced the highest crash rate of 0.97 bicycle crashes per mile per year, while four-lane facilities experienced slightly greater proportion of fatal crashes.
- Low-speed facilities experienced greater number of bicycle crashes while high-speed facilities experienced more severe crashes.

CHAPTER 4
BICYLCLE HOT SPOT IDENTIFICATION AND ANALYSIS

This chapter focuses on identifying and analyzing locations with high bicycle crash frequencies in Florida. The chapter is divided into five major sections. The first section discusses the approach used to identify bicycle crash hot spots using spatial analysis in ArcGIS. It also includes the list of top five bicycle crash hot spots in each FDOT district. The second section focuses on analyzing the bicycle hot spots. The police report review process to identify specific bicycle crash types and patterns is also discussed in this section. The third section provides the collision-condition diagrams of bicycle crash clusters. The crash contributing factors and relevant potential countermeasures are discussed in the fourth section. Finally, the chapter concludes with a summary of the analysis results.

4.1 Identification of Bicycle Hot Spots

4.1.1 Data

The following shapefiles were used to identify bicycle hot spots in each of the seven FDOT districts:

- 2011-2014 crash data for both on-system and off-system roads
- 2014 NavStreets map
- On-system road network
- Off-system road network

The crash data shapefiles for the years 2011-2014 were downloaded from the FDOT Unified Basemap Repository (UBR) for both on-system and off-system roads. The variable CNTOFCYCLS that provides information on the number of bicyclists involved in a crash was used to identify bicycle crashes.

The 2014 NavStreets Map, also downloaded from the FDOT UBR, is a basemap with linear referencing system (LRS) for all public roadways in Florida. The on-system road network shapefile, maintained by the FDOT Transportation Statistics Office, provides spatial information on active main-line roads maintained by FDOT. Similarly, the off-system road network shapefile, also maintained by the FDOT Transportation Statistics Office, provides spatial information on city or county owned roads that are not maintained by FDOT.

4.1.2 Methodology

GIS techniques were used to identify the top five bicycle crash hot spots in each district. The process involved the following steps:

Step 1: Create a network dataset from the NavStreets streets feature class using NavStreets Processing Tool (ArcGIS Team Network Analyst, 2015).

A network dataset incorporates an advanced connectivity model that can represent complex scenarios such as multimodal transportation networks. The 2014 NavStreets shapefile did not include a network dataset, and therefore, a network dataset was first created.

The ArcGIS has a set of tools to automatically create a network dataset from the NavStreets shapefile. These tools are available in the Geoprocessing Model and Script Tool Gallery under Vendor Street Data Processing Tools for ArcGIS 10. Specifically, these tools process shapefile data from NavStreets into a file geodatabase network dataset. They import the street feature classes into the file geodatabase and add the appropriate fields to these feature classes for modeling overpasses/underpasses, one-way streets, travel times, hierarchy, and driving directions. They also create feature classes and tables for modeling turn restrictions and signpost guidance. Figure 4-1 provides the screenshot of the function to create network dataset.

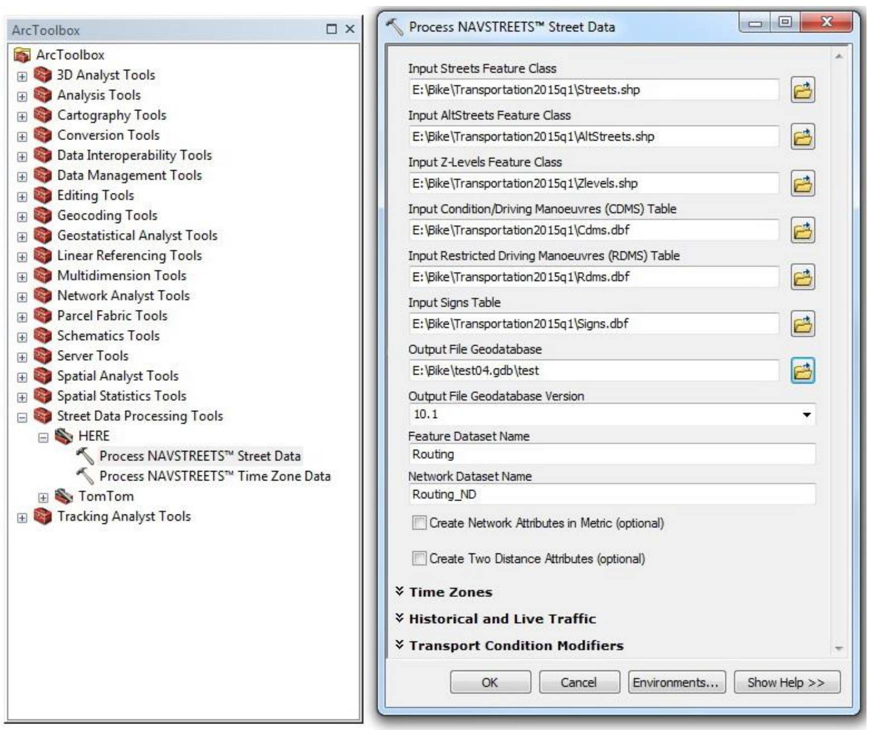


Figure 4-1: Create Network Dataset

Step 2: Make a service area network analysis layer and choose the following settings:

- Use NavStreets network dataset
- Impedance attribute: miles
- Travel to and from
- Default break value: 0.1 (miles)
- Accumulators: miles
- Hierarchy: uncheck (checking assumes higher capacity road is chosen)
- Line generator: True Lines, Overlap Lines
- Polygon generator: No polygons
- Restrictions:

- Allow U-turns
- Avoid carpool roads, express lanes, ferries, gates, limited access roads, private roads, toll roads, and walking

Figure 4-2 shows the screenshot of the service area network analysis layer properties.

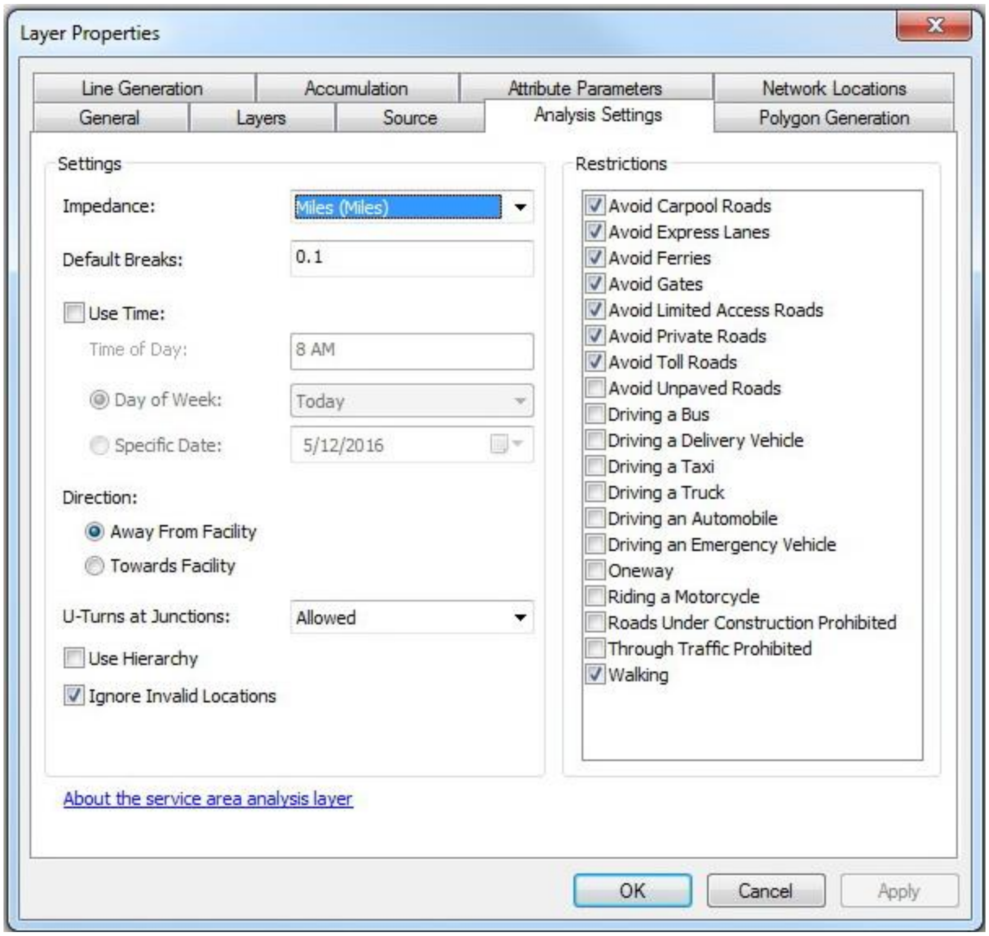


Figure 4-2: Service Area Network Analysis Layer Properties: Analysis Settings

Step 3: Add the 2011-2014 on-system and off-system crash shapefiles. Identify bicycle crashes by selecting crashes with CNTOFCYCLS > 0. From 2011-2014, there are a total of 24,765 bicycle crashes, as summarized in Table 4-1. Next, add the crash locations from the 2011-2014 crash data shapefiles and choose the following settings (see Figure 4-3):

- Unit: Miles
- Tolerance: 0.1
- Find closest among all classes – checked
- Append to existing locations
- Exclude restricted portions of the network

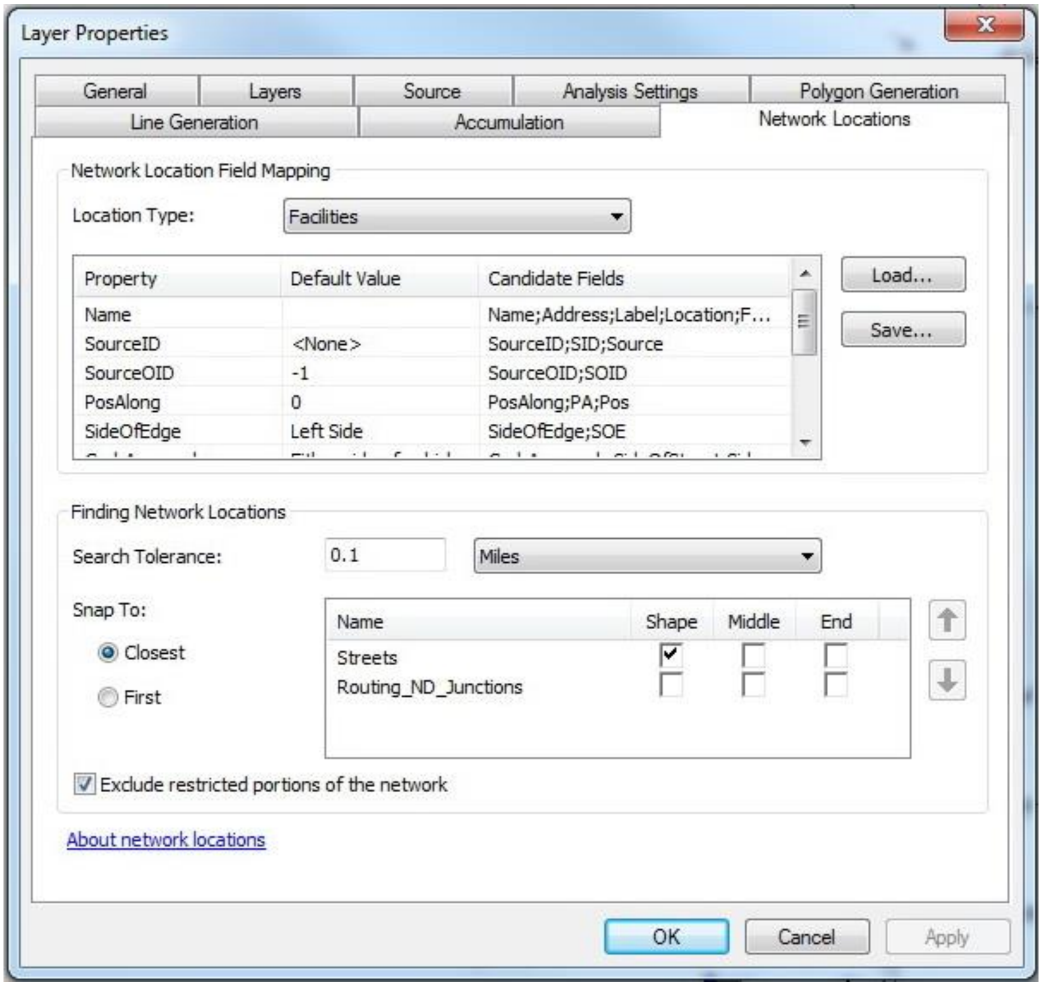


Figure 4-3: Service Area Network Analysis Layer Properties: Network Locations

Step 4: Add the crash locations as facilities. Figure 4-4 gives the spatial distribution of bicycle crashes in Florida. From Figure 4-4, it can be inferred that a majority of bicycle crashes occurred along the coastline, and in major urban areas including Jacksonville, Miami, Orlando, Tallahassee, and Tampa.

Table 4-1: 2011-2014 Bicycle Crash Statistics

Year	Bicycle Crashes on On-System Roads	Bicycle Crashes on Off-System Roads	Total Bicycle Crashes
2011	2,523	2,706	5,229
2012	3,090	3,051	6,141
2013	3,241	3,382	6,623
2014	3,181	3,591	6,772
Total (2011-2014)	12,035	12,730	24,765

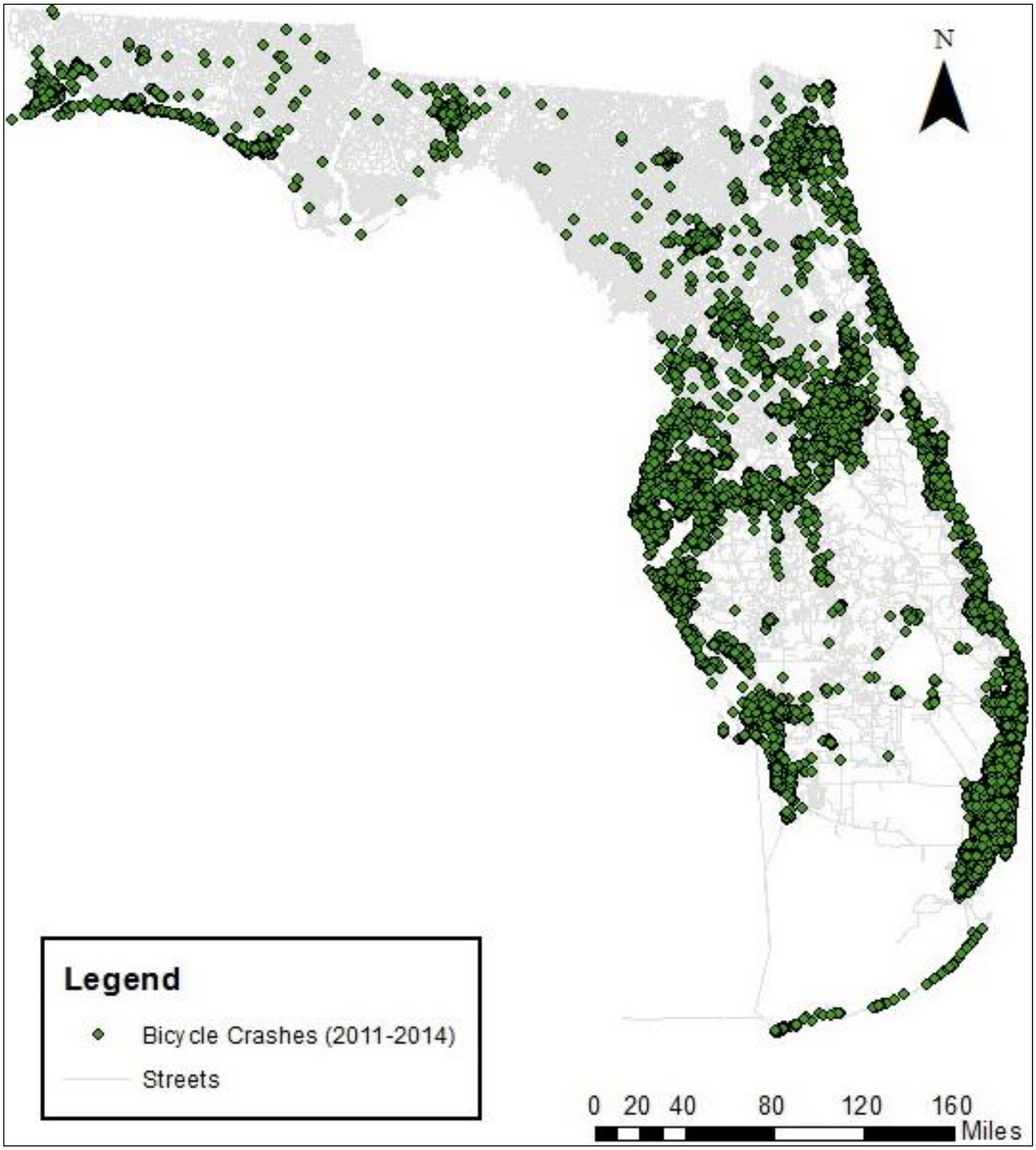


Figure 4-4: Spatial Distribution of Bicycle Crashes in Florida

Step 5: Run Solve tool to generate service areas. A total of 424,676 lines are generated. Figure 4-5 gives the screenshot of the result after running Solve tool in ArcGIS.

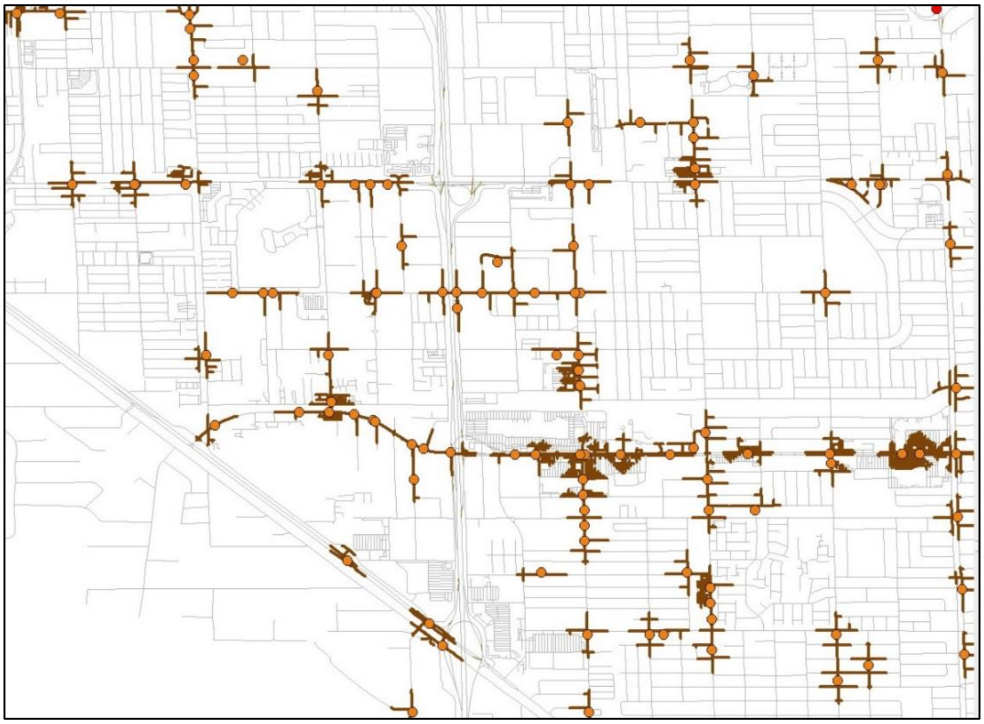


Figure 4-5: Result after Running Solve Tool in ArcGIS

Step 6: Export lines generated by Solve tool to a shapefile. Figure 4-6 shows the screenshot of the line-based service area shapefile (known as Crash Lines shapefile) generated in this step.

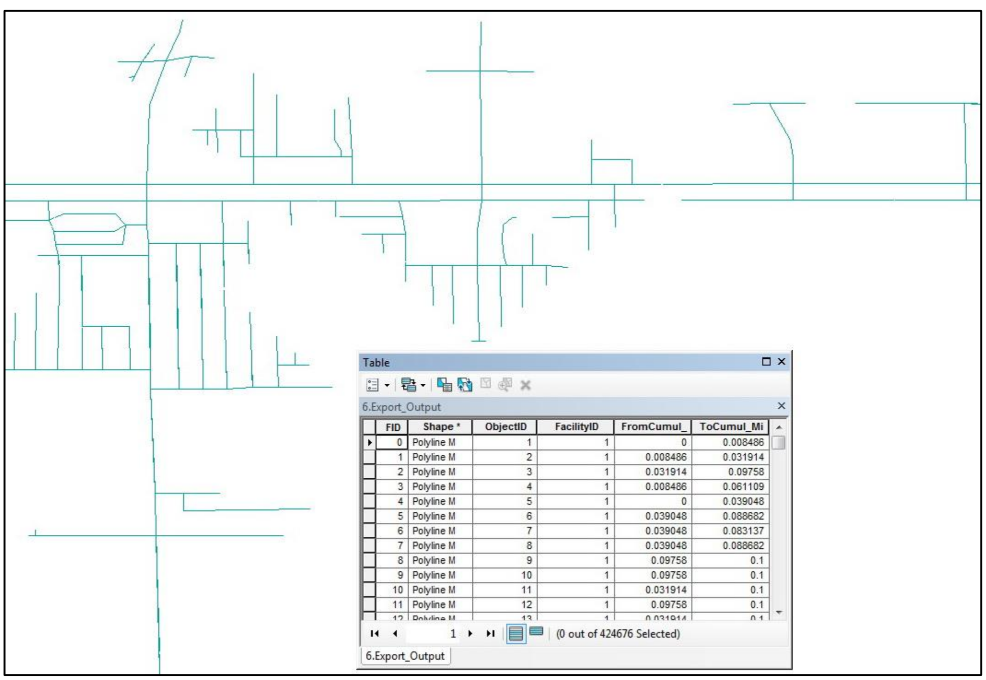


Figure 4-6: Result after Exporting Lines Generated by Solve Tool to a Shapefile

Step 7: Project the Crash Lines shapefile onto the projected coordinate system: UTM – NAD 83, as shown in Figure 4-7.

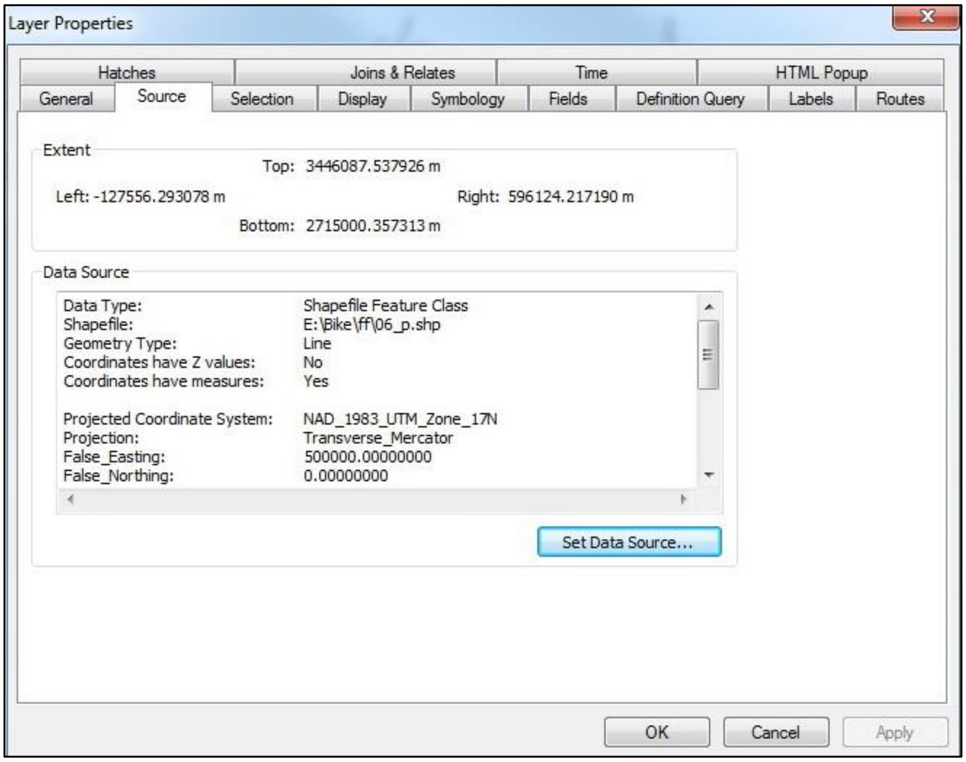
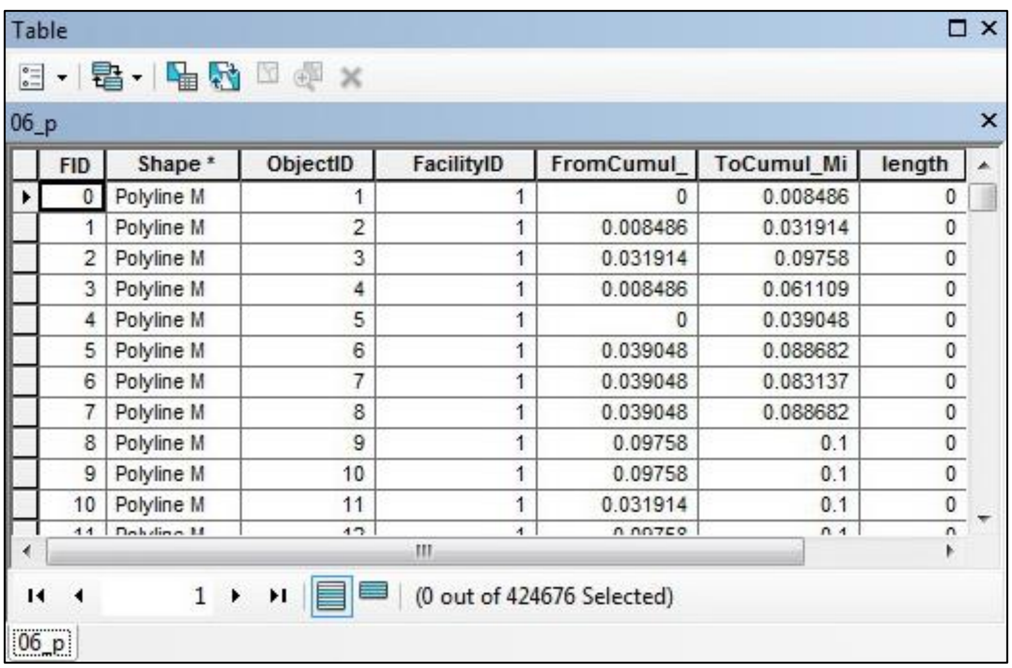


Figure 4-7: Change the Projected Coordinate System of the Crash Lines Shapefile to UTM-NAD 83

Step 8: Add field "Length", as shown in Figure 4-8.



Table

06_p

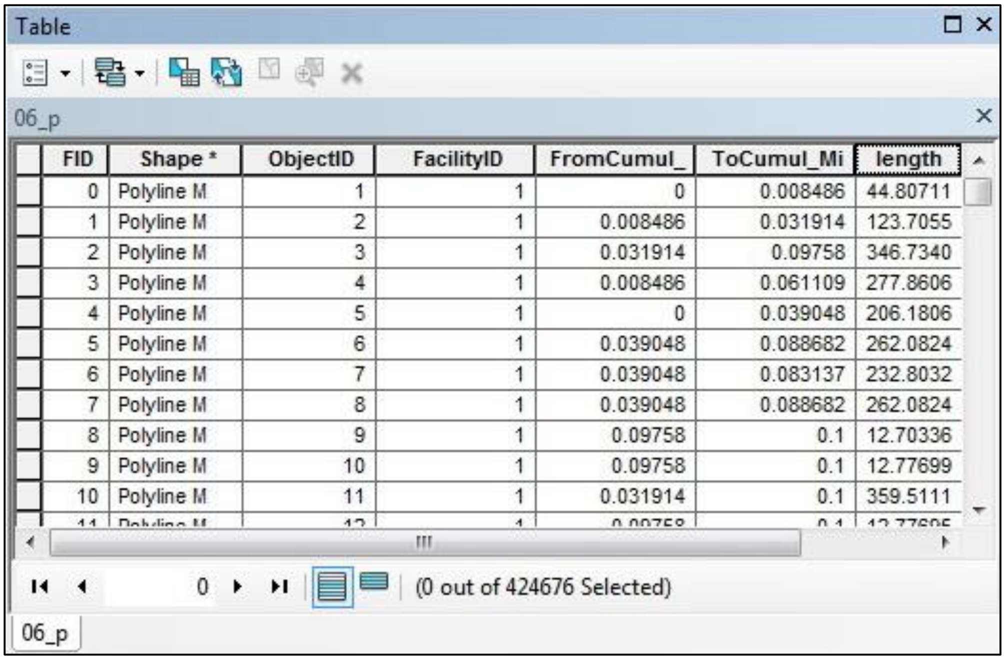
FID	Shape *	ObjectID	FacilityID	FromCumul_	ToCumul_Mi	length
0	Polyline M	1	1	0	0.008486	0
1	Polyline M	2	1	0.008486	0.031914	0
2	Polyline M	3	1	0.031914	0.09758	0
3	Polyline M	4	1	0.008486	0.061109	0
4	Polyline M	5	1	0	0.039048	0
5	Polyline M	6	1	0.039048	0.088682	0
6	Polyline M	7	1	0.039048	0.083137	0
7	Polyline M	8	1	0.039048	0.088682	0
8	Polyline M	9	1	0.09758	0.1	0
9	Polyline M	10	1	0.09758	0.1	0
10	Polyline M	11	1	0.031914	0.1	0

1 (0 out of 424676 Selected)

06_p

Figure 4-8: Add Length Field to the Crash Lines Attribute Table

Step 9: Calculate the geometry in the length field, as shown in Figure 4-9.



Table

06_p

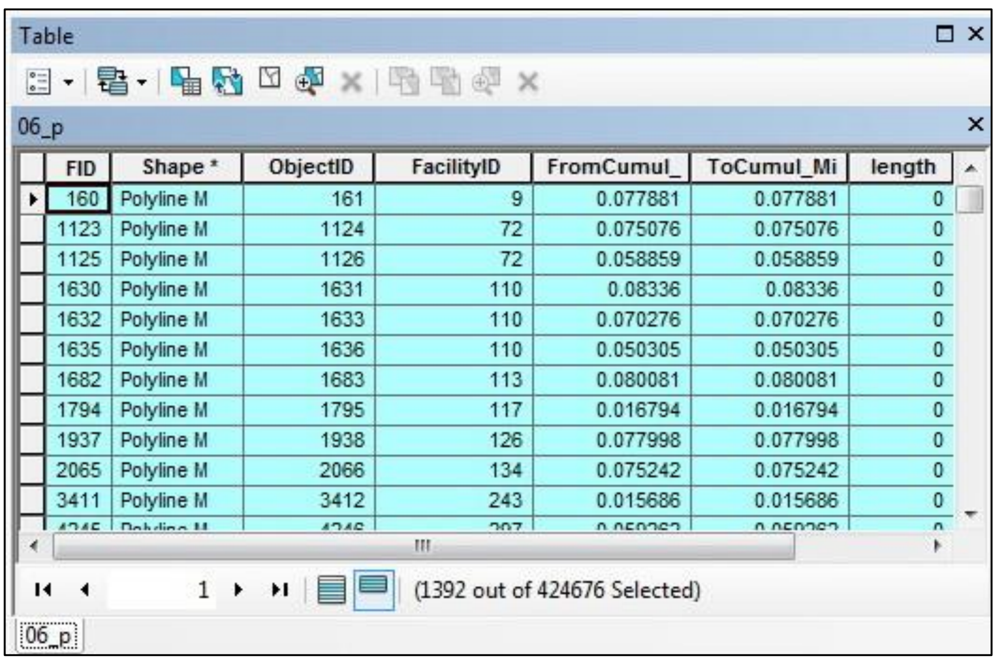
FID	Shape *	ObjectID	FacilityID	FromCumul_	ToCumul_Mi	length
0	Polyline M	1	1	0	0.008486	44.80711
1	Polyline M	2	1	0.008486	0.031914	123.7055
2	Polyline M	3	1	0.031914	0.09758	346.7340
3	Polyline M	4	1	0.008486	0.061109	277.8606
4	Polyline M	5	1	0	0.039048	206.1806
5	Polyline M	6	1	0.039048	0.088682	262.0824
6	Polyline M	7	1	0.039048	0.083137	232.8032
7	Polyline M	8	1	0.039048	0.088682	262.0824
8	Polyline M	9	1	0.09758	0.1	12.70336
9	Polyline M	10	1	0.09758	0.1	12.77699
10	Polyline M	11	1	0.031914	0.1	359.5111

0 (0 out of 424676 Selected)

06_p

Figure 4-9: Calculate the Length of Each Feature in the Crash Lines Shapefile

Step 10: Use “Select By Attributes” function to select all records where ‘length’ = 0, as shown in Figure 4-10. A total of 1,392 lines are selected.



Table

06_p

FID	Shape *	ObjectID	FacilityID	FromCumul_	ToCumul_Mi	length
160	Polyline M	161	9	0.077881	0.077881	0
1123	Polyline M	1124	72	0.075076	0.075076	0
1125	Polyline M	1126	72	0.058859	0.058859	0
1630	Polyline M	1631	110	0.08336	0.08336	0
1632	Polyline M	1633	110	0.070276	0.070276	0
1635	Polyline M	1636	110	0.050305	0.050305	0
1682	Polyline M	1683	113	0.080081	0.080081	0
1794	Polyline M	1795	117	0.016794	0.016794	0
1937	Polyline M	1938	126	0.077998	0.077998	0
2065	Polyline M	2066	134	0.075242	0.075242	0
3411	Polyline M	3412	243	0.015686	0.015686	0

1 (1392 out of 424676 Selected)

06_p

Figure 4-10: Records with Zero Length in the Crash Lines Attribute Table

Step 11: Delete all selected rows, as shown in Figure 4-11. The final table includes a total of 423,284 records.

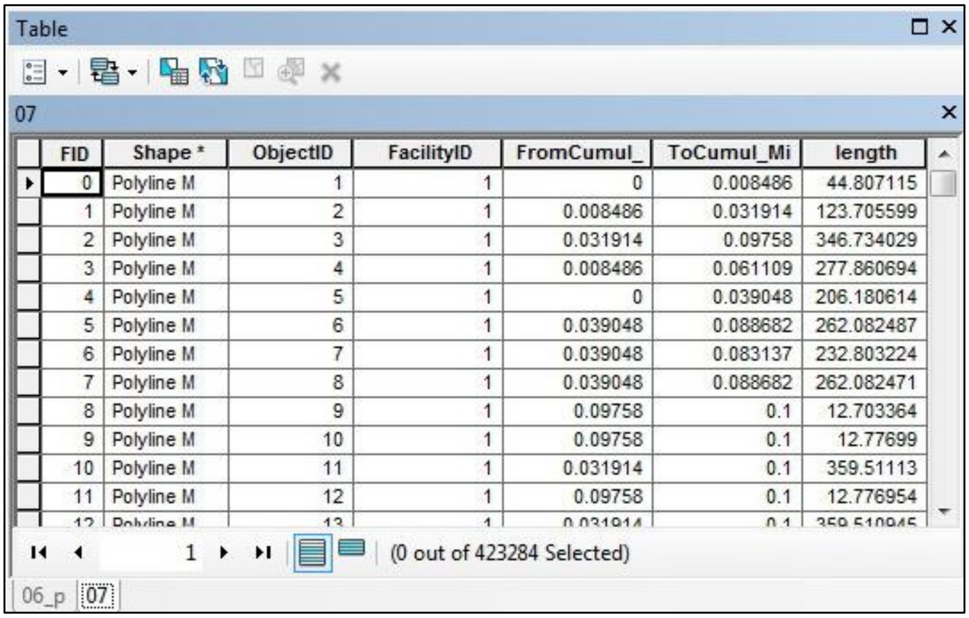


Figure 4-11: Final Crash Lines Attribute Table

Step 12: Delete the "Length" field.

Step 13: Use the "Select By Location" function to select all the features from the NavStreets shapefile which touch the boundary of the Crash Lines shapefile. A total of 554 records are selected. Figure 4-12 shows the "Select By Location" window and the NavStreets attribute table with the selected records.

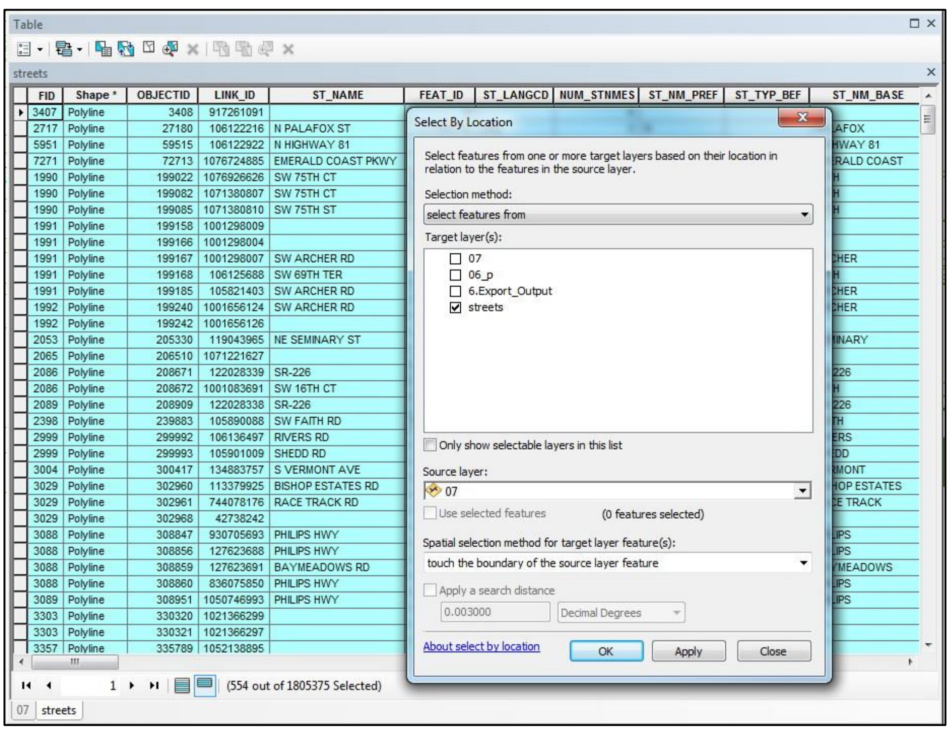


Figure 4-12: Features in the NavStreets Shapefile That Touch the Boundary of the Crash Lines Shapefile

Step 14: From the features selected in Step 13, remove those that have their centroid in the Crash Lines shapefile. A total of 480 features are selected, as shown in Figure 4-13.

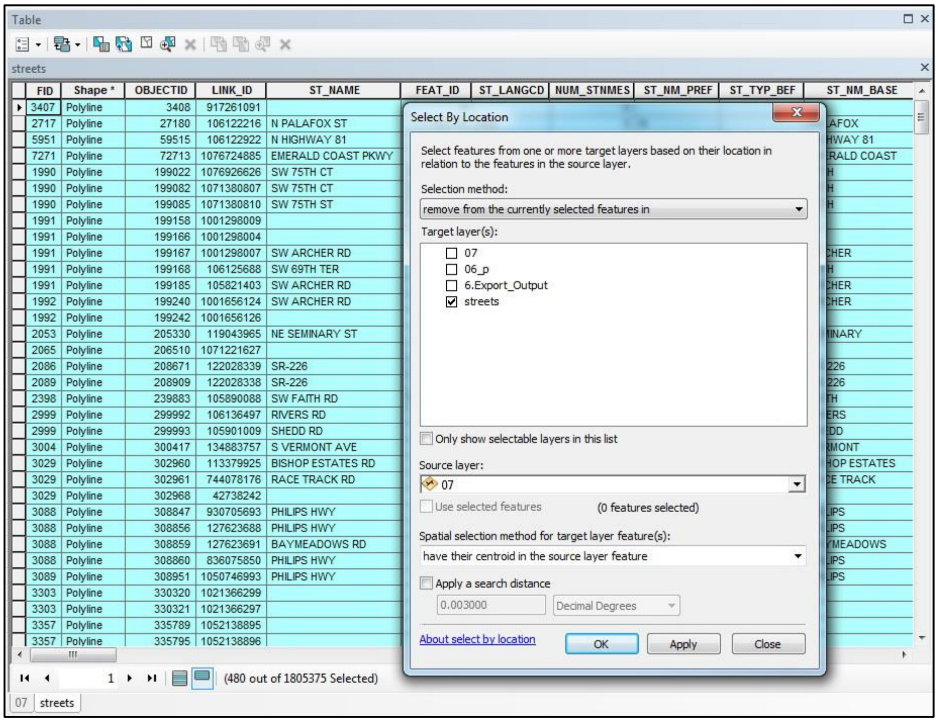
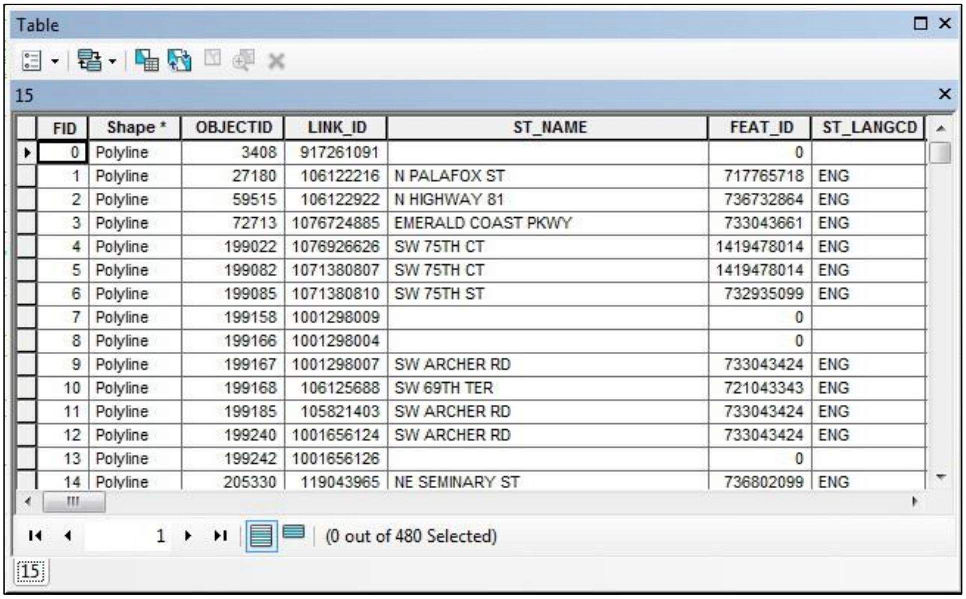


Figure 4-13: Features in the NavStreets Shapefile That Have Their Centroid in the Crash Lines Shapefile

Step 15: Export the selected features to a new shapefile. As shown in Figure 4-14, a total of 480 features are exported.



FID	Shape *	OBJECTID	LINK_ID	ST_NAME	FEAT_ID	ST_LANGCD
0	Polyline	3408	917261091		0	
1	Polyline	27180	106122216	N PALAFOX ST	717765718	ENG
2	Polyline	59515	106122922	N HIGHWAY 81	736732864	ENG
3	Polyline	72713	1076724885	EMERALD COAST PKWY	733043661	ENG
4	Polyline	199022	1076926626	SW 75TH CT	1419478014	ENG
5	Polyline	199082	1071380807	SW 75TH CT	1419478014	ENG
6	Polyline	199085	1071380810	SW 75TH ST	732935099	ENG
7	Polyline	199158	1001298009		0	
8	Polyline	199166	1001298004		0	
9	Polyline	199167	1001298007	SW ARCHER RD	733043424	ENG
10	Polyline	199168	106125688	SW 69TH TER	721043343	ENG
11	Polyline	199185	105821403	SW ARCHER RD	733043424	ENG
12	Polyline	199240	1001656124	SW ARCHER RD	733043424	ENG
13	Polyline	199242	1001656126		0	
14	Polyline	205330	119043965	NE SEMINARY ST	736802099	ENG

Figure 4-14: New Shapefile with Features in the NavStreets Shapefile That Have Their Centroid in the Crash Lines Shapefile

Step 16: Use "Select by Attributes" function to select and delete records from the new shapefile created in Step 15 which match the following criteria:

- CONTRACC = Y (controlled access) ***OR***
- RAMP = Y ***OR***
- AR_PEDEST = N (Access Restriction Pedestrian)

This step removes records such as freeways and ramps that are access restricted. As shown in Figure 4-15, a total of 8 records are selected and removed.

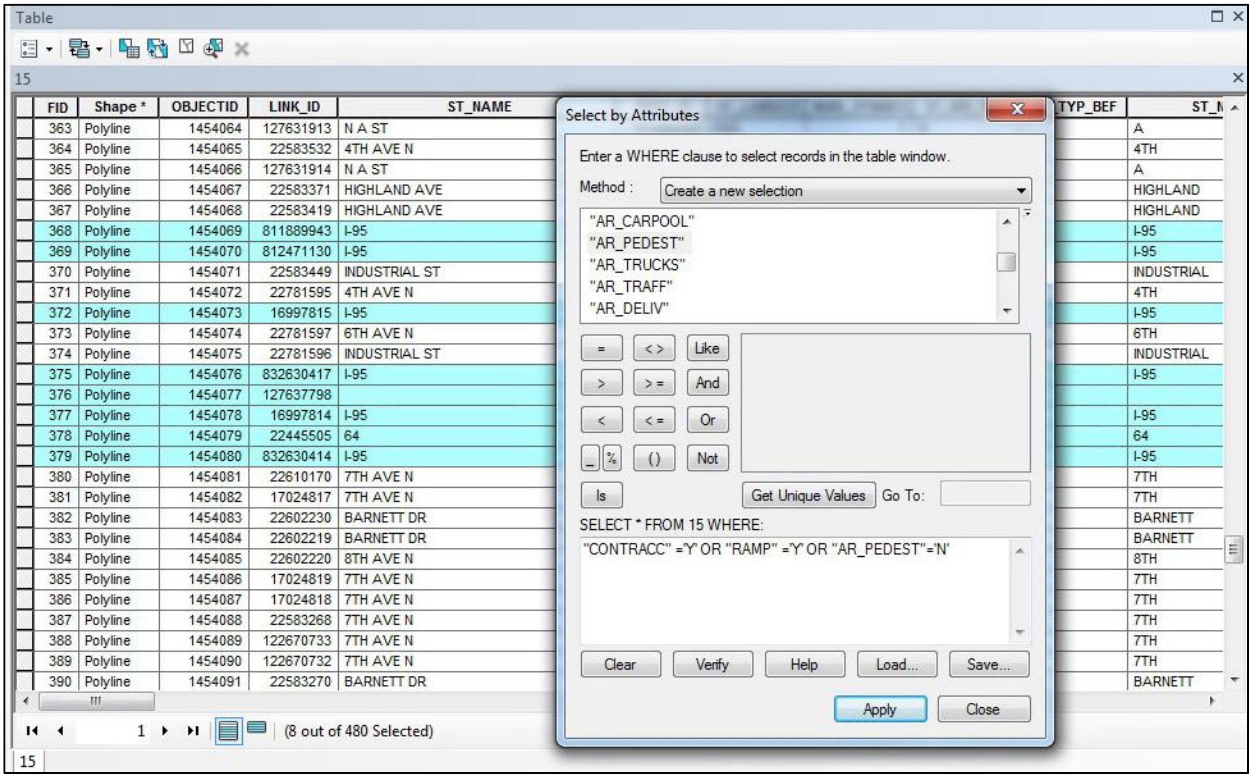
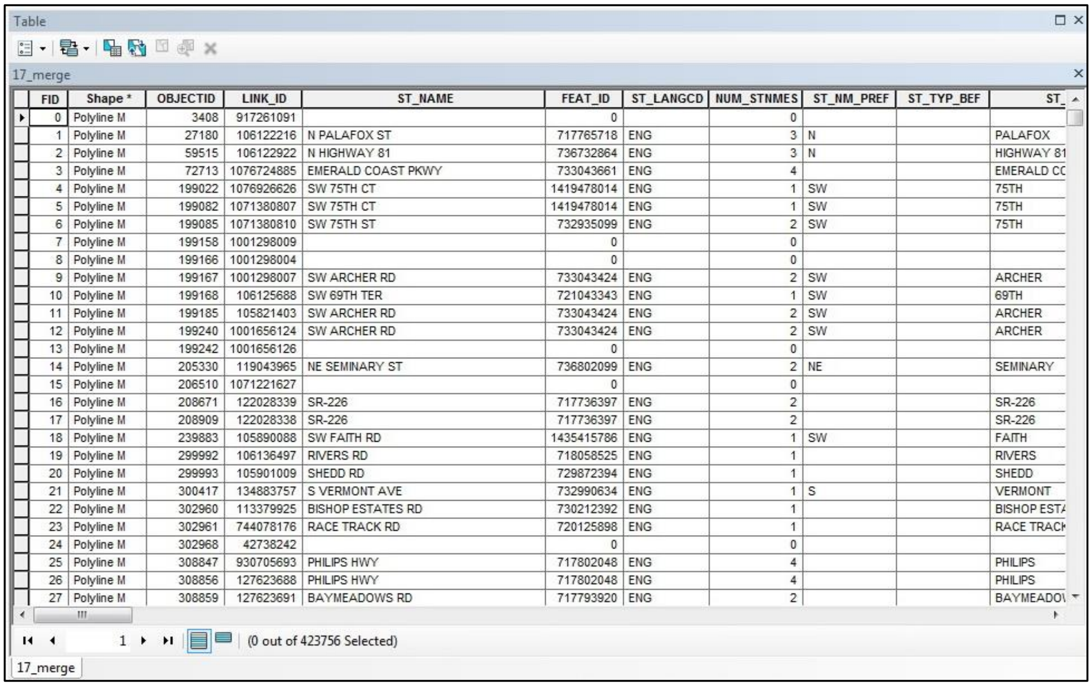


Figure 4-15: Select and Remove Segments with Restricted Access

Step 17: Merge the shapefile exported from NavStreets with the Crash Lines shapefile exported from the Service Area layer. A total of 423,756 records are merged. Figure 4-16 shows the screenshot of the attribute table of the updated NavStreets shapefile.



FID	Shape *	OBJECTID	LINK_ID	ST_NAME	FEAT_ID	ST_LANGCD	NUM_STNMES	ST_NM_PREF	ST_TYP_BEF	ST_
0	Polyline M	3408	917261091		0		0			
1	Polyline M	27180	106122216	N PALAFOX ST	717765718	ENG	3	N		PALAFOX
2	Polyline M	59515	106122922	N HIGHWAY 81	736732864	ENG	3	N		HIGHWAY 81
3	Polyline M	72713	1076724885	EMERALD COAST PKWY	733043661	ENG	4			EMERALD CC
4	Polyline M	199022	1076926626	SW 75TH CT	1419478014	ENG	1	SW		75TH
5	Polyline M	199082	1071380807	SW 75TH CT	1419478014	ENG	1	SW		75TH
6	Polyline M	199085	1071380810	SW 75TH ST	732935099	ENG	2	SW		75TH
7	Polyline M	199158	1001298009		0		0			
8	Polyline M	199166	1001298004		0		0			
9	Polyline M	199167	1001298007	SW ARCHER RD	733043424	ENG	2	SW		ARCHER
10	Polyline M	199168	106125688	SW 69TH TER	721043343	ENG	1	SW		69TH
11	Polyline M	199185	105821403	SW ARCHER RD	733043424	ENG	2	SW		ARCHER
12	Polyline M	199240	1001656124	SW ARCHER RD	733043424	ENG	2	SW		ARCHER
13	Polyline M	199242	1001656126		0		0			
14	Polyline M	205330	119043965	NE SEMINARY ST	736802099	ENG	2	NE		SEMINARY
15	Polyline M	206510	1071221627		0		0			
16	Polyline M	208671	122028339	SR-226	717736397	ENG	2			SR-226
17	Polyline M	208909	122028338	SR-226	717736397	ENG	2			SR-226
18	Polyline M	239883	105890088	SW FAITH RD	1435415786	ENG	1	SW		FAITH
19	Polyline M	299992	106136497	RIVERS RD	718058525	ENG	1			RIVERS
20	Polyline M	299993	105901009	SHEDD RD	729872394	ENG	1			SHEDD
21	Polyline M	300417	134883757	S VERMONT AVE	732990634	ENG	1	S		VERMONT
22	Polyline M	302960	113379925	BISHOP ESTATES RD	730212392	ENG	1			BISHOP ESTA
23	Polyline M	302961	744078176	RACE TRACK RD	720125898	ENG	1			RACE TRACK
24	Polyline M	302968	42738242		0		0			
25	Polyline M	308847	930705693	PHILIPS HWY	717802048	ENG	4			PHILIPS
26	Polyline M	308856	127623688	PHILIPS HWY	717802048	ENG	4			PHILIPS
27	Polyline M	308859	127623691	BAYMEADOWS RD	717793920	ENG	2			BAYMEADO\

(0 out of 423756 Selected)

17_merge

Figure 4-16: Updated NavStreets Shapefile

Step 18: Project the updated NavStreets shapefile onto the GCS_WGS_1984 geographic coordinate system, as shown in Figure 4-17. This step helps with running the buffer function.

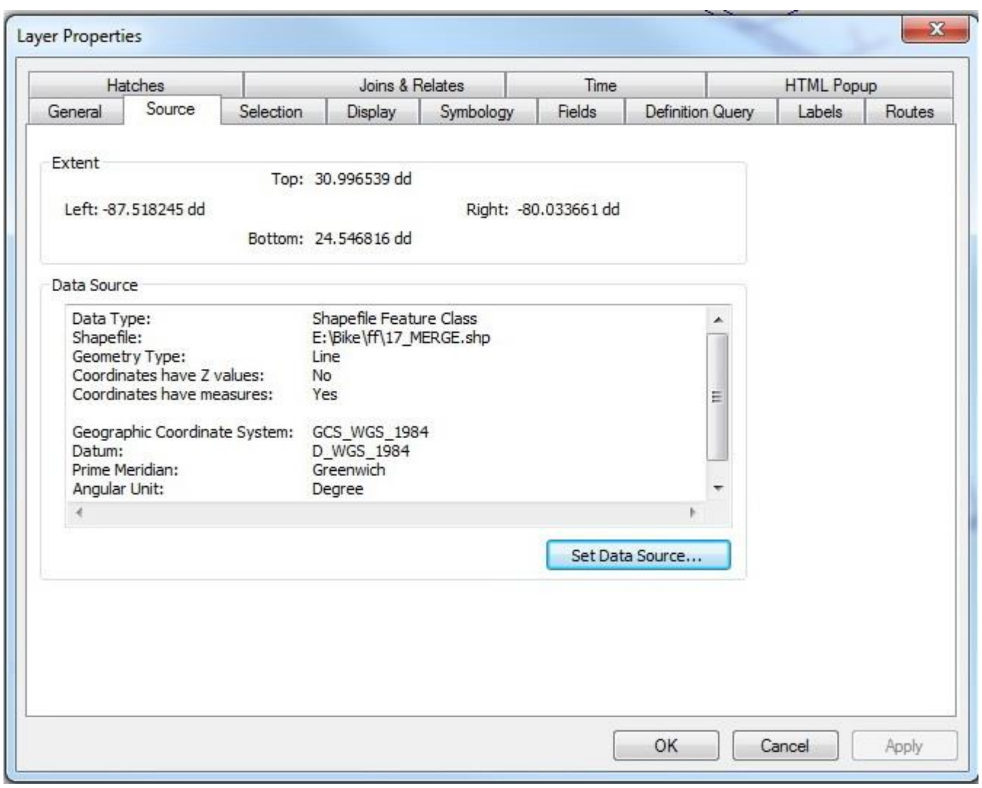


Figure 4-17: Change the Geographic Coordinate System of the Updated NavStreets Shapefile to GCS_WGS_1984

Step 19: Create a 10-ft buffer around the features in the Crash Lines shapefile. Select the Dissolve "ALL" buffers option (see Figure 4-18).

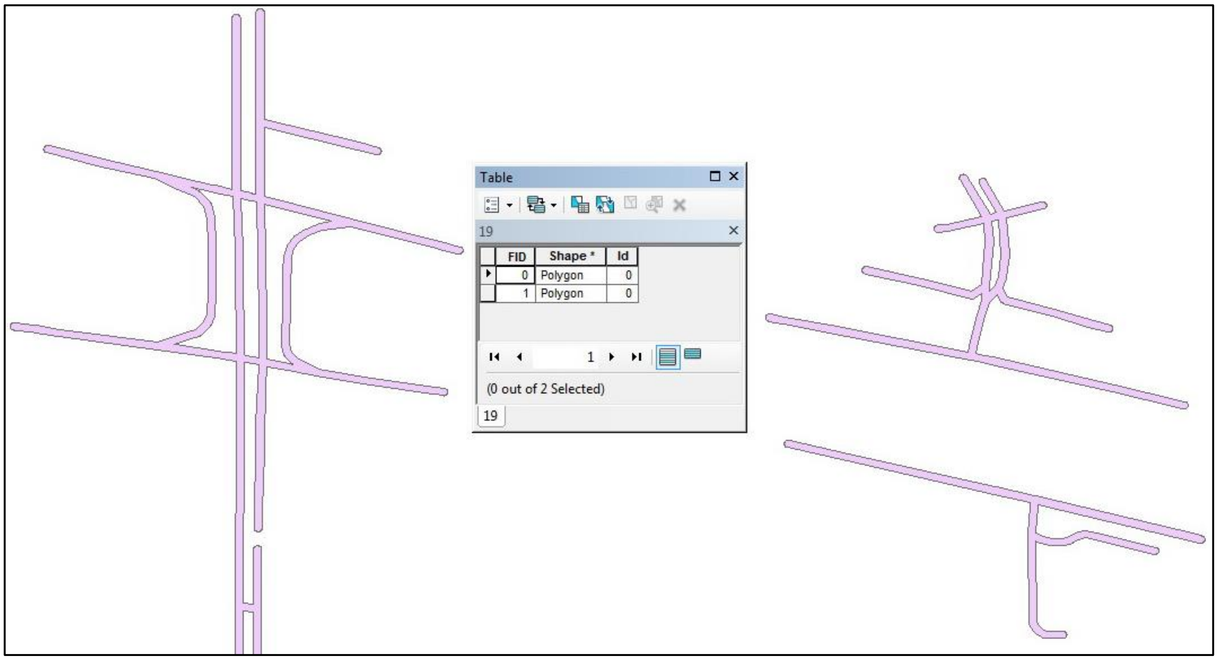


Figure 4-18: 10-ft Buffers Created Around the Features in the Crash Lines Shapefile

Step 20: Run Multi-part to Single-part tool on the buffer file to create a Single-part Crash Lines Buffer shapefile. A total of 10,831 buffer are generated (see Figure 4-19).

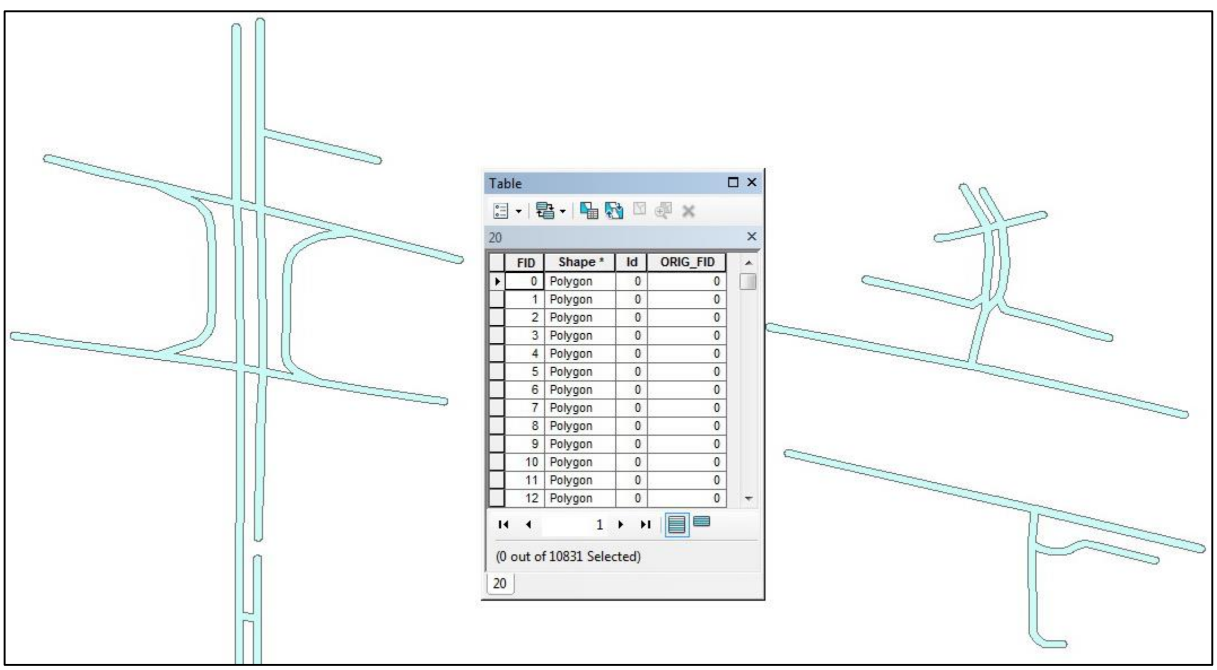


Figure 4-19: Single-part Crash Lines Buffer Shapefile

Step 21: Add a field named "AREA_ID" in the Single-part Crash Lines Buffer shapefile. Calculate this field as FID field+1, as shown in Figure 4-20. This step updates the records such that the AREA_ID is a non-zero integer.

Table

20

FID	Shape *	Id	ORIG_FID	AREA_ID
0	Polygon	0	0	1
1	Polygon	0	0	2
2	Polygon	0	0	3
3	Polygon	0	0	4
4	Polygon	0	0	5
5	Polygon	0	0	6
6	Polygon	0	0	7
7	Polygon	0	0	8
8	Polygon	0	0	9
9	Polygon	0	0	10
10	Polygon	0	0	11
11	Polygon	0	0	12
12	Polygon	0	0	13

0 (0 out of 10831 Selected)

20

Figure 4-20: Single-part Crash Lines Buffer Shapefile Attribute Table with New Area ID

Step 22: Use the 'Spatial Join' function to spatially join the Single-part Crash Lines Buffer shapefile to the Crash Lines shapefile to select features in the Crash Lines shapefile which intersect the Single-part Crash Lines Buffer shapefile. Keep only the AREA_ID field. Run as a 'one to many' spatial join. As can be seen in Figure 4-21, a total of 423,284 lines are generated.

Table

22

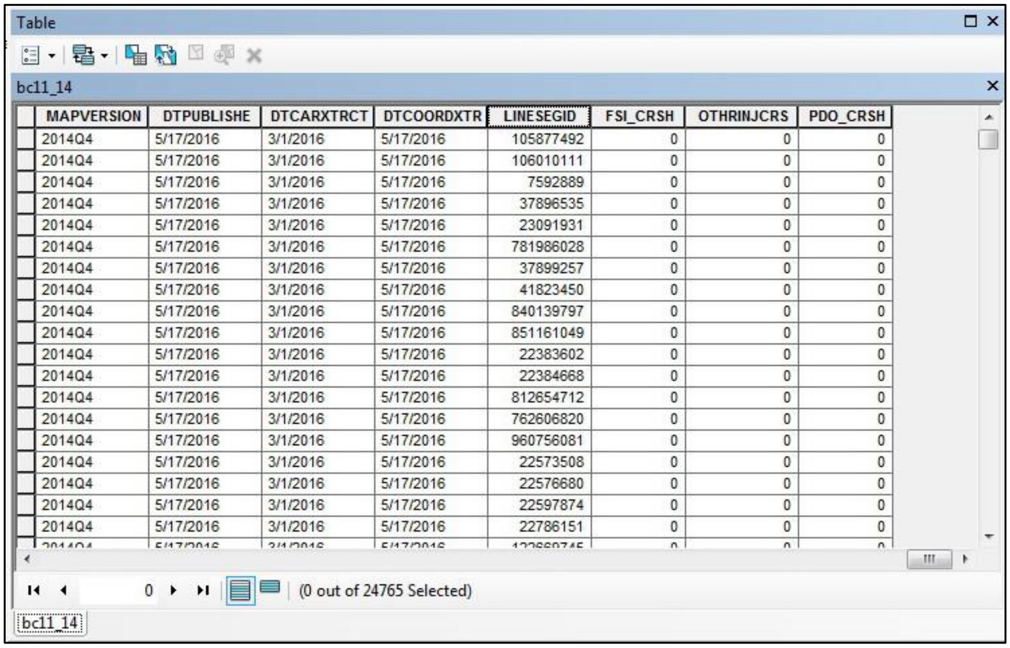
FID	Shape *	Join_Count	TARGET_FID	JOIN_FID	AREA_ID
0	Polyline M	1	0	9857	9858
1	Polyline M	1	1	9857	9858
2	Polyline M	1	2	9857	9858
3	Polyline M	1	3	9857	9858
4	Polyline M	1	4	9857	9858
5	Polyline M	1	5	9857	9858
6	Polyline M	1	6	9857	9858
7	Polyline M	1	7	9857	9858
8	Polyline M	1	8	9857	9858
9	Polyline M	1	9	9857	9858
10	Polyline M	1	10	9857	9858
11	Polyline M	1	11	9857	9858
12	Polyline M	1	12	9857	9858

1 (0 out of 423284 Selected)

22

Figure 4-21: Single-part Crash Lines Buffer Shapefile Attribute Table after Being Spatially Joined to the Crash Lines Shapefile

Step 23: Add the following fields to the Crash Location shapefile: “FSI_CRSH”, “OTHRINJCRSH”, and “PDO_CRSH”. These three fields represent fatal and serious injury (FSI) crashes, other injury crashes, and property damage only (PDO) crashes, respectively. Figure 4-22 shows the screenshot of the crash location shapefile attribute table with the three new fields.



MAPVERSION	DTPUBLISHE	DTCARXTRCT	DTCOORDXTR	LINESEGID	FSI_CRSH	OTHRINJCRS	PDO_CRSH
2014Q4	5/17/2016	3/1/2016	5/17/2016	105877492	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	106010111	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	7592889	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	37896535	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	23091931	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	781986028	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	37899257	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	41823450	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	840139797	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	851161049	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	22383602	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	22384668	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	812654712	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	762606820	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	960756081	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	22573508	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	22576680	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	22597874	0	0	0
2014Q4	5/17/2016	3/1/2016	5/17/2016	22786151	0	0	0

Figure 4-22: Crash Location Shapefile Attribute Table with New Fields: FSI_CRSH, OTHRINJCRSH, and PDO_CRSH

Step 24: Use the following queries within the “Select By Attributes” function in the Crash Location shapefile to populate FSI_CRSH, OTHRINJCRSH, and PDO_CRSH fields:

- FSI_CRSH = “CNTOFFATL” >0 or “CNTOFSVINJ” >0
- OTHRINJCRSH = “CNTOFINJ” >0 and !(“CNTOFFATL” >0 or “CNTOFSVINJ” >0)
- PDO_CRSH = “CNTOFINJ” = 0 and “CNTOFFATL” = 0

Figure 4-23 shows a sample query in the field calculator to populate FSI_CRSH field.

Step 25: Use the “Spatial Join” function to spatially join the Crash Location shapefile to the Single-part Crash Lines Buffer shapefile to identify crashes which are within 40 ft of the buffer. Run the join as a ‘one to many’ spatial join. Add the FSI_CRSH, OTHRINJCRSH, and PDO_CRSH fields; keep the AREA_ID, DISTRICT and DOTCOUNTY fields (see Figure 4-24). This step generated a total of 24,450 records.

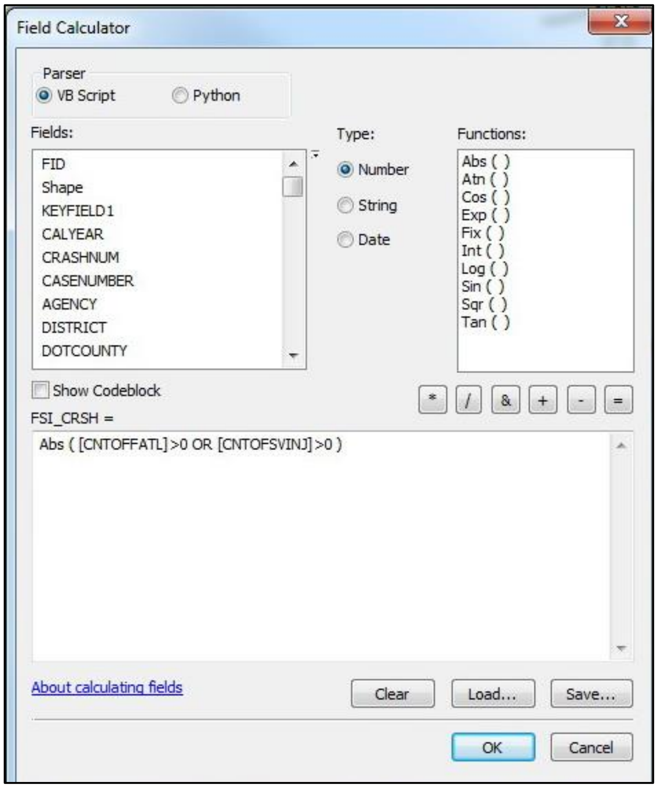


Figure 4-23: Field Calculator to Populate FSI_CRSH Field

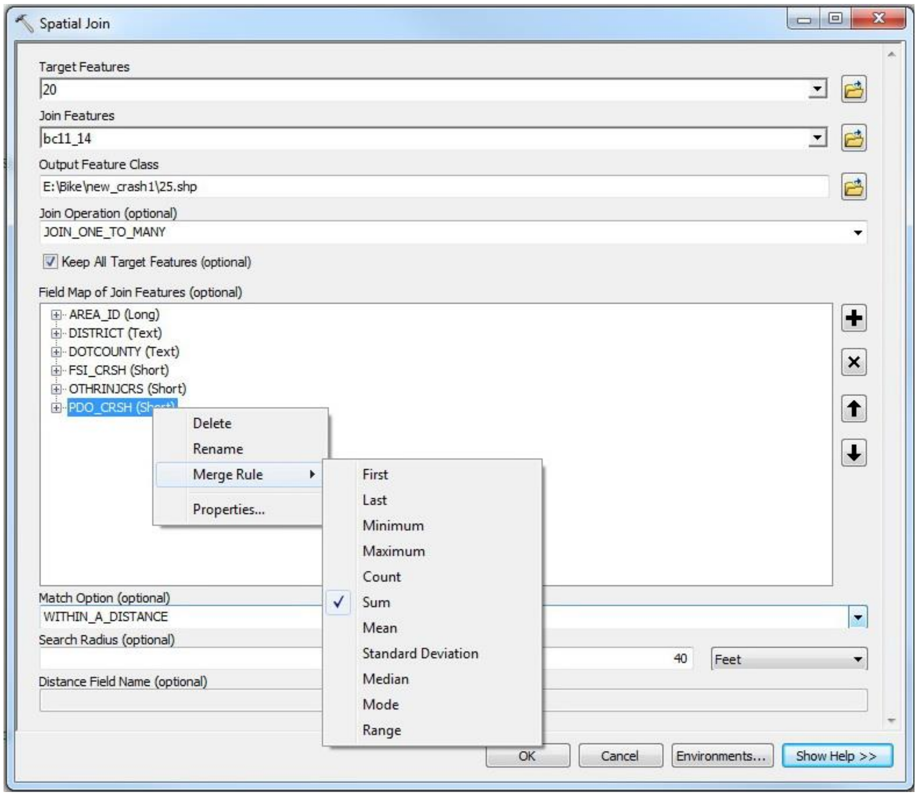
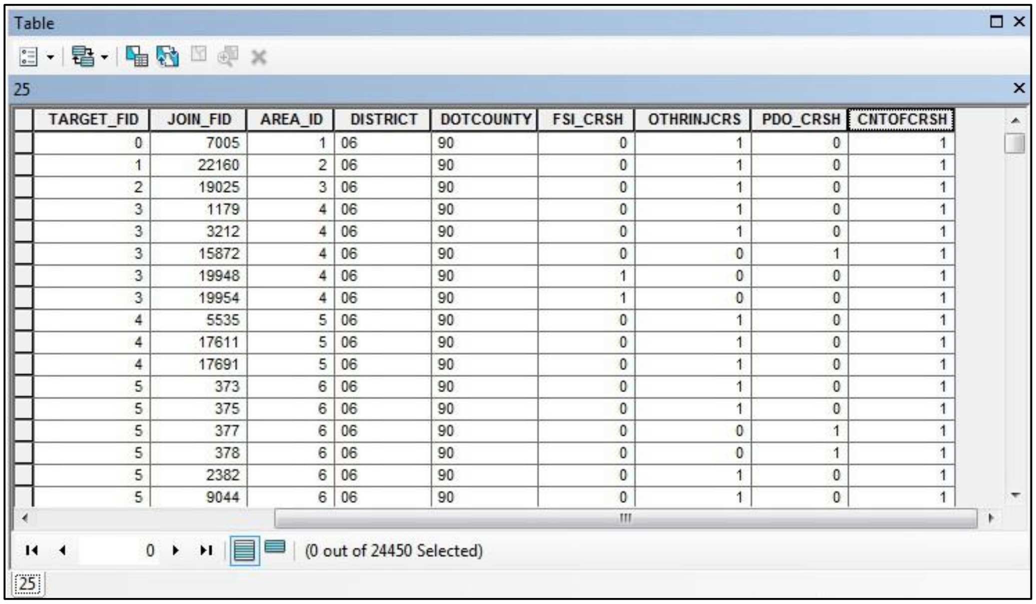


Figure 4-24: Use "Spatial Join" to Join the Crash Location Shapefile to the Single-part Crash Lines Buffer Shapefile

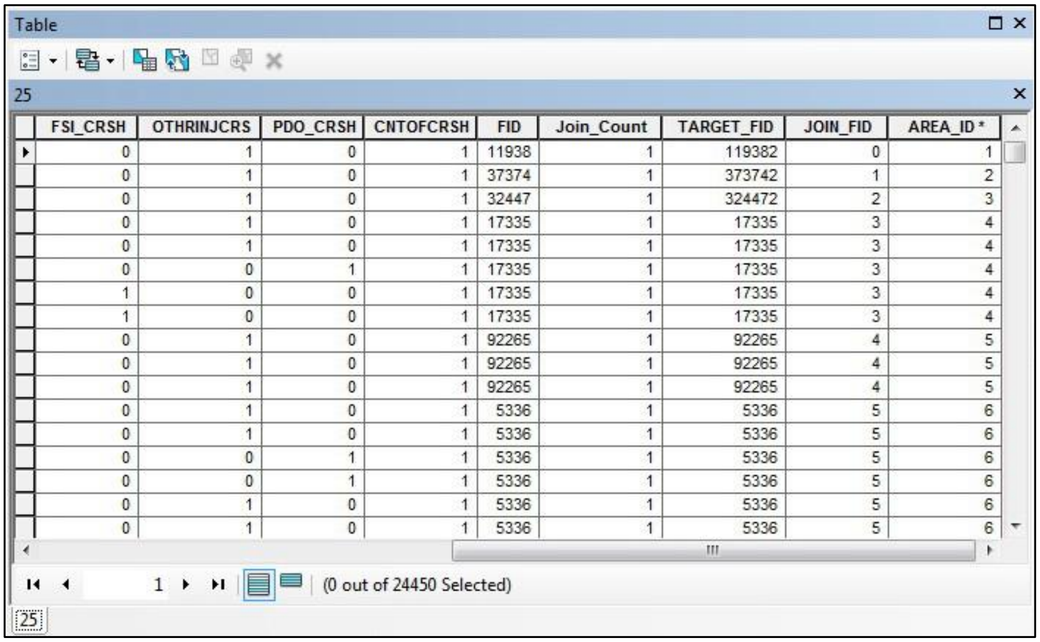
Step 26: Add the "CNTOFCRSH" field to the Single-part Crash Lines Buffer shapefile. Calculate the CNTOFCRSH field using the following query: CNTOFCRSH = Join_Count. Delete the Join_Count field after using the field calculator. Figure 4-25 shows the attribute table of the Single-part Crash Lines Buffer shapefile with the CNTOFCRSH field.



TARGET_FID	JOIN_FID	AREA_ID	DISTRICT	DOTCOUNTY	FSI_CRSH	OTHRINJCRS	PDO_CRSH	CNTOFCRSH
0	7005	1	06	90	0	1	0	1
1	22160	2	06	90	0	1	0	1
2	19025	3	06	90	0	1	0	1
3	1179	4	06	90	0	1	0	1
3	3212	4	06	90	0	1	0	1
3	15872	4	06	90	0	0	1	1
3	19948	4	06	90	1	0	0	1
3	19954	4	06	90	1	0	0	1
4	5535	5	06	90	0	1	0	1
4	17611	5	06	90	0	1	0	1
4	17691	5	06	90	0	1	0	1
5	373	6	06	90	0	1	0	1
5	375	6	06	90	0	1	0	1
5	377	6	06	90	0	0	1	1
5	378	6	06	90	0	0	1	1
5	2382	6	06	90	0	1	0	1
5	9044	6	06	90	0	1	0	1

Figure 4-25: Step 26 Result – Attribute Table of Single-part Crash Lines Buffer Shapefile with CNTOFCRSH Field

Step 27: Use "Join" function to join the Single-part Crash Lines Buffer and the Crash Lines shapefiles based on the AREA_ID field (see Figure 4-26).

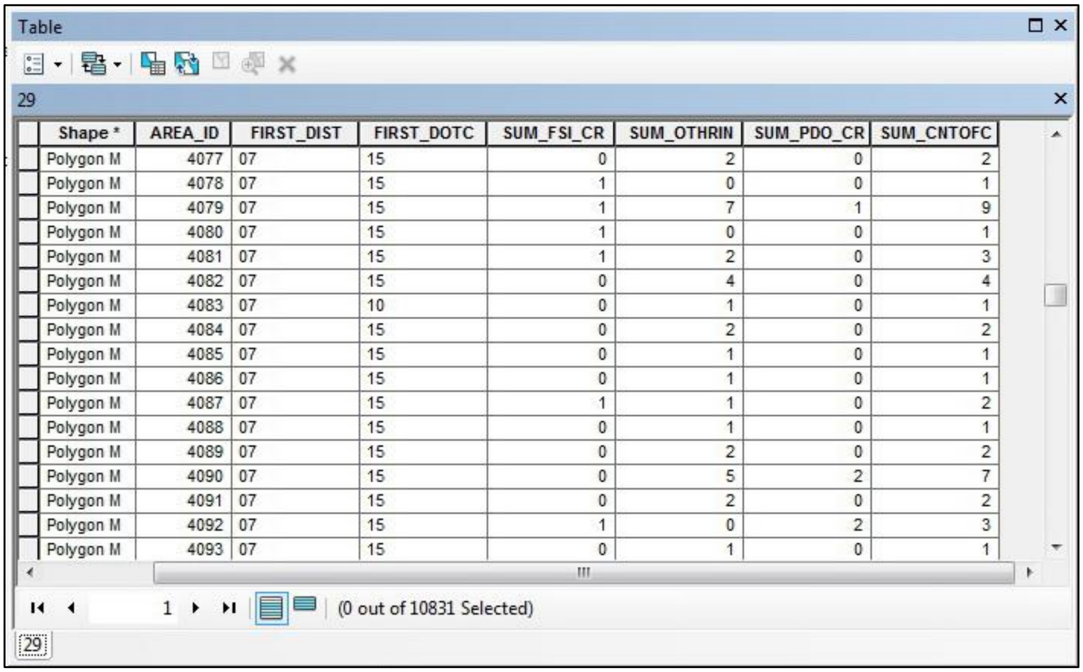


FSI_CRSH	OTHRINJCRS	PDO_CRSH	CNTOFCRSH	FID	Join_Count	TARGET_FID	JOIN_FID	AREA_ID *
0	1	0	1	11938	1	119382	0	1
0	1	0	1	37374	1	373742	1	2
0	1	0	1	32447	1	324472	2	3
0	1	0	1	17335	1	17335	3	4
0	1	0	1	17335	1	17335	3	4
0	0	1	1	17335	1	17335	3	4
1	0	0	1	17335	1	17335	3	4
1	0	0	1	17335	1	17335	3	4
0	1	0	1	92265	1	92265	4	5
0	1	0	1	92265	1	92265	4	5
0	1	0	1	92265	1	92265	4	5
0	1	0	1	5336	1	5336	5	6
0	1	0	1	5336	1	5336	5	6
0	0	1	1	5336	1	5336	5	6
0	0	1	1	5336	1	5336	5	6
0	1	0	1	5336	1	5336	5	6
0	1	0	1	5336	1	5336	5	6

Figure 4-26: Single-part Crash Lines Buffer Shapefile Joined with Crash Lines Shapefile

Step 28: Export the result from Step 27 to a new shapefile, Joined Buffer and Crash Lines shapefile.

Step 29: Run the Dissolve tool on this Joined Buffer and Crash Lines shapefile. Dissolve based on the AREA_ID field. Add the crash counts field, and retrieve the first value for each FDOT District and County (see Figure 4-27).



Table

29

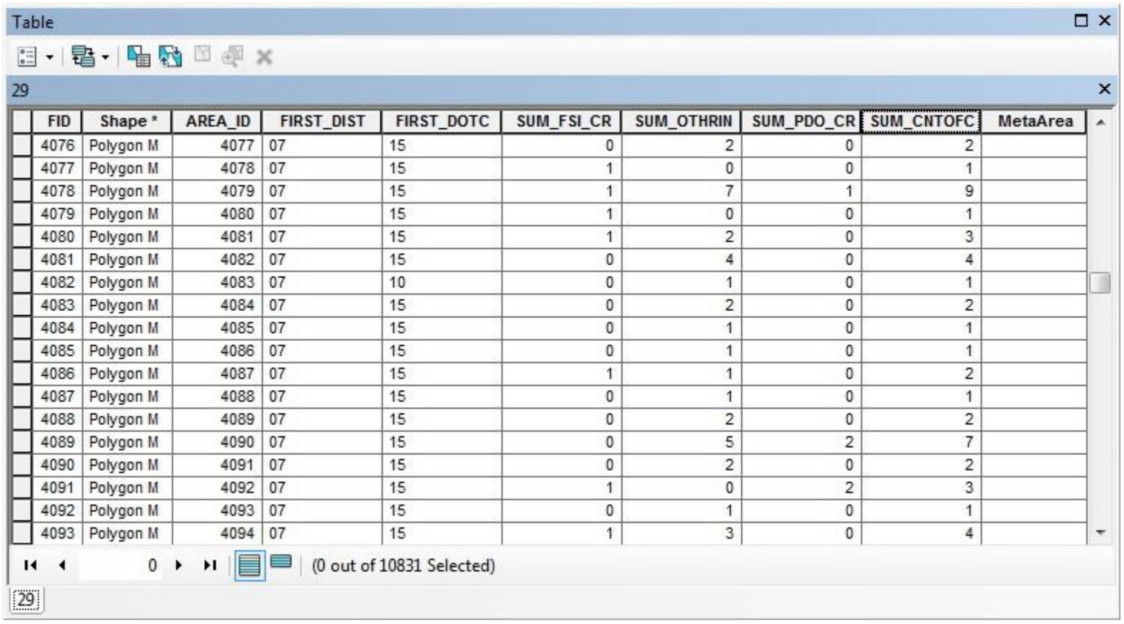
Shape *	AREA_ID	FIRST_DIST	FIRST_DOTC	SUM_FSI_CR	SUM_OTHRIN	SUM_PDO_CR	SUM_CNTOFC
Polygon M	4077	07	15	0	2	0	2
Polygon M	4078	07	15	1	0	0	1
Polygon M	4079	07	15	1	7	1	9
Polygon M	4080	07	15	1	0	0	1
Polygon M	4081	07	15	1	2	0	3
Polygon M	4082	07	15	0	4	0	4
Polygon M	4083	07	10	0	1	0	1
Polygon M	4084	07	15	0	2	0	2
Polygon M	4085	07	15	0	1	0	1
Polygon M	4086	07	15	0	1	0	1
Polygon M	4087	07	15	1	1	0	2
Polygon M	4088	07	15	0	1	0	1
Polygon M	4089	07	15	0	2	0	2
Polygon M	4090	07	15	0	5	2	7
Polygon M	4091	07	15	0	2	0	2
Polygon M	4092	07	15	1	0	2	3
Polygon M	4093	07	15	0	1	0	1

1 (0 out of 10831 Selected)

29

Figure 4-27: Dissolved Joined Crash Buffer Shapefile (Step 29 Result)

Step 30: Add a new text field – MetaArea (see Figure 4-28).



Table

29

FID	Shape *	AREA_ID	FIRST_DIST	FIRST_DOTC	SUM_FSI_CR	SUM_OTHRIN	SUM_PDO_CR	SUM_CNTOFC	MetaArea
4076	Polygon M	4077	07	15	0	2	0	2	
4077	Polygon M	4078	07	15	1	0	0	1	
4078	Polygon M	4079	07	15	1	7	1	9	
4079	Polygon M	4080	07	15	1	0	0	1	
4080	Polygon M	4081	07	15	1	2	0	3	
4081	Polygon M	4082	07	15	0	4	0	4	
4082	Polygon M	4083	07	10	0	1	0	1	
4083	Polygon M	4084	07	15	0	2	0	2	
4084	Polygon M	4085	07	15	0	1	0	1	
4085	Polygon M	4086	07	15	0	1	0	1	
4086	Polygon M	4087	07	15	1	1	0	2	
4087	Polygon M	4088	07	15	0	1	0	1	
4088	Polygon M	4089	07	15	0	2	0	2	
4089	Polygon M	4090	07	15	0	5	2	7	
4090	Polygon M	4091	07	15	0	2	0	2	
4091	Polygon M	4092	07	15	1	0	2	3	
4092	Polygon M	4093	07	15	0	1	0	1	
4093	Polygon M	4094	07	15	1	3	0	4	

0 (0 out of 10831 Selected)

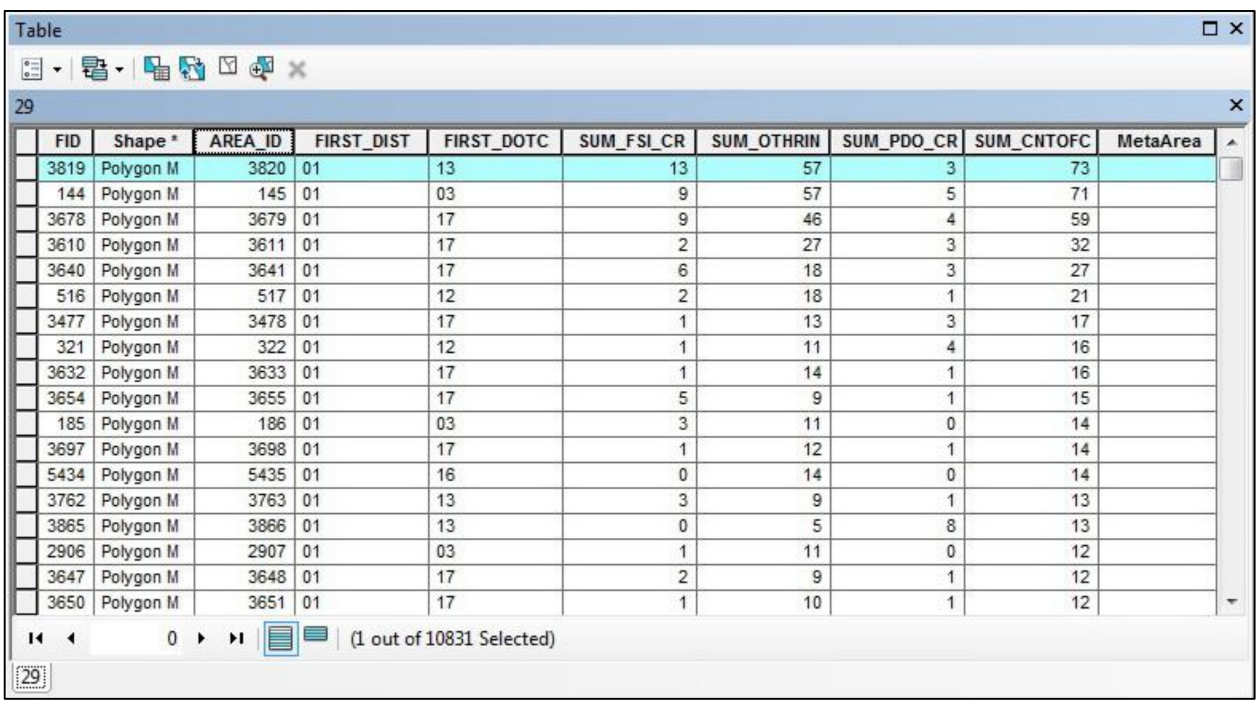
29

Figure 4-28: Crash Buffer Shapefile Attribute Table with New MetaArea Field

Step 31: Sort the locations by the FDOT District field in ascending order and the count of crashes ("SUM_CNTOFC") field in descending order (see Figure 4-29).

Figure 4-29: Advanced Table-sorting Window

Step 32: For the first district, select the top crash location, as shown in Figure 4-30.



Table

29

FID	Shape *	AREA_ID	FIRST_DIST	FIRST_DOTC	SUM_FSI_CR	SUM_OTHRIN	SUM_PDO_CR	SUM_CNTOFC	MetaArea
3819	Polygon M	3820	01	13	13	57	3	73	
144	Polygon M	145	01	03	9	57	5	71	
3678	Polygon M	3679	01	17	9	46	4	59	
3610	Polygon M	3611	01	17	2	27	3	32	
3640	Polygon M	3641	01	17	6	18	3	27	
516	Polygon M	517	01	12	2	18	1	21	
3477	Polygon M	3478	01	17	1	13	3	17	
321	Polygon M	322	01	12	1	11	4	16	
3632	Polygon M	3633	01	17	1	14	1	16	
3654	Polygon M	3655	01	17	5	9	1	15	
185	Polygon M	186	01	03	3	11	0	14	
3697	Polygon M	3698	01	17	1	12	1	14	
5434	Polygon M	5435	01	16	0	14	0	14	
3762	Polygon M	3763	01	13	3	9	1	13	
3865	Polygon M	3866	01	13	0	5	8	13	
2906	Polygon M	2907	01	03	1	11	0	12	
3647	Polygon M	3648	01	17	2	9	1	12	
3650	Polygon M	3651	01	17	1	10	1	12	

0 (1 out of 10831 Selected)

29

Figure 4-30: Select the Highest Crash Location in District One

Step 33: Use "Select by Location" function to select features that are within 250 feet of the selected feature from the shapefile generated in Step 29 (Dissolved Joined Crash Buffer shapefile) (see Figure 4-31).

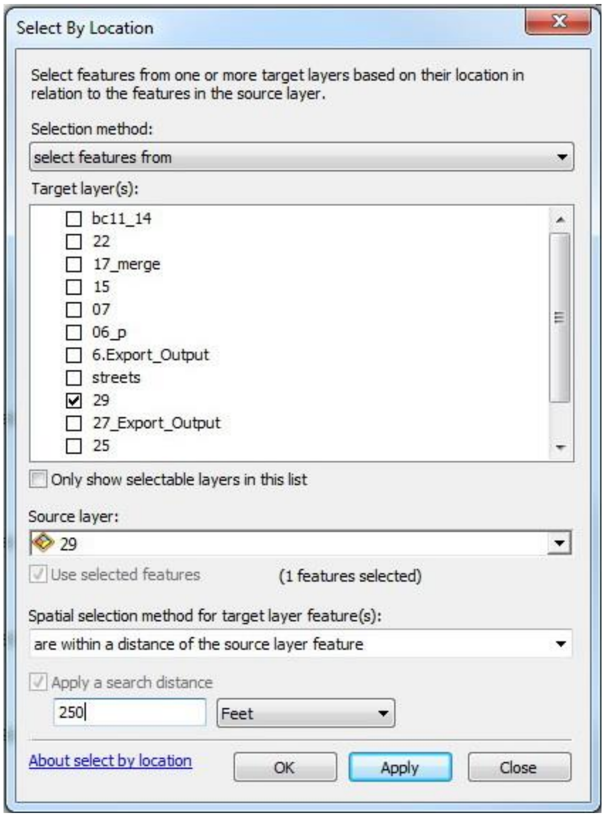


Figure 4-31: Select-by-Location Window to Identify High Crash Locations

Step 34: Repeat the selection until the number of locations selected does not increase. Figure 4-32 shows a high crash location in District One.

Step 35: Populate the MetaArea field for the selected records using the District.Rank format (e.g., 1.1, 1.2, 1.3, etc.), as shown in Figure 4-33. For example, a MetaArea value of 1.1 means that this location is the top location (rank 1) in District One.

Step 36: Repeat Steps 32-35 to identify top 5 locations. Again, repeat these steps for each district.

Step 37: Remove all the records with missing MetaArea ID, using the following query: NOT MetaArea = ‘’. This step resulted in a total of 181 records. Figure 4-34 gives the screenshot of the attribute table with the final list of top five bicycle high crash locations in each district.

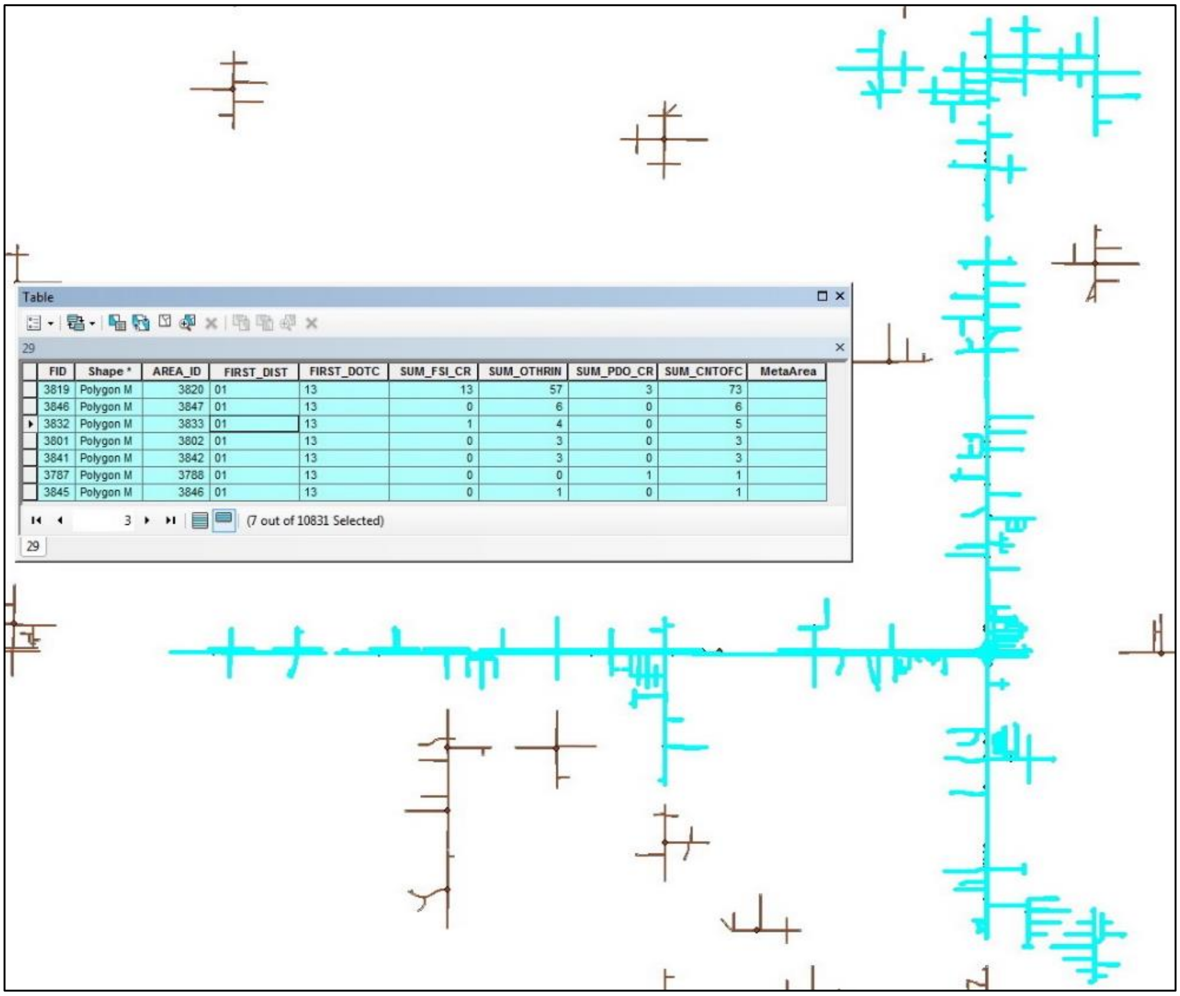


Figure 4-32: High Crash Location in District One

Table

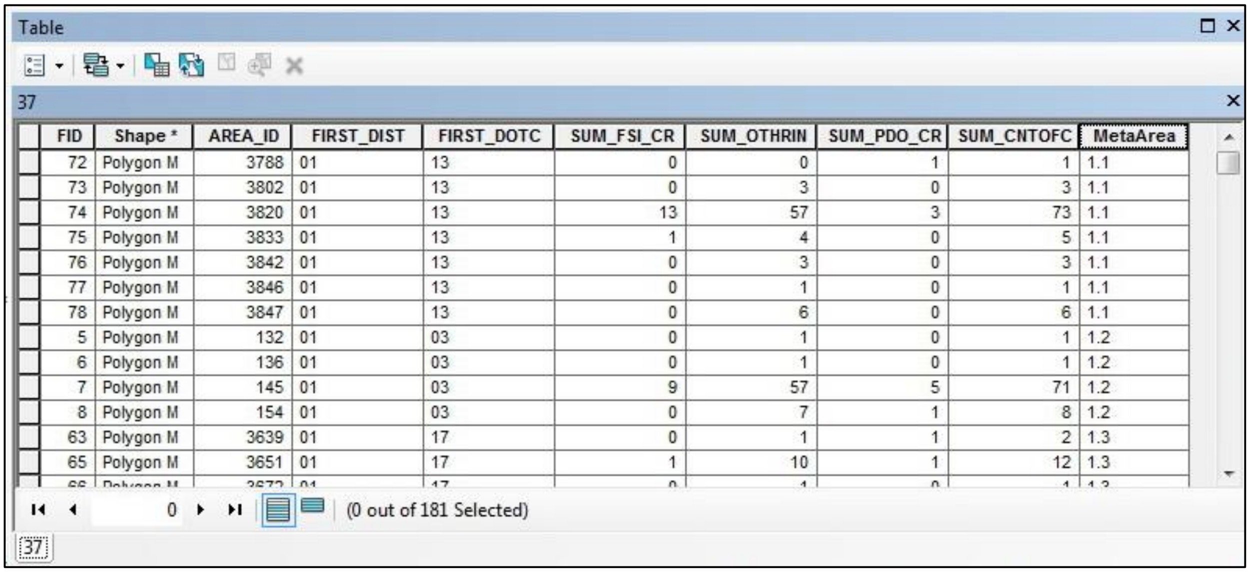
29

FID	Shape *	AREA_ID	FIRST_DIST	FIRST_DOTC	SUM_FSI_CR	SUM_OTHRIN	SUM_PDO_CR	SUM_CNTOFC	MetaArea
3819	Polygon M	3820	01	13	13	57	3	73	1.1
3846	Polygon M	3847	01	13	0	6	0	6	1.1
3832	Polygon M	3833	01	13	1	4	0	5	1.1
3801	Polygon M	3802	01	13	0	3	0	3	1.1
3841	Polygon M	3842	01	13	0	3	0	3	1.1
3787	Polygon M	3788	01	13	0	0	1	1	1.1
3845	Polygon M	3846	01	13	0	1	0	1	1.1

7 (7 out of 10831 Selected)

29

Figure 4-33: Attribute Table with Populated MetaArea



FID	Shape *	AREA_ID	FIRST_DIST	FIRST_DOTC	SUM_FSI_CR	SUM_OTHRIN	SUM_PDO_CR	SUM_CNTOFC	MetaArea
72	Polygon M	3788	01	13	0	0	1	1	1.1
73	Polygon M	3802	01	13	0	3	0	3	1.1
74	Polygon M	3820	01	13	13	57	3	73	1.1
75	Polygon M	3833	01	13	1	4	0	5	1.1
76	Polygon M	3842	01	13	0	3	0	3	1.1
77	Polygon M	3846	01	13	0	1	0	1	1.1
78	Polygon M	3847	01	13	0	6	0	6	1.1
5	Polygon M	132	01	03	0	1	0	1	1.2
6	Polygon M	136	01	03	0	1	0	1	1.2
7	Polygon M	145	01	03	9	57	5	71	1.2
8	Polygon M	154	01	03	0	7	1	8	1.2
63	Polygon M	3639	01	17	0	1	1	2	1.3
65	Polygon M	3651	01	17	1	10	1	12	1.3

Figure 4-34: Attribute Table with the Final List of Top Five High Crash Locations in Each District

Step 38: Run the Dissolve tool based on the MetaArea ID field (see Figure 4-35). Add crash counts/stats field, get the first value for FDOT District and County. A total of 36 records are generated.

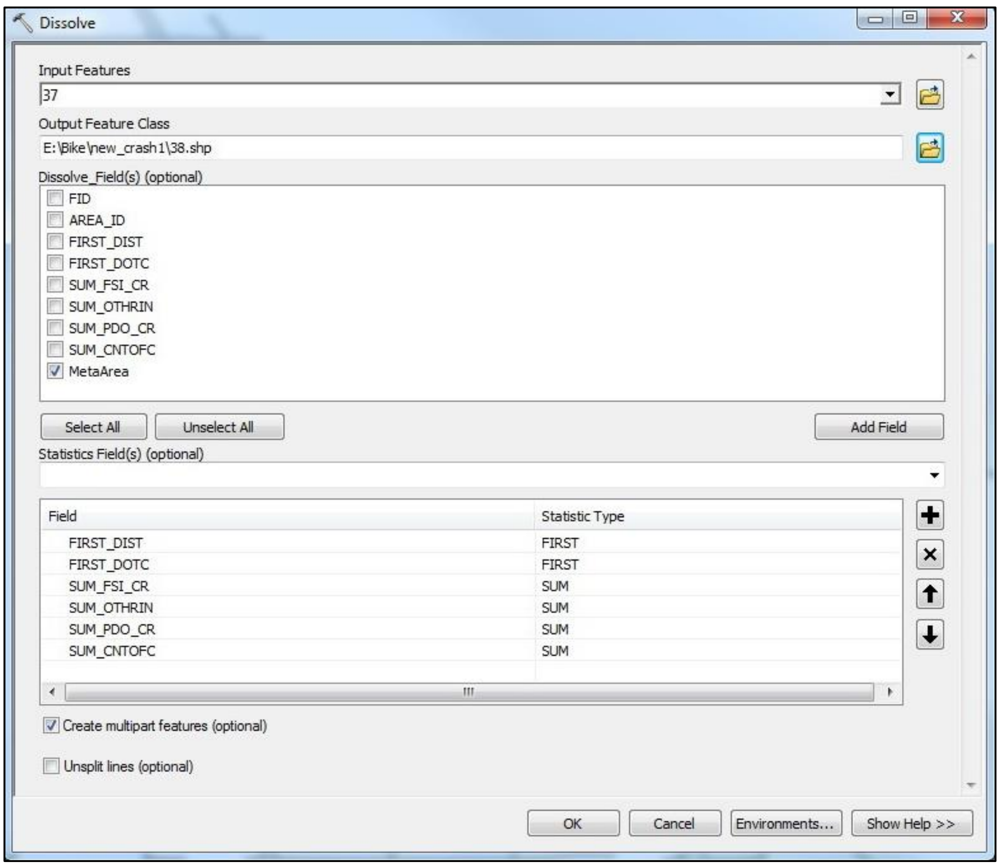


Figure 4-35: Dissolve Tool Setting Window

Step 39: Add a field "EPDO_SCORE" and choose Double as the data type, as shown in Figure 4-36.

Figure 4-36: Add Field Window to Add EPDO_SCORE Field

Step 40: Calculate the Equivalent Property Damage Only (EPDO) Weights. Table 4-2 gives the standard crash costs for the five injury severity levels.

Table 4-2: Standard Crash Costs for Different Injury Severity Levels

Injury Level	Crash Count	Standard Crash Cost	Total Crash Cost
PDO (PDO)	567,140	$7,600	$4,310,264,000
Possible (C)	231,458	$96,600	$22,358,842,800
Non-Incapacitating (B)	146,879	$155,480	$22,836,746,920
Incapacitating (A)	52,433	$574,080	$30,100,736,640
Fatal (K)	7,608	$10,120,000	$76,992,960,000

Source: 2013 Statewide Segment Averages from FDOT Crash Analysis Reporting (CAR) System.

The information given in Table 4-2 is used to obtain the weighting scores for PDO, other injury, and FSI crashes. The following steps are used to calculate the EPDO scores:

- Calculate the Cost per Crash for each grouping using the following equations:

$$PDO\ Injury\ Crash\ Cost = \frac{Cost\ of\ PDO\ Crashes}{\#\ of\ PDO\ Crashes} \tag{4-1}$$

Note that this will equal the standard crash cost for PDO.

$$Other\ Injury\ Crash\ Cost = \frac{Total\ Cost\ \ of\ (B{+}C)\ \ Crashes}{Total\ \#\ of\ (B{+}C)\ Crashes} \tag{4-2}$$

$$FSI\ Crash\ Cost = \frac{Total\ Cost\ of\ (K{+}A)\ Crashes}{Total\ \#\ of\ (K{+}A)\ Crashes} \tag{4-3}$$

- Using the Cost per Crash calculated in Equations 1 through 3, calculate the ratio between the Other Injury and FSI crashes to the PDO crashes. Table 4-3 gives the final weighting scores for different injury severity levels.

$$PDO\ Weight = \frac{PDO\ Crash\ Cost}{PDO\ Crash\ Cost} = 1.0 \tag{4-4}$$

$$Other\ Injury\ Weight = \frac{Other\ Injury\ \ Crash\ Cost}{PDO\ Crash\ Cost} \tag{4-5}$$

$$FSI\ Weight = \frac{FSI\ Crash\ Cost}{PDO\ Crash\ Cost} \tag{4-6}$$

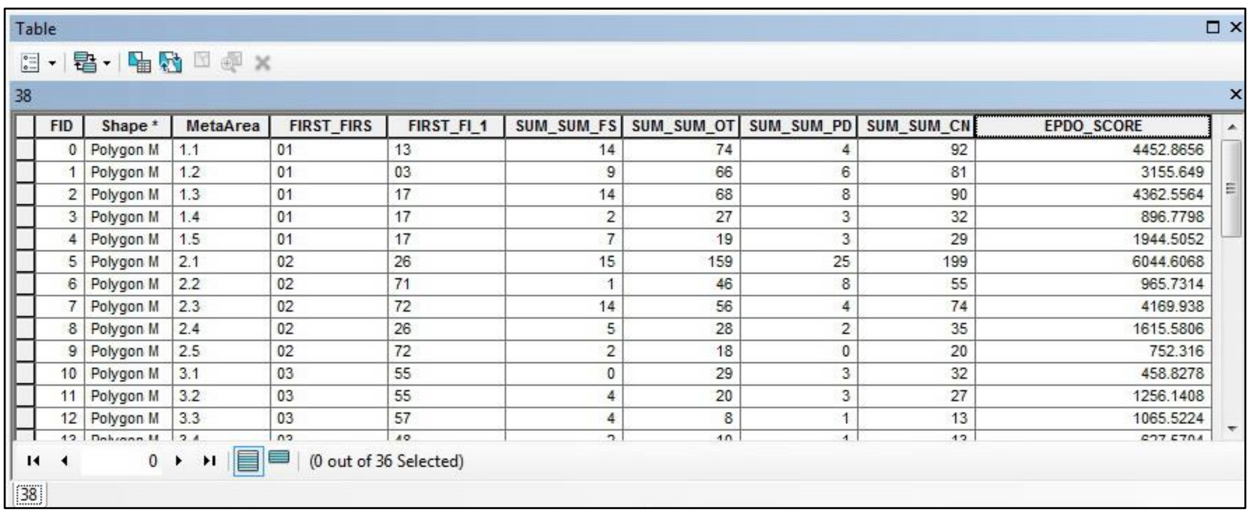
Table 4-3: Weighting Scores for Different Injury Severity Levels

Injury Weight	Crash Count	Crash Cost – Total	Cost Per Crash	Weight
PDO	567,140	$4,310,264,000	$7,600.00	1.0000
Other Injury	378,337	$45,195,589,720	$119,458.55	15.7182
Fatal and Serious Injury	60,041	$107,093,696,640	$1,783,676.09	234.6942

Step 41: Calculate the EPDO_SCORE field using the following Python code in the field calculator:

EPDO_SCORE = (!FSI_CRSH!*FSI Weight) + (OTHRINJCRSH*Other Injury Weight) + (!PDO_CRSH!)

Figure 4-37 shows the screenshot of the attribute table with the final EPDO scores for the five high crash locations in each district.



Table

38

FID	Shape *	MetaArea	FIRST_FIRS	FIRST_FI_1	SUM_SUM_FS	SUM_SUM_OT	SUM_SUM_PD	SUM_SUM_CN	EPDO_SCORE
0	Polygon M	1.1	01	13	14	74	4	92	4452.8656
1	Polygon M	1.2	01	03	9	66	6	81	3155.649
2	Polygon M	1.3	01	17	14	68	8	90	4362.5564
3	Polygon M	1.4	01	17	2	27	3	32	896.7798
4	Polygon M	1.5	01	17	7	19	3	29	1944.5052
5	Polygon M	2.1	02	26	15	159	25	199	6044.6068
6	Polygon M	2.2	02	71	1	46	8	55	965.7314
7	Polygon M	2.3	02	72	14	56	4	74	4169.938
8	Polygon M	2.4	02	26	5	28	2	35	1615.5806
9	Polygon M	2.5	02	72	2	18	0	20	752.316
10	Polygon M	3.1	03	55	0	29	3	32	458.8278
11	Polygon M	3.2	03	55	4	20	3	27	1256.1408
12	Polygon M	3.3	03	57	4	8	1	13	1065.5224

0 (0 out of 36 Selected)

38

Figure 4-37: Attribute Table with the Final EPDO_SCORE Values for the Top Five High Crash Locations in Each District

4.2 Analysis of Bicycle Hot Spots

Table 4-4 gives the final list of bicycle high crash locations in each district. For each location, it also includes the total number of crashes by severity and the final EPDO score. Appendix A provides the satellite images of these locations.

Table 4-4: District-wide List of Bicycle Hot Spots

Meta Area	Final Rank In Each District	District	County	Total FSI Crashes	Total Other Injury Crashes	Total PDO Crashes	Total Crashes	EPDO Score
1.1	1	1	13	14	74	4	92	4,452.87
1.2	3		03	9	66	6	81	3,155.65
1.3	2		17	14	68	8	90	4,362.56
1.4	4		17	2	27	3	32	896.78
1.5	5		17	7	19	3	29	1,944.51
2.1	1	2	26	15	159	25	199	6,044.61
2.2	3		71	1	46	8	55	965.73
2.3	2		72	14	56	4	74	4,169.94
2.4	4		26	5	28	2	35	1,615.58
2.5	5		72	2	18	0	20	752.32
3.1	1	3	55	0	29	3	32	458.83
3.2	2		55	4	20	3	27	1,256.14
3.3	3		57	4	8	1	13	1,065.52
3.4	3		48	2	10	1	13	627.57
3.5	3		48	1	11	1	13	408.59
4.1	1	4	86	22	167	43	232	7,831.21
4.2	5		93	8	51	6	65	2,685.18
4.3	3		93	12	62	11	85	3,801.86
4.4	4		93	10	56	5	71	3,232.16
4.5	2		86	12	78	14	104	4,056.35
5.1	4	5	75	3	32	2	37	1,209.07
5.2	2		75	14	61	12	87	4,256.53
5.3	5		75	3	26	3	32	1,115.76
5.4	1		79	8	72	11	91	3,020.26
5.5	3		75	12	30	7	49	3,294.88
6.1	1	6	87	27	232	68	327	1,0051.37
6.2	2		90	45	186	31	262	13,515.82
6.3	3		87	15	122	42	179	5,480.03
6.4	5		87	5	55	8	68	2,045.97
6.5	4		87	14	79	22	115	4,549.46
7.1	1	7	10	15	69	11	95	4,615.97
7.2	2		10	11	55	5	71	3,451.14
7.3	3		15	10	50	10	70	3,142.85
7.4	5		15	7	41	4	52	2,291.31
7.5	4		15	12	37	7	56	3,404.90
Total				**359**	**2,201**	**394**	**2,954**	**119,244.98**

Note: The final rank in each district in based on total crashes.

4.2.1 Data Preparation

The bicycle hot spots listed in Table 4-4 experienced a total of 2,954 bicycle crashes during the four year analysis period. Police Crash Report Review System (PCRRS), a web-based application, was used to review police crash reports of these 2,954 bicycle crashes to collect information that is not typically available in the crash summary records. The following information was collected for each bicycle crash:

- *Bicycle Crash*
  - Yes
  - No

- *At-Fault Road User*
  - Bicyclist
  - Driver
  - None

- *Crash Location*
  - Signalized intersections
  - Unsignalized locations (including unsignalized intersections and mid-block sections)
  - Not on roadway

- *Presence of Bicycle Lanes*

- *Bicyclist's Maneuver at the Time of the Crash*
  - Bicyclist was crossing the street
  - Bicyclist was riding along the roadway

- *Bicyclist's Trip Direction at the Time of the Crash*
  - Bicyclist was riding with traffic
  - Bicyclist was riding against traffic

- *Presence of Sidewalk*

- *Presence of On-Street Parking*

- *Position of Bicyclist at the Time of the Crash*
  - Sidewalk
  - Crosswalk
  - Travel lane
  - Bicycle lane
  - Driveway
  - Paved shoulder
  - Non-roadway

- *Crash Cause*

- Bicyclist ride-out at stop sign
- Motorist drive-out at stop sign
- Bicyclist ride-out at intersection
- Motorist drive-out at mid-block section
- Motorist turns left facing bicyclist
- Bicyclist ride-out at residential driveway
- Bicyclist turns left in front of traffic
- Motorist turns right at intersection
- Other

Note that all the above information was collected by reviewing descriptions and illustrative sketches in the police reports and the aerial images of crash locations. The following sections discuss the bicycle crash patterns identified from reviewing the police crash reports.

4.2.2 Bicycle Crash Statistics at Hot Spots

Of the 2,954 bicycle crashes that occurred at the bicycle hot spots identified in Table 4-4, only 2,888 crashes were found to be bicycle-related. In other words, 66 crashes (i.e., 2.2%) were incorrectly identified in the crash summary records as bicycle crashes. The rest of the analysis is based on the 2,888 bicycle crashes that occurred during 2011-2014 at the bicycle hot spots identified in Section 4.1.

4.2.3 At-Fault Road User

For each bicycle crash, the at-fault road user (i.e., driver, or bicyclist, or both) was identified by reviewing the descriptions in the police reports. Table 4-5 provides these statistics. Drivers were found to be at-fault in 45.7% (1,321 of 2,888 bicycle crashes) of the crashes while bicyclists were at-fault in 30.2% (871 of 2,888 bicycle crashes) of the crashes. Both bicyclists and drivers were found to be at-fault in very few crashes (0.8%, 22 of 2,888 bicycle crashes). Note that at-fault road users could not be determined for about 22% of crashes (637 of 2,888 bicycle crashes) as the police crash reports did not provide enough information. It can be inferred from the table that crashes involving at-fault bicyclists resulted in a slightly greater percentage of fatal crashes compared to those involving at-fault drivers.

Table 4-5: Statistics by At-Fault Road User

At-fault Road User	Fatal Crashes		Injury Crashes		Total Crashes[1]	
Driver	4	(0.3 %)	1,157	(87.6 %)	1,321	(100%)
Bicyclist	7	(0.8 %)	742	(85.2 %)	871	(100%)
Bicyclist and Driver	0	(0.0 %)	21	(95.4 %)	22	(100%)
None	0	(0.0 %)	32	(86.5 %)	37	(100%)
Not Sure	6	(0.9 %)	535	(84.0 %)	637	(100%)
Total	**17**	**(0.6 %)**	**2,487**	**(86.1 %)**	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

When the driver was found to be at-fault, the following were the most frequent contributing causes:

- failed to yield right-of-way to bicyclists,

- disregarded traffic signal or other traffic control, and
- careless driving.

When the bicyclist was found to be at-fault, the most frequent contributing causes were:

- disregarded traffic signal or other traffic control, and
- failed to yield right-of-way to drivers.

4.2.4 Crash Locations

Table 4-6 gives bicycle crash statistics by crash location and crash severity. As can be observed from the table, bicycle crash locations were divided into two broader groups: signalized locations (i.e., signalized intersections), and unsignalized locations (i.e., unsignalized intersections and mid-block sections). Bicycle crashes were found to be more frequent at signalized intersections, constituting about 54% (1,553 of 2,888) of all bicycle crashes that occurred at hot spots. Unsignalized locations experienced a greater proportion of fatal crashes (0.8%, 10 of 1,302) compared to signalized locations (0.5%, 7 of 1,553).

Table 4-6: Statistics by Crash Location

Crash Location	Fatal Crashes		Injury Crashes		Total Crashes[1]	
Signalized Intersection	7	(0.5%)	1,309	(84.3%)	1,553	(100%)
Unsignalized Location	10	(0.8%)	1,148	(88.2%)	1,302	(100%)
Not Roadway	0	(0. 0%)	9	(81.8%)	11	(100%)
Not Sure	0	(0. 0%)	21	(95.5%)	22	(100%)
Total	**17**	(0.6%)	**2,487**	(86.1%)	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.2.5 Presence of Bicycle Lanes

Table 4-7 provides bicycle crash statistics by presence of bicycle lanes and crash severity. A majority of bicycle crashes (77.1%, 2,227 of 2,888) occurred at locations with no bicycle lanes. It can be inferred from the table that bicycle crashes at locations with no bicycle lanes (0.6%, 14 of 2,227) resulted in a greater proportion of fatalities compared to the bicycle crashes at locations with bicycle lanes (0.3%, 2 of 614).

Table 4-7: Statistics by Presence of Bicycle Lanes

Presence of Bicycle Lane	Fatal Crashes		Injury Crashes		Total Crashes[1]	
No	14	(0.6%)	1,911	(85.8%)	2,227	(100%)
Yes	2	(0.3%)	532	(86.6%)	614	(100%)
Not Sure	1	(2.1%)	44	(93.6%)	47	(100%)
Total	**17**	(0.6%)	**2,487**	(86.1%)	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.2.6 Bicyclist's Maneuver at the Time of the Crash

Crossing a roadway was found to be a critical maneuver for bicyclists; 73% of bicyclists (2,103 of 2,888) were hit while crossing the streets, and 13 out of 2,103 crashes resulted in fatalities. Riding along the roadway also constituted about 25% of bicycle crashes (717 of 2,888). Crossing the street was found to result in a greater proportion of fatal crashes compared to riding along the roadway. Table 4-8 summarizes these results.

Table 4-8: Statistics by Bicyclist's Maneuver at the Time of the Crash

Bicyclist Maneuver at the Time of the Crash	Fatal Crashes		Injury Crashes		Total Crashes[1]	
Crossing the Street	13	(0.6%)	1,816	(86.4%)	2,103	(100%)
Riding along the Roadway	3	(0.4%)	615	(85.8%)	717	(100%)
Not Sure	1	(1.5%)	56	(82.4%)	68	(100%)
Total	**17**	(0.6%)	**2,487**	(86.1%)	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.2.7 Bicyclist's Trip Direction

Bicycles are considered as vehicles and therefore the law requires bicyclists to ride along the roadway with traffic. Bicyclist's crash proportion when riding along the roadway with traffic was found to be three times higher compared to riding along the roadway facing traffic. This could be because of the fact that a majority of bicyclists follow the law and ride along the roadway in the same direction as other vehicles on the road. However, as is evident from the statistics provided in Table 4-9, crashes involving bicyclists riding along the roadway facing traffic are severe compared to those involving bicyclists riding with traffic.

Table 4-9: Statistics by Bicyclist's Trip Direction When Riding along the Roadway

Bicyclist's Trip Direction when Riding along the Roadway	Fatal Crashes		Injury Crashes		Total Crashes[1]	
With Traffic	2	(0.4%)	464	(85.9%)	540	(100%)
Facing Traffic	1	(0.7%)	133	(85.8%)	155	(100%)
Not Sure	0	(0.0%)	18	(81.9%)	22	(100%)
Total	**3**	(0.4%)	**615**	(85.8%)	**717**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.2.8 Presence of Sidewalk

Table 4-10 provides the bicycle crash statistics by presence of sidewalk and crash severity. Locations with sidewalks experienced a smaller percentage of fatal crashes compared to locations without sidewalks. In terms of bicycle crash frequency, a majority of bicycle crashes were found to occur at locations with sidewalk. However, these statistics need to be interpreted with caution as exposure is not reflected in these statistics.

Table 4-10: Statistics by Presence of Sidewalk

Presence of Sidewalk	Fatal Crashes		Injury Crashes		Total Crashes[1]	
Yes	16	(0.6%)	2,411	(86.1%)	2,799	(100%)
No	1	(1.5%)	53	(81.5%)	65	(100%)
Not Sure	0	(0.0%)	23	(95.8%)	24	(100%)
Total	**17**	(0.6%)	**2,487**	(86.1%)	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.2.9 Presence of On-Street Parking

As can be observed from Table 4-11, a majority of bicycle crashes occurred at locations with no on-street parking. As very few crashes occurred at locations with on-street parking, no conclusion could be made on the impact of on-street parking on bicycle crash severity.

Table 4-11: Statistics by Presence of On-Street Parking

Presence of On-Street Parking	Fatal Crashes		Injury Crashes		Total Crashes[1]	
No	17	(0.7%)	2,131	(86.1%)	2,474	(100%)
Yes	0	(0.0%)	294	(85.5%)	344	(100%)
Not Sure	0	(0.0%)	62	(88.6%)	70	(100%)
Total	**17**	(0.6%)	**2,487**	(86.1%)	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.2.10 Position of Bicyclists at the Time of the Crash

Table 4-12 presents the statistics based on the position of bicyclists at the time of the crash. Almost 56% (1,607 of 2,888) of bicycle crashes occurred at crosswalks. Travel lane and driveways are the next two locations where bicycle crashes occurred frequently. More fatal crashes occurred at driveways compared to other locations. Although crosswalks experienced a majority of bicycle crashes, they resulted in a smaller proportion of fatal crashes.

Table 4-12: Statistics by Bicyclist's Position at the Time of the Crash

Bicyclist's Position During Crash	Fatal Crashes		Injury Crashes		Total Crashes[1]	
Crosswalk	5	(0.3%)	1,382	(86.0%)	1,607	(100%)
Travel Lane	4	(0.6%)	539	(85.0%)	634	(100%)
Driveway	6	(1.9%)	285	(88.2%)	323	(100%)
Bicycle Lane	1	(0.7%)	135	(88.8%)	152	(100%)
Sidewalk	1	(0.8%)	110	(86.6%)	127	(100%)
Paved Shoulder	0	(0.0%)	3	(100.0%)	3	(100%)
Non-Roadway	0	(0.0%)	1	(100.0%)	1	(100%)
Other	0	(0.0%)	19	(76.0%)	25	(100%)
Unknown	0	(0.0%)	13	(81.3%)	16	(100%)
Total	**17**	(0.6%)	**2,487**	(86.1%)	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.2.11 Crash Type

Table 4-13 provides the statistics by bicycle crash type and crash severity. Bicycle crashes involving motorists turning right (17%, 477 of 2,888) were found to be the most frequent bicycle crash type. Bicycle crashes occurring at an intersection, signalized or unsignalized, where the bicyclist failed to yield (i.e., ride out at intersection) was found to be the second most frequent bicycle crash scenario. Furthermore, these crashes were found to be relatively more severe, with 1.09% of them resulted in fatalities.

Table 4-13: Statistics by Bicycle Crash Type

Crash Type	Fatal Crashes		Injury Crashes		Total Crashes[1]	
Motorist Right Turn	2	(0.4%)	426	(89.3%)	477	(100%)
Ride out at Intersection	4	(1.1%)	315	(85.6%)	368	(100%)
Drive out at Stop Sign	0	(0.0%)	244	(89.4%)	273	(100%)
Motorist Left Turn - Facing Bicyclist	0	(0.0%)	123	(90.4%)	136	(100%)
Ride out at Stop Sign	0	(0.0%)	90	(88.2%)	102	(100%)
Drive out at Midblock	0	(0.0%)	61	(87.1%)	70	(100%)
Bicyclist Left Turn in front of Traffic	0	(0.0%)	25	(89.3%)	28	(100%)
Ride out at Residential Driveway	0	(0.0%)	6	(85.7%)	7	(100%)
Other	11	(0.8%)	1,150	(80.6%)	1,427	(100%)
Total	**17**	(0.6%)	**2,487**	(86.1%)	**2,888**	(100%)

[1] Total crashes include crashes with no injury and unknown injury.

4.3 Collision-Condition Diagrams

The bicycle hot spots identified in Table 4-4 experienced a total of 2,954 bicycle crashes. Locations of these crashes were reviewed closely to identify crash clusters. Top four clusters that experienced at least five bicycle crashes in each district from 2011-2014 were identified. A total of 28 crash clusters were identified and analyzed. Table 4-14 lists the bicycle crash clusters by district ranked based on total bicycle crash frequency during 2011-2014.

Table 4-14: Bicycle Crash Clusters

No.	Location	Roadway ID	Dist.	Crash Severity			
				Fatal/ Severe	Injury	No Injury	Total Crashes
1	Cortez Rd W near 26th St W in Bradenton	13040000	D1	4	4	0	8
2	Estey Ave near Airport Pulling Rd S in Naples	03000000	D1	1	5	0	6
3	17th St near N Washington Blvd in Sarasota	17120000	D1	2	4	1	7
4	Bee Ridge Rd near S Beneva Rd in Sarasota	17008000	D1	0	6	0	6
5	NW 13th St near NW 10th Ave in Gainesville	26010000	D2	0	7	0	7
6	SW 34th St near SW Archer Rd in Gainesville	26250000	D2	1	5	0	6
7	NW 13th St near W University Ave in Gainesville	26070000	D2	1	3	1	5
8	W University Ave near SW 2nd Ave in Gainesville	26070168	D2	0	6	0	6
9	N 9th Ave near Springhill Dr in Brent	48003000	D3	1	5	1	7
10	Racetrack Rd NW near Richpien Rd in Fort Walton Beach	57003000	D3	2	3	2	7
11	W Call St near Conradi St in Tallahassee	55000000	D3	0	5	1	6
12	N Macomb St near W Tennessee St in Tallahassee	55000000	D3	0	5	0	5
13	Forest Hill Blvd near S Military Trail in West Palm Beach	93070000	D4	0	9	0	9
14	S Ocean Blvd near E Atlantic Ave in Delray Beach	93060000	D4	2	5	1	8
15	S Military Trail near Cresthaven Blvd in Lake Worth	93070000	D4	1	5	1	7
16	S Military Trail near Clemens St in Lake Worth	93070000	D4	1	4	0	5
17	N Alafaya Trail near Lokanotosa Trail in Orlando	75037000	D5	2	2	2	6
18	N Alafaya Trail near Challenger Pkwy in Orlando	75037000	D5	2	2	2	6
19	W Michigan St near S Orange Ave in Orlando	75040000	D5	0	7	0	7
20	N Nova Rd near W International Speedway Blvd in Daytona Beach	79060000	D5	1	5	0	6
21	Duval St near Angela St in Key West	90000000	D6	1	4	1	6
22	Washington Ave near 9th St in Miami Beach	87000000	D6	0	5	1	6
23	N Roosevelt Blvd near 5th St in Key West	90010000	D6	1	4	0	5
24	5th St near Washington Ave in Miami Beach	87060000	D6	1	3	2	6
25	34th St N near 62nd Ave N in St. Petersburg	15150000	D7	0	10	0	10
26	34th St N near 70th Ave N in Pinellas Park	15150000	D7	0	4	3	7
27	E Floribraska Ave near N Nebraska Ave in Tampa	10040000	D7	2	2	2	6
28	E Busch Blvd near N Nebraska Ave in Tampa	10040000	D7	2	4	0	6

Figures 4-38 through 4-65 plot the collision-condition diagrams of the 28 bicycle crash clusters in Florida. In these diagrams, the locations of all bicycle crashes were plotted on the satellite images. The figures also provide additional information on the injury severity of the bicyclist using the following color codes:

- red – bicyclist fatality/severe injury
- yellow – injury to bicyclist
- green – no injury to bicyclist

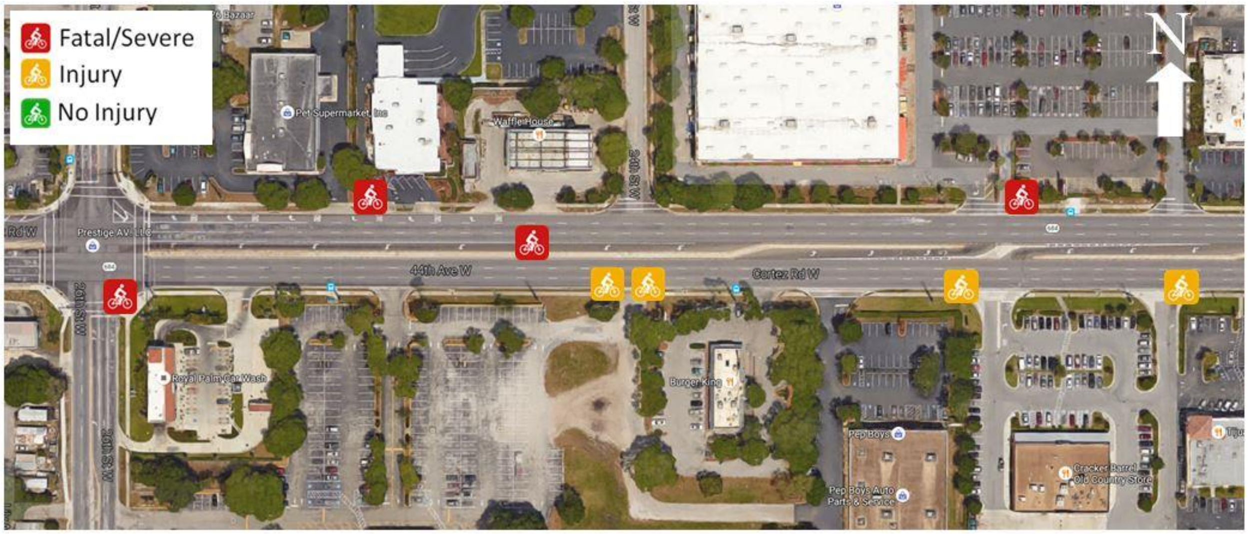


Figure 4-38: Cortez Rd W near 26th St W in Bradenton (Roadway ID 13040000) (Map)

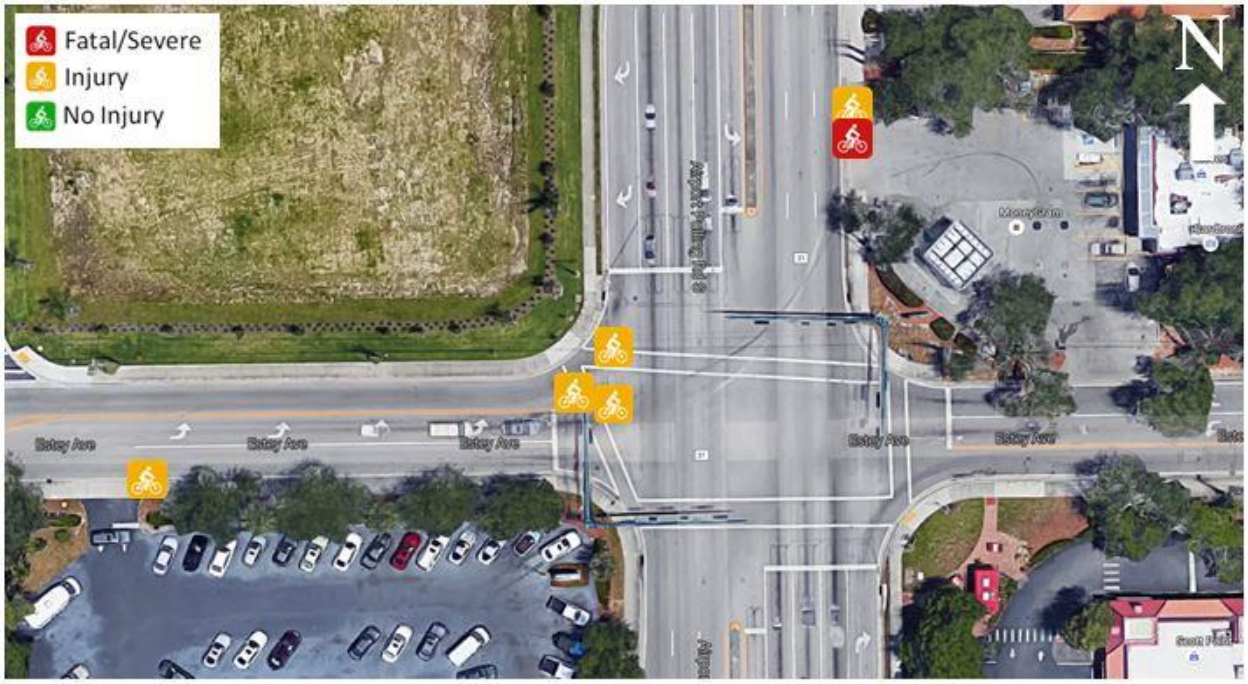


Figure 4-39: Estey Ave near Airport Pulling Rd S in Naples (Roadway ID: 03000000) (Map)

Figure 4-40: 17th St near N Washington Blvd in Sarasota
(Roadway ID: 17120000) ([Map])

Figure 4-41: Bee Ridge Rd near S Beneva Rd in Sarasota
(Roadway ID: 17008000) ([Map])

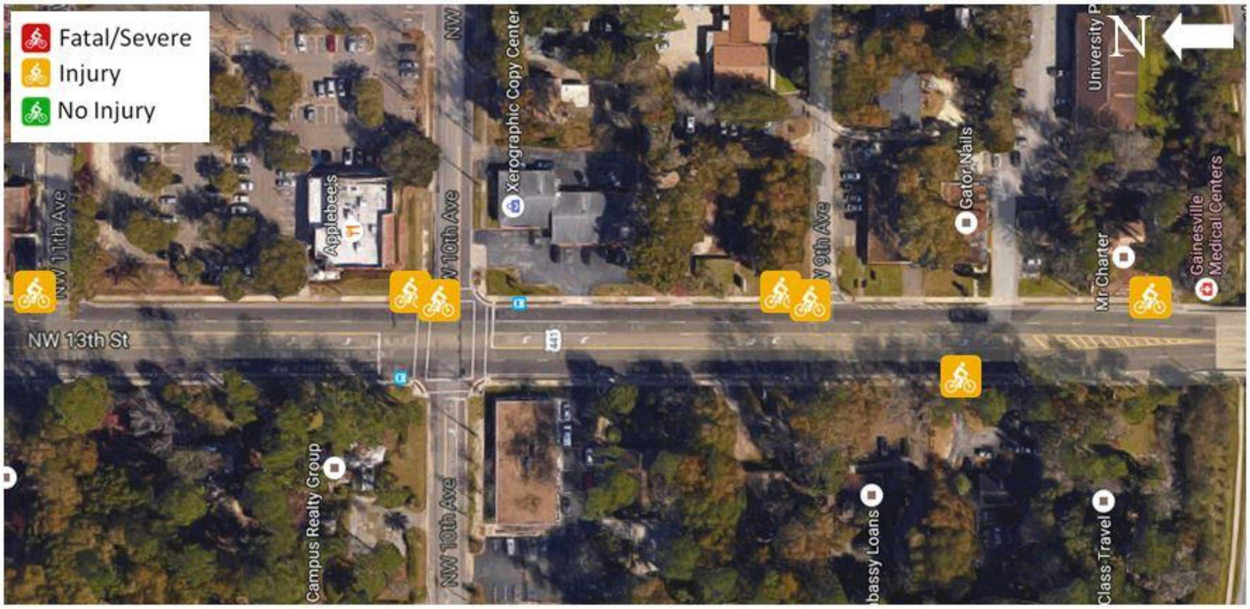


Figure 4-42: NW 13th St near NW 10th Ave in Gainesville (Roadway ID: 26010000) ([Map](#))

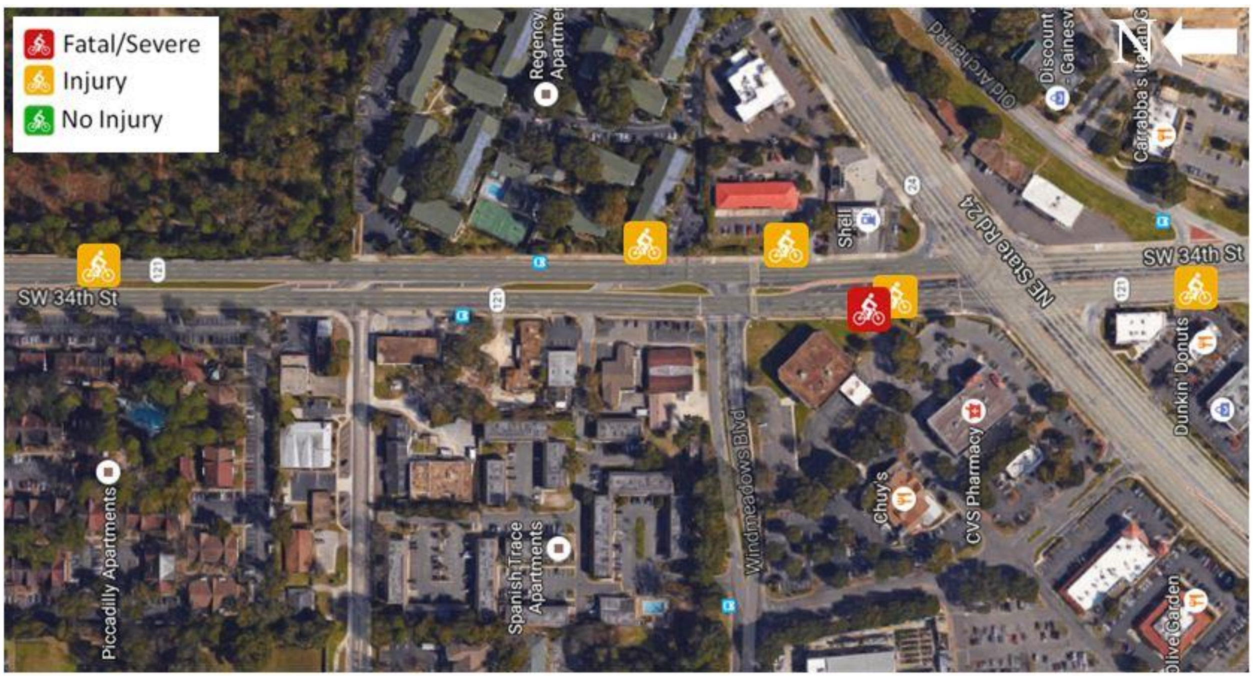


Figure 4-43: SW 34th St near SW Archer Rd in Gainesville (Roadway ID: 26250000) ([Map](#))

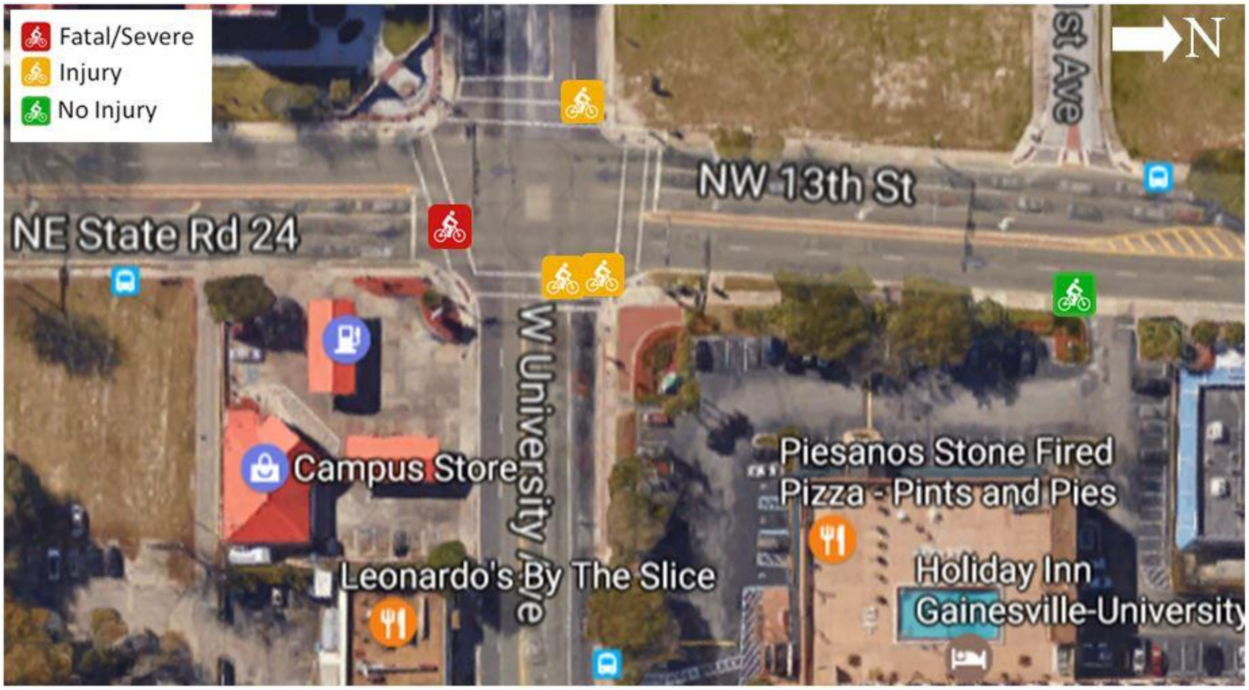


Figure 4-44: NW 13th St near W University Ave in Gainesville (Roadway ID: 26070000 ([Map]))

Figure 4-45: W University Ave near SW 2nd Ave in Gainesville (Roadway ID: 26070168) ([Map])

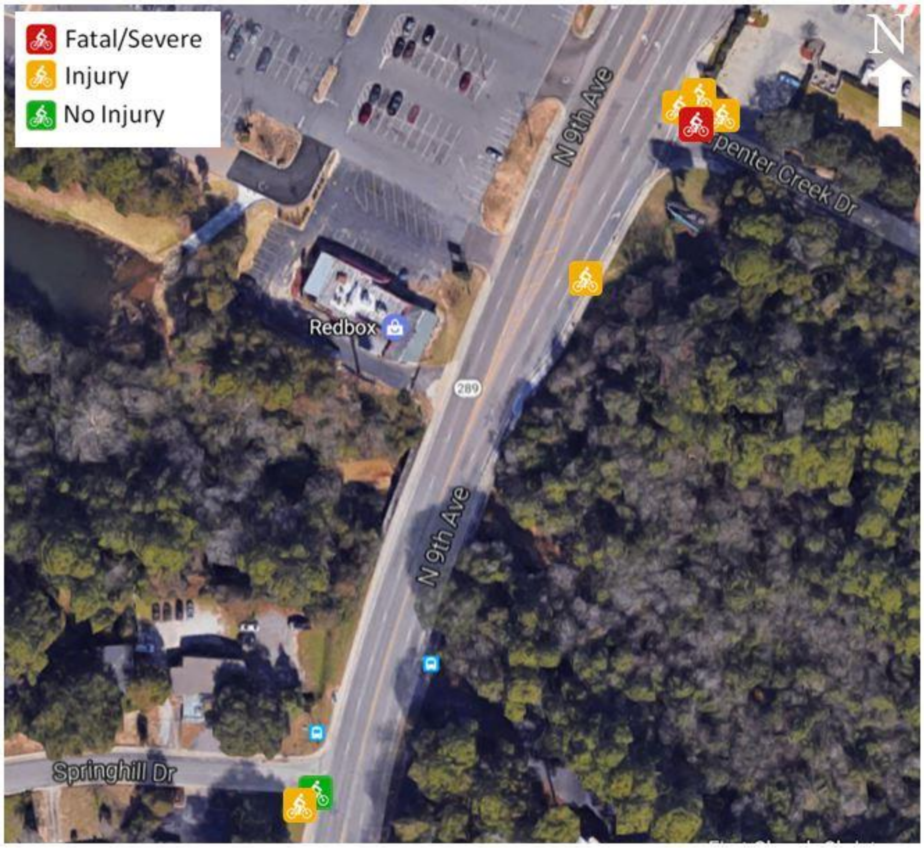


Figure 4-46: N 9th Ave near Springhill Dr in Brent (Roadway ID: 48003000) (Map)

Figure 4-47: Racetrack Rd NW near Richpien Rd in Fort Walton Beach (Roadway ID: 57003000) (Map)

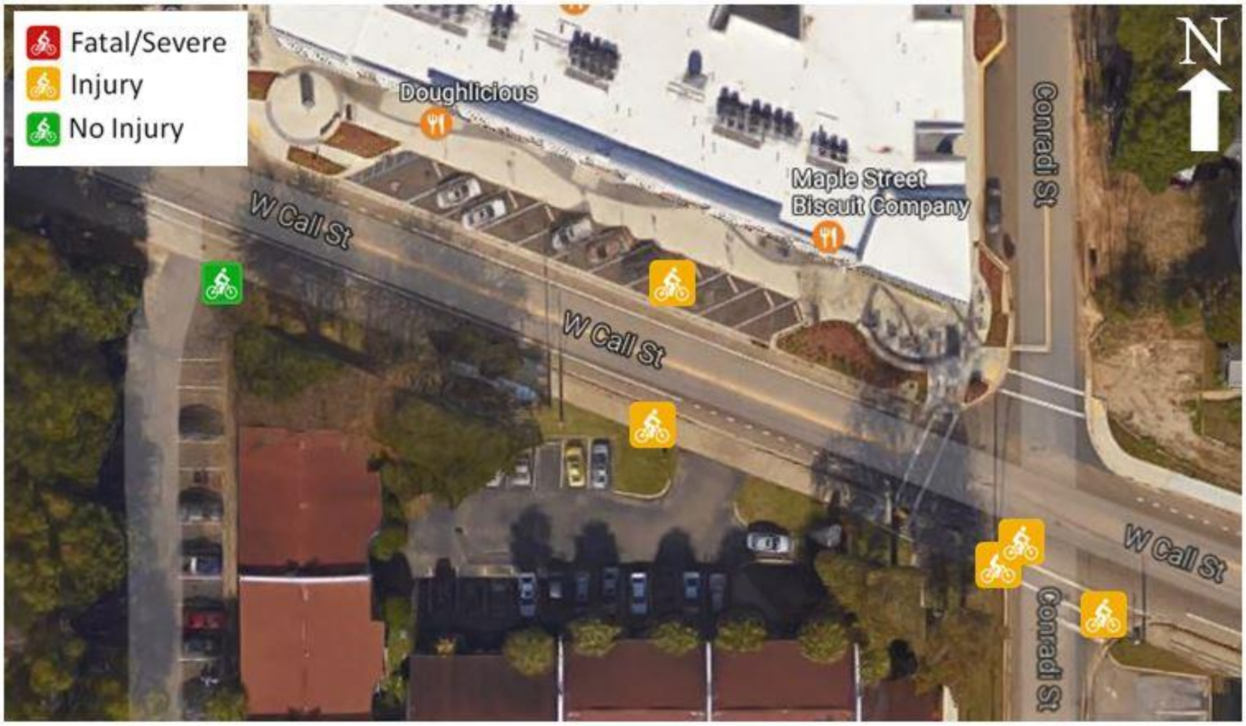


Figure 4-48: W Call St near Conradi St in Tallahassee (Roadway ID: 55000000) (Map)

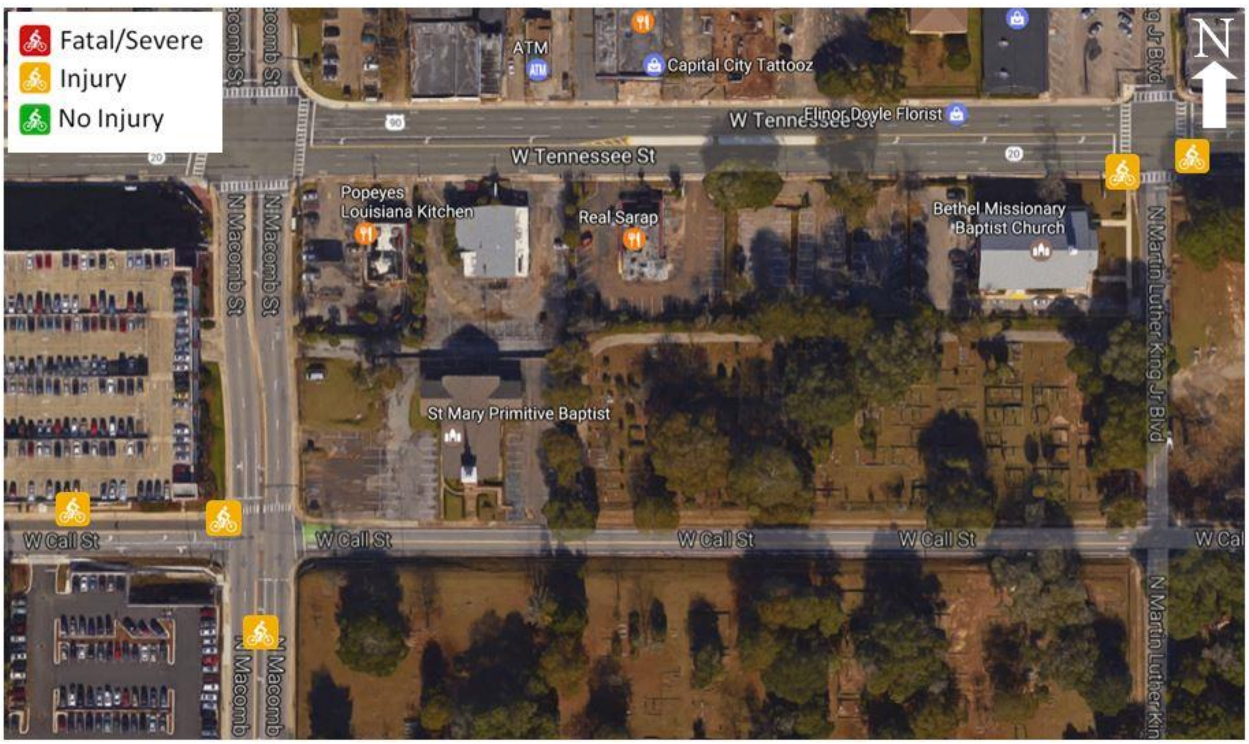


Figure 4-49: N Macomb St near W Tennessee St in Tallahassee (Roadway ID: 55000000) (Map)

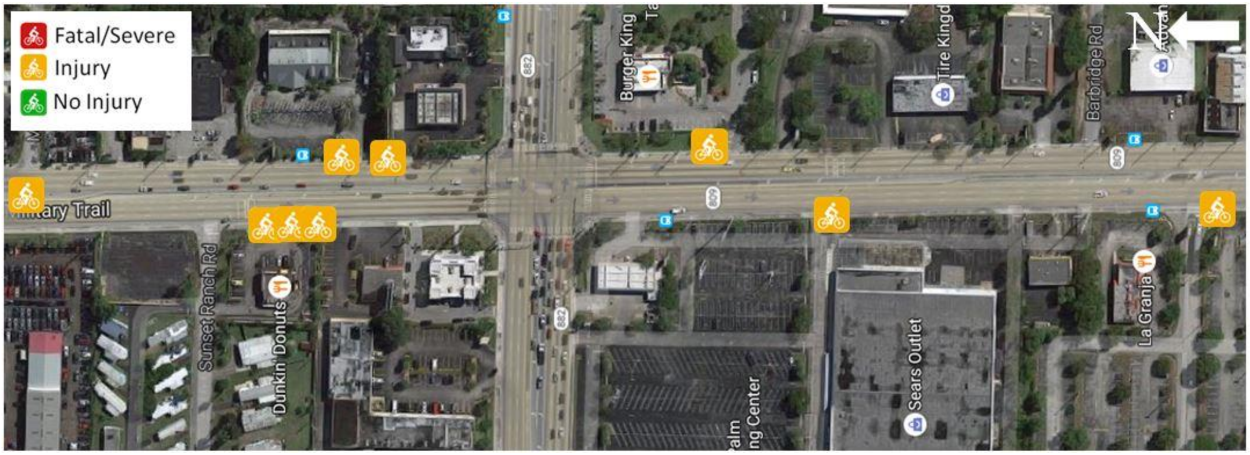


Figure 4-50: Forest Hill Blvd near S Military Trail in West Palm Beach (Roadway ID: 93070000) ([Map](#))

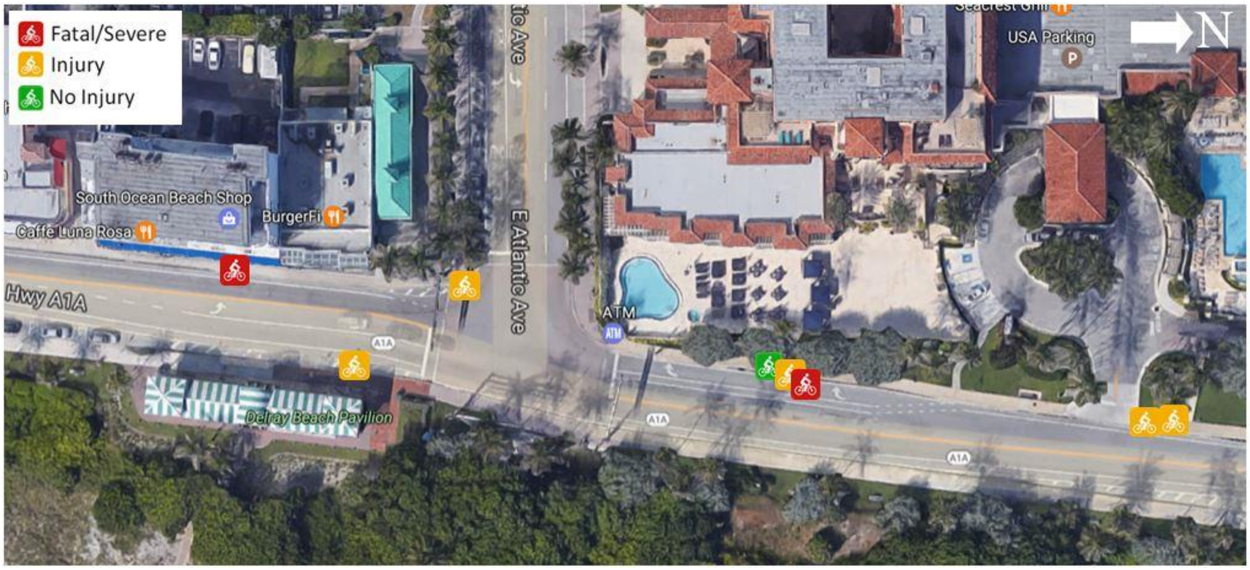


Figure 4-51: S Ocean Blvd near E Atlantic Ave in Delray Beach (Roadway ID: 93060000) ([Map](#))

Figure 4-52: S Military Trail near Cresthaven Blvd in Lake Worth (Roadway ID: 93070000)(Map)

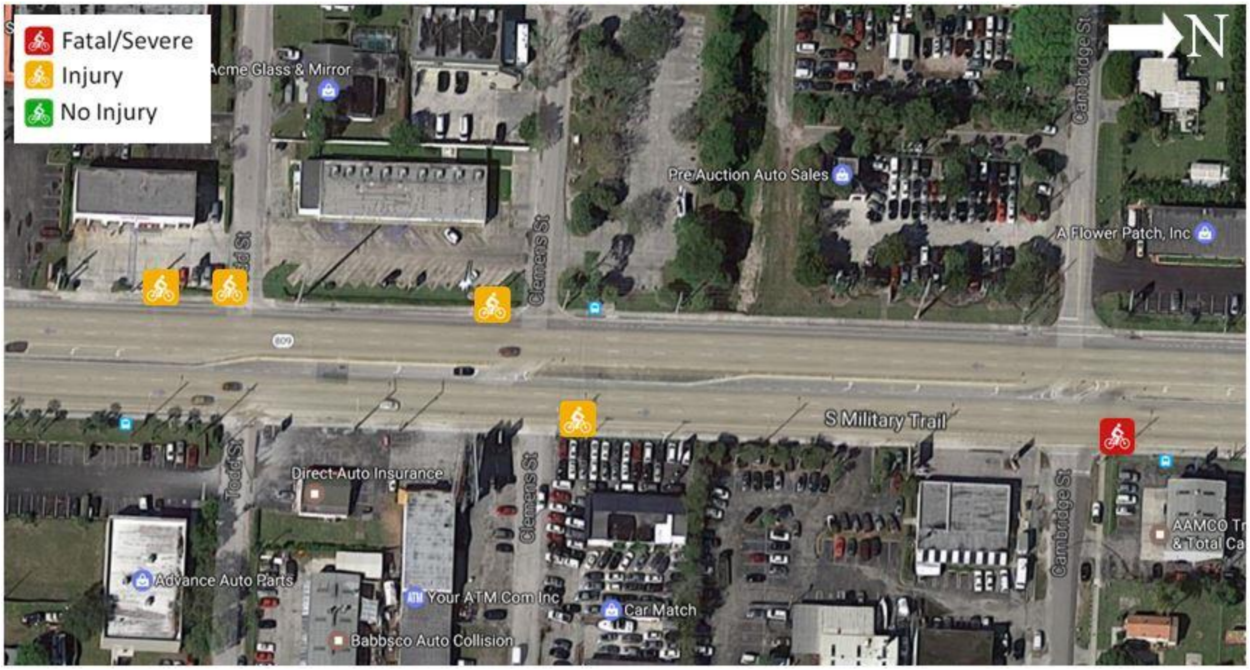


Figure 4-53: S Military Trail near Clemens St in Lake Worth (Roadway ID: 93070000) (Map)

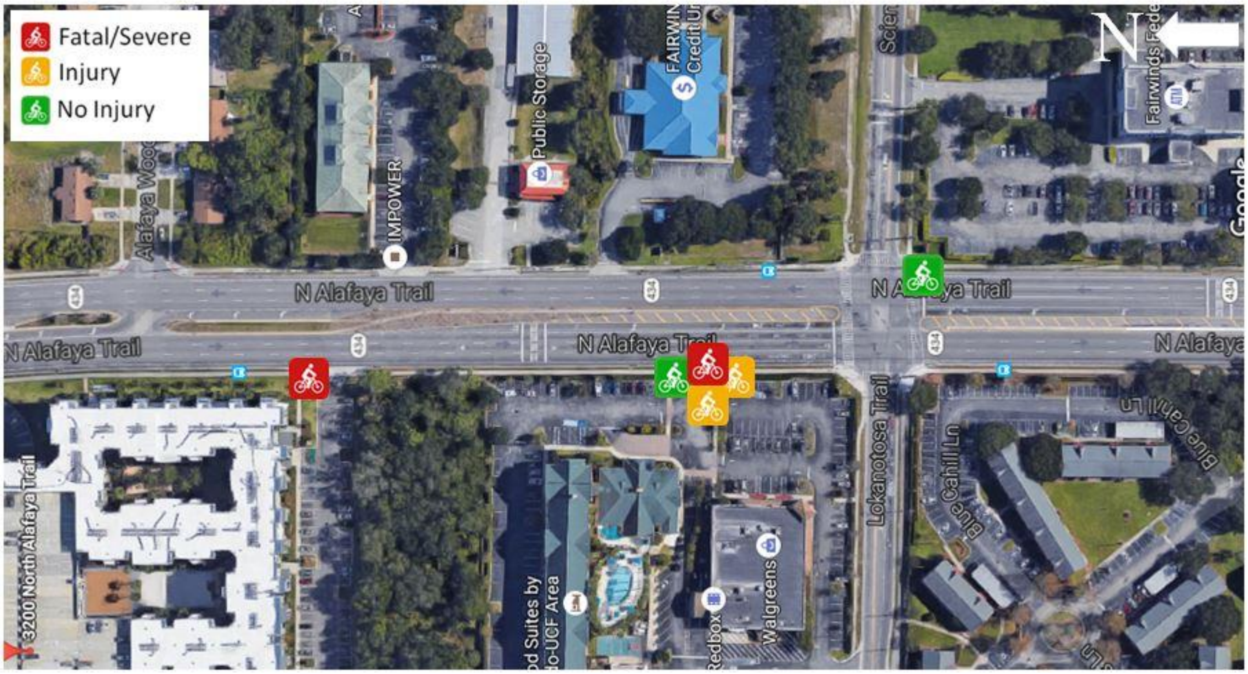


Figure 4-54: N Alafaya Trail near Lokanotosa Trail in Orlando
(Roadway ID: 75037000) ([Map](#))

Figure 4-55: N Alafaya Trail near Challenger Pkwy in Orlando
(Roadway ID: 75037000) ([Map](#))

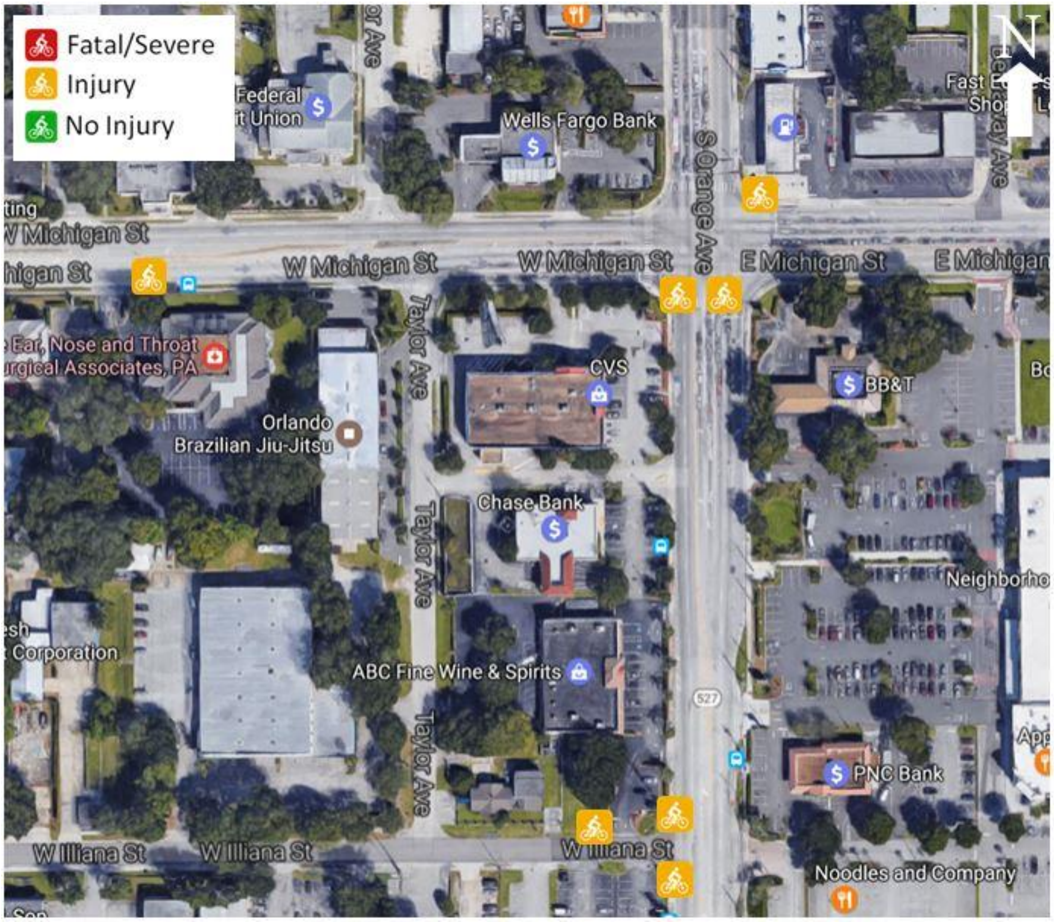


Figure 4-56: W Michigan St near S Orange Ave in Orlando (Roadway ID: 75040000) ([Map])

Figure 4-57: N Nova Rd near W International Speedway Blvd in Daytona Beach (Roadway ID: 79060000) ([Map](#))

Figure 4-58: Duval St near Angela St in Key West (Roadway ID: 90000000) ([Map](#))

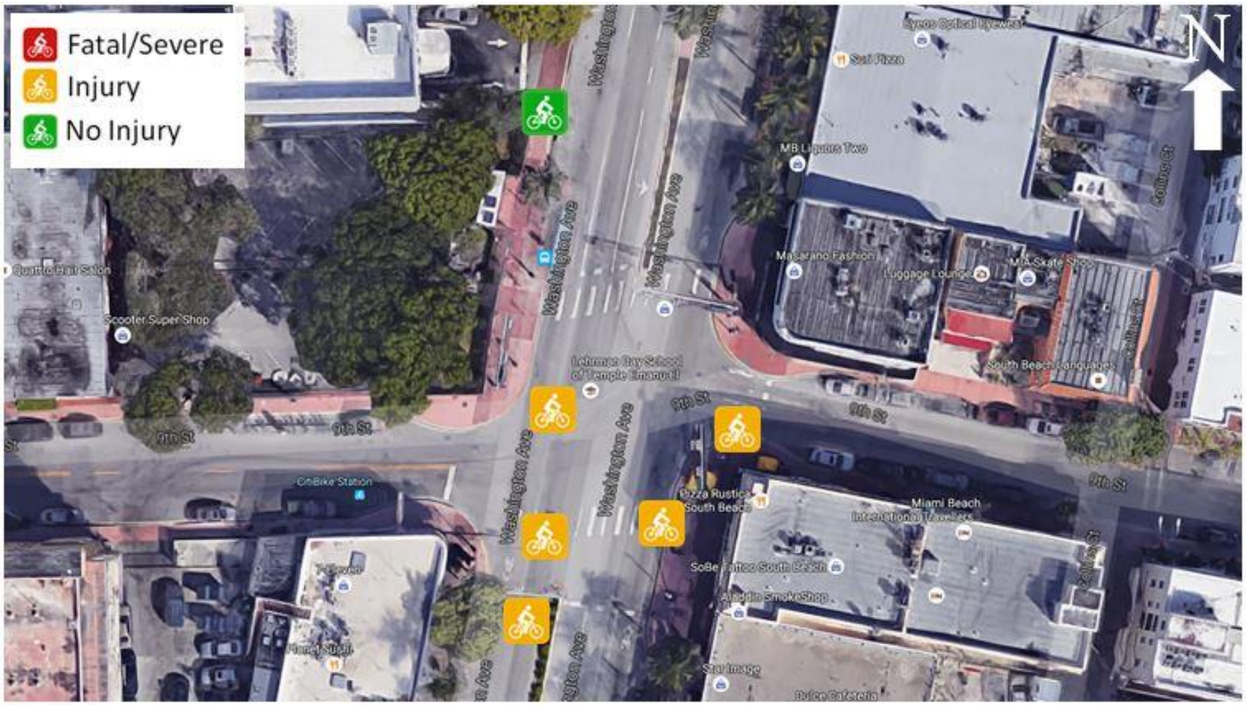


Figure 4-59: Washington Ave near 9th St in Miami Beach (Roadway ID: 87000000) ([Map](#))

Figure 4-60: N Roosevelt Blvd near 5th St in Key West (Roadway ID: 90010000) ([Map](#))

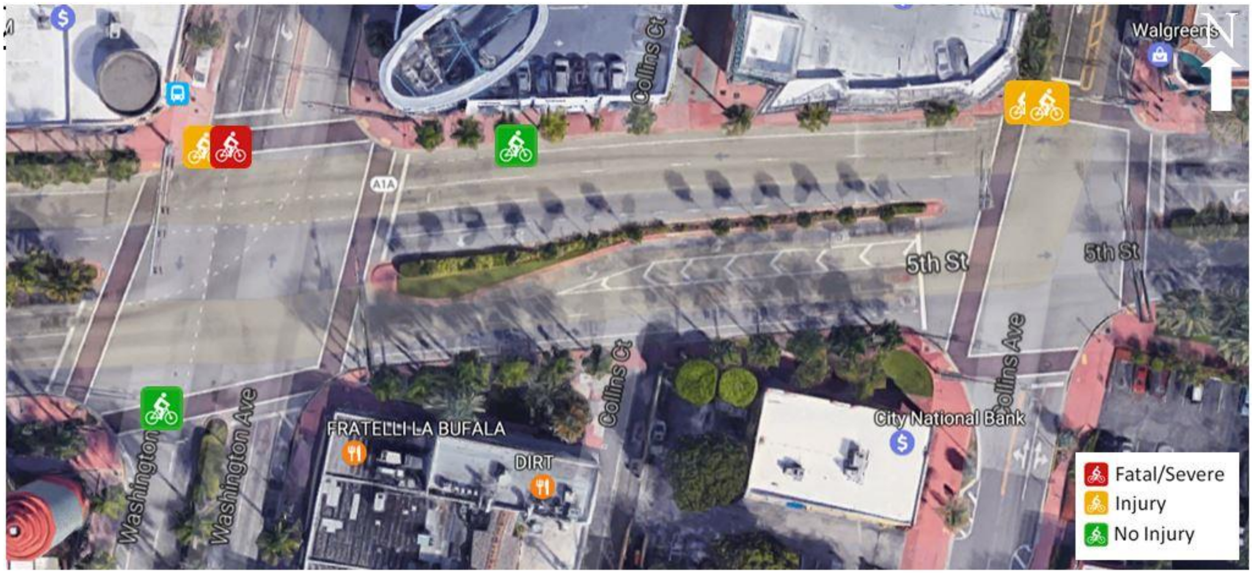


Figure 4-61: 5th St near Washington Ave in Miami Beach (Roadway ID: 87060000) ([Map]())

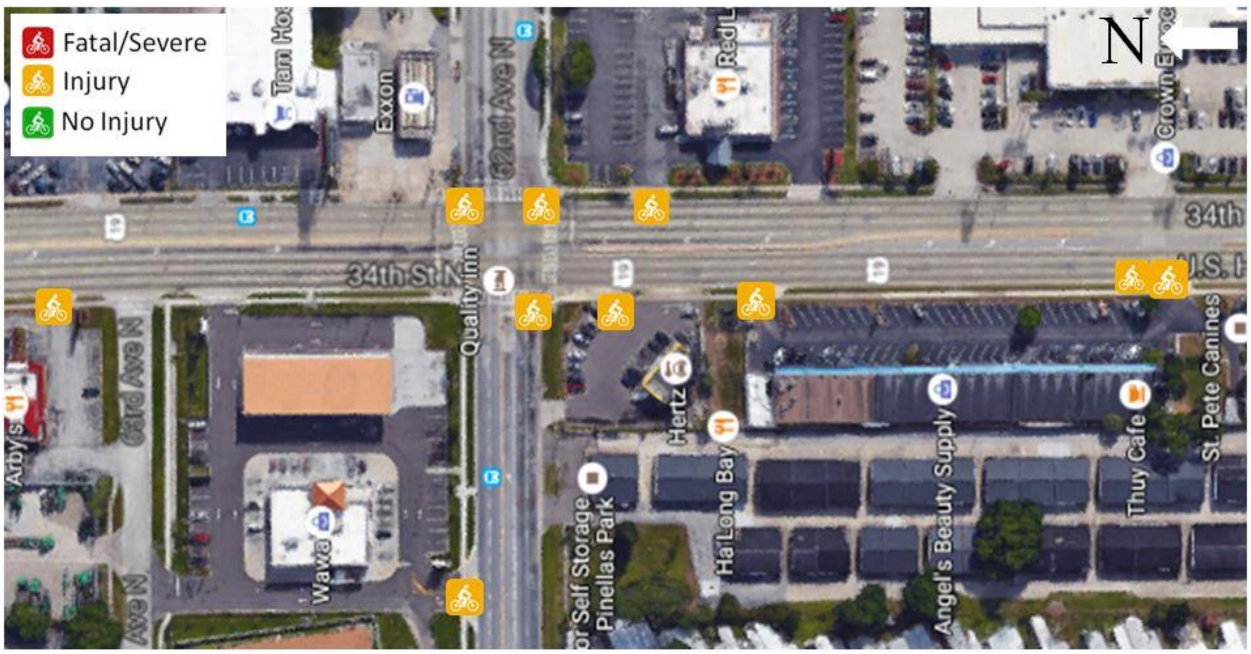


Figure 4-62: 34th St N near 62nd Ave N in St. Petersburg (Roadway ID: 15150000) ([Map]())

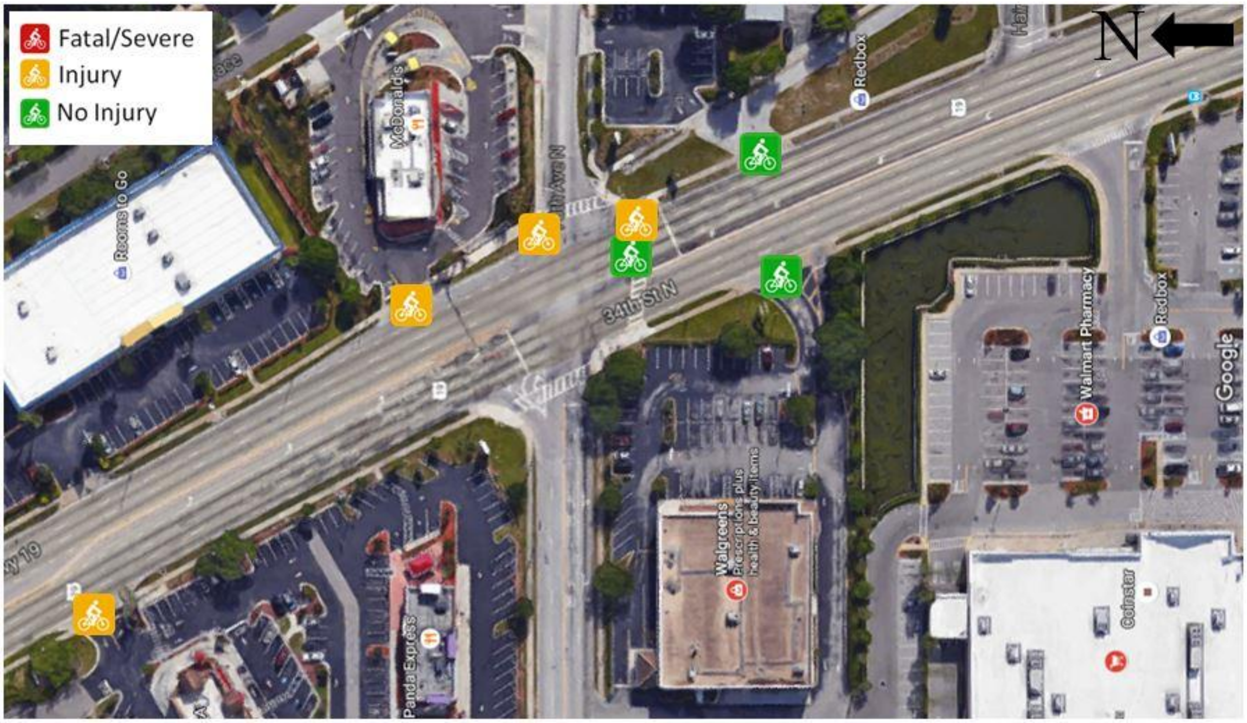


Figure 4-63: 34th St N near 70th Ave N in Pinellas Park (Roadway ID: 15150000) ([Map](#))

Figure 4-64: E Floribraska Ave near N Nebraska Ave in Tampa (Roadway ID: 10040000) ([Map](#))

Figure 4-65: E Busch Blvd near N Nebraska Ave in Tampa (Roadway ID: 10040000) ([Map](#))

4.4 Crash Contributing Factors and Potential Countermeasures

This section focuses on reviewing the police crash reports of bicycle crashes to identify factors that adversely affect the safety of bicyclists. The illustrative sketches and descriptions in the police reports of 2,888 bicycle crashes that occurred at the bicycle hot spots were reviewed, and the crash contributing factors related to these crashes were analyzed. The analysis identified the following major bicycle crash types:

- Motorist turns right while bicyclist is crossing the street
- Motorist turns left facing bicyclist
- Bicyclist rides out at intersection
- Motorist drives out at stop sign

It can be inferred from Table 4-13 that the first two crash types resulted in relatively more fatal crashes, while the other two types resulted in injury crashes. The following sections discuss these four crash types in detail. A discussion on potential countermeasures for each of these four crash types is also provided. It is worth noting that countermeasures included in this section would benefit both bicyclists and pedestrians.

4.4.1 Crashes Involving Right-Turning Vehicles

This crash type has two different scenarios: bicyclist riding *parallel* to the motorist, and bicyclist riding *perpendicular* to the motorist (i.e., bicyclist crossing the motorist). When bicyclists ride parallel to the motorists, especially at intersections, motorists often make a right turn unaware of the presence of bicyclists. Figure 4-66 illustrates this crash scenario. In this scenario, bicyclists are often found riding in the bicycle lane and crossing the road when they have the right of way. Drivers are found to be at-fault as they fail to yield to bicyclists.

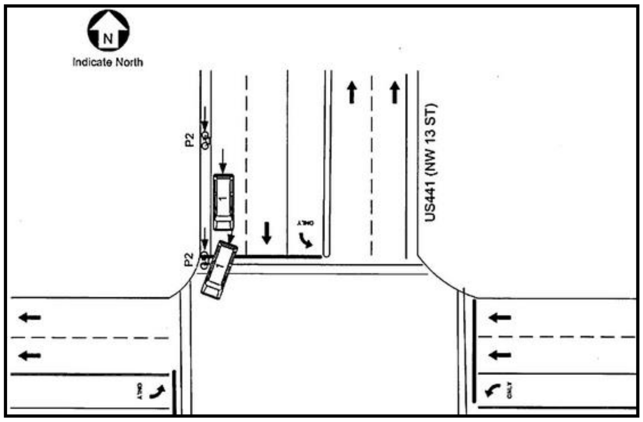


Figure 4-66: Bicycle Crash Involving Right-Turning Vehicle (Crash No. 821185140)

Bicycle crashes involving right-turning vehicles at unsignalized intersections were observed frequently. These crashes were found to often involve a motorist turning right from a side street or a driveway, and a bicyclist riding on the major street. At minor-road stop controlled and signalized intersections, motorists often make a right turn unaware of the bicyclist on the main street. Figure 4-67 illustrates this crash scenario. Drivers are considered to be at-fault in these scenarios as the driver is required to wait and look for bicyclists, pedestrians and traffic on the main street before making the right turn. In these scenarios, bicyclists are found to typically ride in the bicycle lane and cross the road when they have the right-of-way, thus hit the passenger side door of the vehicle during the crash.

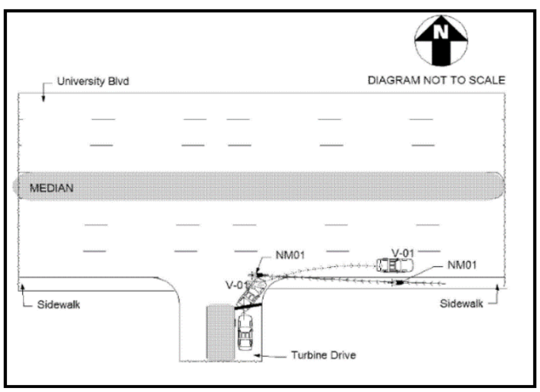


Figure 4-67: Driver Turns Right from Side Street While Bicyclist Rides along Main Street (Crash No. 836875880)

The right-turning vehicles are required to yield to bicyclists and pedestrians before making the turn; however, not all motorists comply with this traffic regulation. Sometimes the drivers do not expect other road users at these locations during their turn movements. A right-turn signal light could address this issue. However, turn restrictions could improve safety at locations where both the motorist turning proportion, and bicyclist and pedestrian volumes crossing the street are high.

At intersections with high right-turning traffic and pedestrian volumes, a leading pedestrian interval (LPI) could improve pedestrian safety. The LPI, also known as "Pedestrian Head Start" or "Delayed Vehicle Green" provides the "Walk" signal for additional 3-5 seconds before the adjacent through movement phase. This strategy gives pedestrians a head start while crossing the intersection, reducing conflicts between pedestrians in the crosswalk and the right-turning vehicles. At most intersections, since bicyclists and pedestrians use the same path, LPI could help improve bicycle safety as well.

Signal timing could be optimized to accommodate bicyclists. For example, minimum green intervals, red clearance, and extension time could be provided to ensure that bicyclists have sufficient opportunities to safely cross intersections. Bicycle activated signal detection could be used to minimize delay while facilitating safe crossing for the bicyclists. Other improvements including proper signage, colored pavement, curb radius reduction where feasible, sight distance and lighting improvements, speed tables/humps/cushions, etc. also have the potential to improve bicycle safety.

Bicyclists and motorists may not be familiar with all the traffic regulations, and this ignorance could lead to risky and reckless behavior. Traffic safety education targeting both bicyclists and drivers could help change the risk taking behavior of both drivers and bicyclists. Nonetheless, failure of motorists and bicyclists to follow traffic regulations often lead to crashes. Therefore, proper enforcement may increase road users' awareness and improve safety of all road users.

4.4.2 Crashes Involving Left-Turning Vehicles

This scenario where a motorist makes a left turn and finds bicyclist on the motorist's path is very common. The situation is similar to multi-vehicle crashes when drivers make a left turn and fail to yield to oncoming traffic. Typically, the bicyclist gets the green signal to cross the road at the same time when the motorist is permitted to turn left; however, the motorist is required to yield to bicyclists, pedestrians, and other oncoming traffic. Several crashes were however observed at night where motorists often did not see bicyclists as the bicyclists failed to make themselves visible through reflective clothing and bicycle lights. Figure 4-68 illustrates this scenario.

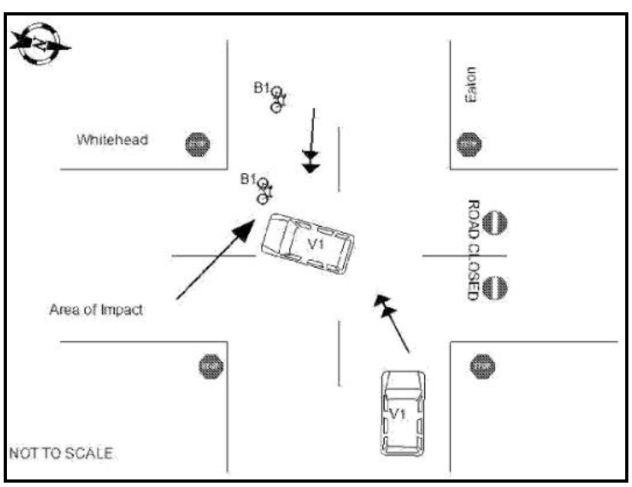


Figure 4-68: Driver Turns Left While Bicyclist Rides along Main Street (Crash No. 840177340)

At signalized intersections with permissive or protected-permissive left-turn phasing, the left-turning traffic has to yield to bicyclists and opposing through traffic prior to accepting the gap and turn. In such scenarios, the left-turning vehicles sometimes fail to yield to bicyclists crossing the street.

Intersections with permissive or protected-permissive left-turn phasing could potentially have a high number of conflicts involving bicyclists, pedestrians, oncoming traffic and left-turning vehicles. These conflicts could be eliminated with a protected left-turn phase. At intersections with a high frequency of bicycle and pedestrian crashes involving left-turning vehicles, the feasibility of providing protected left-turn signal phasing has to be considered. Although the locations may not warrant installation of protected left-turn signal phasing, their installation is recommended at locations with high bicycle and pedestrian activity such as at school zones and near special-event facilities. Furthermore, adding special bicycle-pedestrian signal phasing, such as exclusive protected bicycle-pedestrian signal could improve the overall safety of the location.

At unsignalized intersections and at midblock locations, motorists making left turn onto the side street could potentially hit a bicyclist riding on the major street. Figure 4-69 illustrates this scenario where a vehicle was making a left turn onto a driveway from opposite side of the major roadway, and hit the bicyclist who was riding along the major roadway. As can be observed from this scenario, mid-block openings encourage drivers to make a left turn from the far side of the road, but could increase the probability of bicycle or pedestrian crashes, especially at locations with high bicyclist and pedestrian activity.

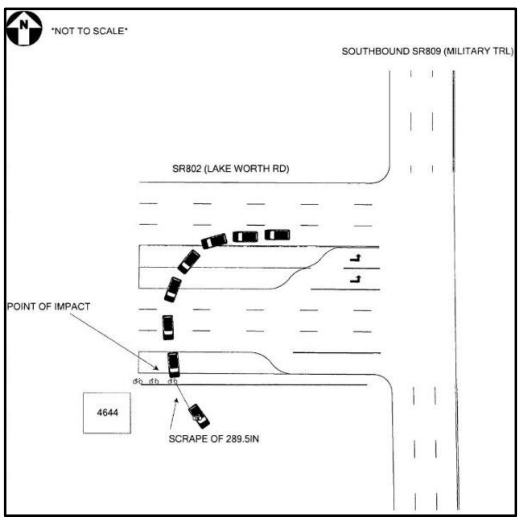


Figure 4-69: Left-turning Vehicle Resulted in Crash (Crash No. 813370290)

4.4.3 Crashes Involving Bicyclists Riding Out at Intersections

Crashes involving bicyclists riding out at intersections (i.e., bicyclists improperly crossing the streets) were found to occur frequently. Two common scenarios regarding this crash type include: bicyclist crossing the intersection from an unexpected location, and bicyclist crossing the intersection when they do not have the right of way. Figure 4-70 illustrates the crash scenario where the bicyclist crossed the intersection suddenly from an unexpected location. Figure 4-71 gives an example of a crash scenario when the bicyclist did not have the right of way. Motorists do not expect bicyclists to cross the street suddenly from unexpected locations, and definitely not when the bicyclists do not have the right of way. Even if the motorists notice the bicyclist, most of the time it is too late for the motorists to stop their vehicles to avoid the crash.

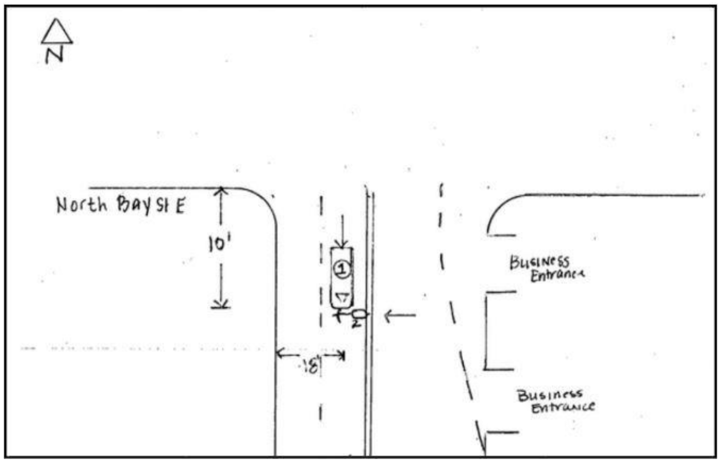
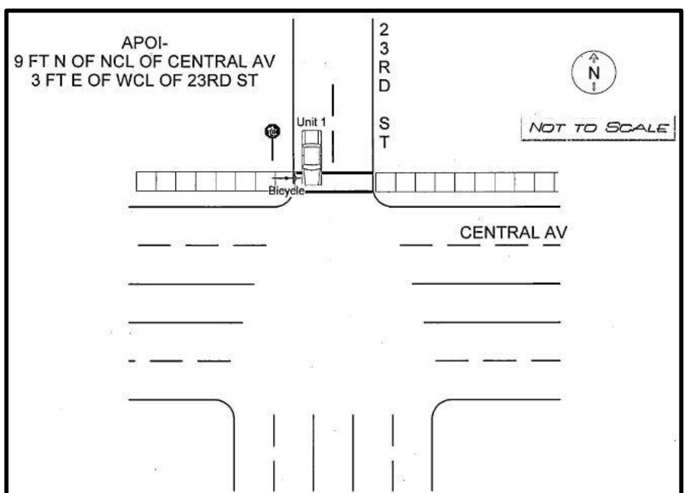


Figure 4-70: Crash Scenario When Bicyclist Rides Out Suddenly from Unexpected Location (Crash No. 519496080)



NARRATIVE	REPORTING AGENCY CASE NUMBER 2012-053732	HSMV CRASH REPORT NUMBER 83511618

-BICYCLE WAS RIDING SB ON THE SIDEWALK ON THE NORTH SIDE OF CENTRAL AV TOWARDS 23RD ST N. V1 WAS STOPPED AT THE STOP SIGN OF SB 23RD ST N FACING CENTRAL AV. V1 WAS CREEPING FOWARD TO SEE AROUND CARS PARKED ALONG THE WAY. BICYCLIST RODE INTO THE RIGHT FRONT FENDER OF V1 WITH THE FRONT OF BIKE. BICYCLIST WAS CITED FOR THE CRASH.

Figure 4-71: Crash Scenario When Bicyclist Rides Out at an Intersection (Crash No. 835116180)

These specific crash types could be attributed to bicyclist's inattention, bicyclist's lack of perceived understanding of speed, and lack of enforcement. Bicyclists are often unaware of the rules and right-of-way at bicycle-vehicle conflict points. Strict and consistent enforcement could change the bicyclist's behavior. Sign and pavement marking improvements and traffic calming measures could improve both bicyclist and pedestrian safety.

4.4.4 Crashes Involving Motorists Driving Out at Stop Signs

Disregarding a stop sign by drivers often result in crashes with bicyclists. Figure 4-72 illustrates this scenario. Review of the police crash reports revealed that bicyclists are often hit by drivers who disregard the stop signs. At a minor-road stop-controlled intersection, bicyclist riding along the main street has the right of way, and the driver on the minor approach has to yield to bicyclists, pedestrians, and vehicles on the main street. However, in several crashes, drivers on the minor approach did not yield to the bicyclists riding on the major street, resulting in often severe bicycle-motor vehicle crashes. In these scenarios, drivers are considered to be at-fault.

Bicycle crashes that involve motorists driving out at a stop sign could be due to lack of drivers' perceived expectancy, understanding, education, and lack of proper enforcement. Therefore, colored pavements, placement of proper signage, speed humps, which can alert drivers to stay cautious might improve bicycle safety. Drivers and bicyclists are often unaware of the rules and right-of-way, especially at unsignalized intersections. Strict and consistent enforcement may change the drivers' behavior and improve bicycle safety.

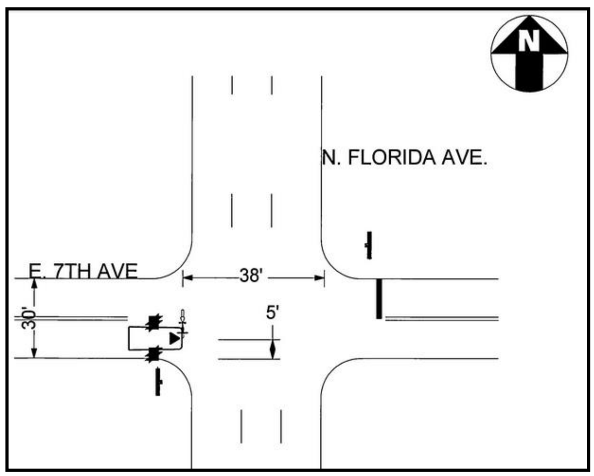


Figure 4-72: Crash at Minor-road Stop-controlled Intersection Where Driver Disregarded a Stop Sign (Crash No. 519551710)

4.4.5 Additional Contributing Factors

In addition to the above-discussed crash types, the following factors and crash types were also observed frequently. Note that the potential countermeasures for these scenarios are similar to what are discussed earlier, and therefore, are not presented again in this section.

- *Inadequate Street Lighting:* Visibility of bicyclists is a serious concern, especially at night. Inadequate street lighting, and lack of reflective gear on bicyclists were found to be one of the major reasons for bicycle crashes at night. Improving street lighting, and encouraging bicyclists to make themselves visible at night by wearing reflective clothing could minimize crash risks involving bicyclists at night.

- *Unconventional Intersection Geometry:* Uncommon intersection geometry sometimes confuses road users, making it difficult to clearly follow the signs and signals. Figure 4-73 gives an example of a bicycle crash at an unconventional intersection.

- *Traffic Violations:* Disregarding traffic rules was found to be a major contributing factor in several bicycle crashes. Both bicyclists and motorists were found to disregard traffic signals. Figure 4-74 shows an example of a crash where the bicyclist was riding against the traffic, made an improper crossing maneuver, and most importantly ignored the traffic signal, resulting in a serious crash. Again, these crashes could be attributed to lack of bicyclist's understanding of the rules of the road, and bicyclist's inattention.

- *Bicyclists Sideswipe Vehicles:* Bicyclists, when they share the road with motor vehicles, sometimes lose control and sideswipe other vehicles (see Figure 4-75). Narrow lanes, high speeds, wide vehicles, and distracted drivers were found to be some of the factors contributing to these types of crashes.

- *Driveways Near Intersections:* Drivers sometimes make sudden lane changing or turning maneuvers when they want to access the driveways (e.g., gas station) in close proximity to intersections. Such sudden maneuvers are not perceived or expected by bicyclists, and often result in crashes.

- *U-turn Maneuvers:* U-turn maneuvers at intersections and also at mid-block openings resulted in crashes involving bicyclists. Figure 4-76 illustrates one such scenario. In this case, both the driver and the bicyclist were attempting to make a U-turn, and resulted in a crash.

- *Bicyclists Hit the Door of Parked Vehicle:* This scenario is quite common, especially at locations with high bicycle activity and availability of on street parking. Drivers often open driver-side doors, and sometimes result in bicyclists hitting the vehicle door (see Figure 4-77).

- *Bicyclists Ride Opposite to the Traffic:* Bicycling on the wrong-way, against the traffic, was found to be one of the leading causes of bicycle crashes. Bicyclists often consider riding against the traffic to be safer as bicyclists could see approaching vehicles, and the drivers could see the bicyclists. However, drivers pulling out of driveways or turning from intersections do not expect traffic coming the wrong way, increasing the possibility of crashes, particularly the more severe head-on crashes. Moreover, these crashes are often serious because of the speed differential between the bicyclist and approaching traffic. Figure 4-78 gives an example of this scenario.

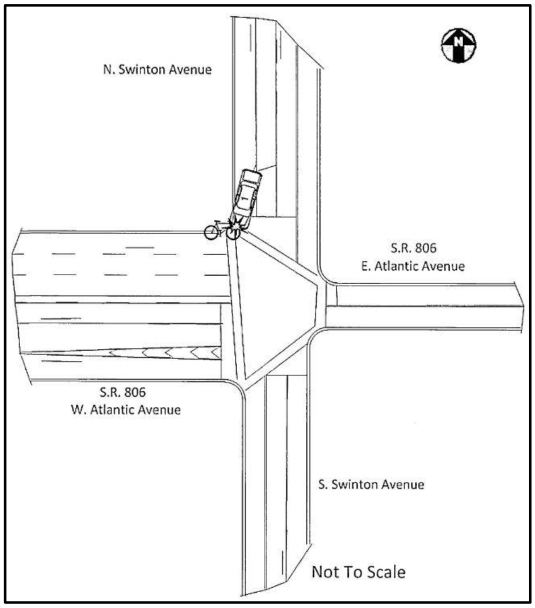


Figure 4-73: Bicycle Crash at an Unconventional Intersection (Crash No. 846913640)

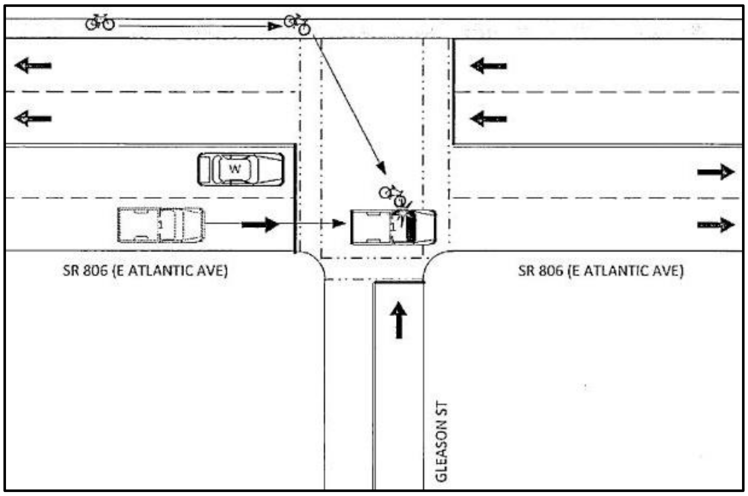


Figure 4-74: Crash Where Bicyclist Violated Traffic Signs (Crash No. 846908950)

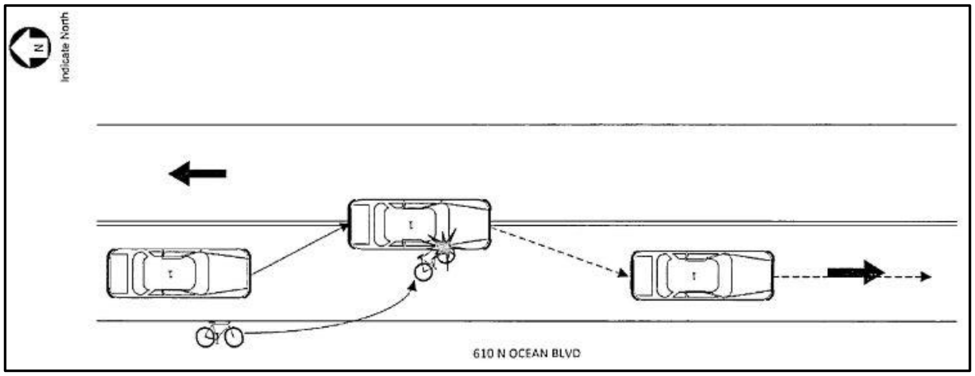


Figure 4-75: A Sideswipe Bicycle Crash (Crash No. 843286450)

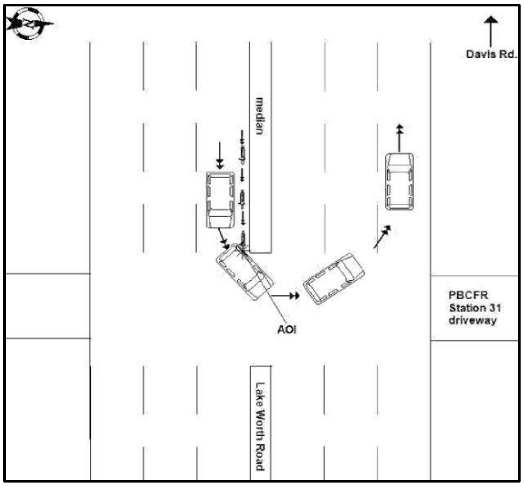


Figure 4-76: Bicycle Crash Involving U-turn Maneuvers (Crash No. 836247400)

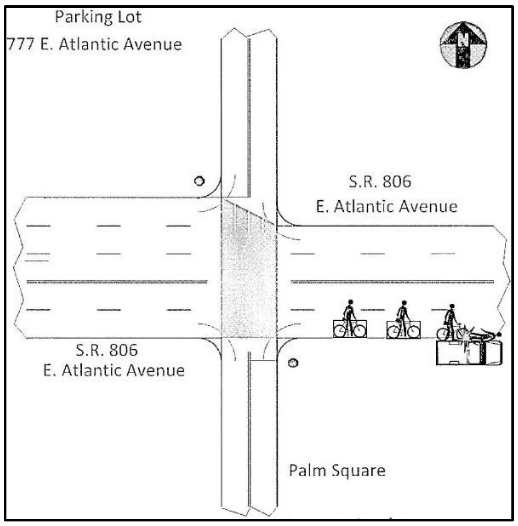


Figure 4-77: Bicycle Crash Involving Parked Vehicle (Crash No. 843282080)

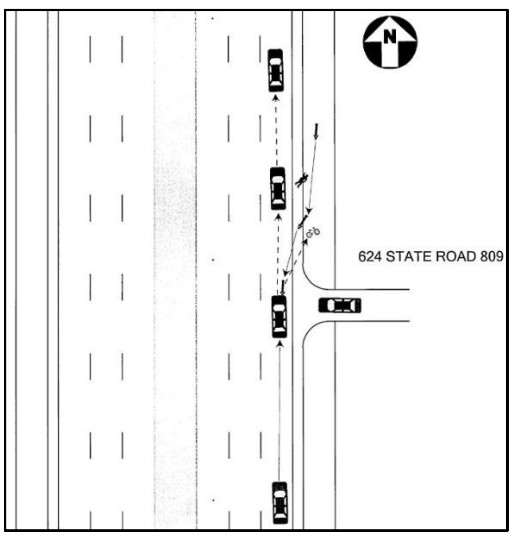


Figure 4-78: A Head-on Bicycle Crash (Crash No. 813392340)

4.5 Summary

This chapter focused on identifying and analyzing locations with high bicycle crash frequencies in Florida. Top five bicycle hot spots in each district were identified using spatial analysis in ArcGIS. Police reports of all the 2,954 bicycle crashes that occurred at these hotspots were reviewed in detail to identify specific bicycle crash types and patterns. The key findings include:

- Drivers were at-fault in 45.7% of the crashes, while bicyclists were at-fault in 30.2% of the crashes.
- Crashes involving at-fault bicyclists resulted in a greater percentage of fatal crashes compared to those involving at-fault drivers.
- Signalized intersections experienced a greater proportion of bicycle crashes compared to unsignalized locations.
- Locations with bicycle lanes experienced a smaller proportion of fatal crashes compared to locations without bicycle lanes.
- Crossing the street was found to result in a greater proportion of fatal crashes compared to riding along the roadway.
- Crashes involving bicyclists riding along the roadway facing traffic resulted in a greater proportion of fatal crashes compared to crashes involving bicyclists riding along with vehicles.
- Crosswalk locations, although experienced a high frequency of bicycle crashes, experienced a relatively low proportion of fatal crashes.

The crash pattern analysis identified the following four major bicycle crash types:

- Motorist turns right while bicyclist is crossing the street
- Motorist turns left facing bicyclist
- Bicyclist rides out at intersection
- Motorist drives out at stop sign

These four crash types were analyzed in detail, and a discussion on potential countermeasures was provided. Engineering countermeasures, including signal optimization, turn restrictions, and sign and pavement marking improvements, could improve the overall safety situation for bicyclists. Agency-wide education campaigns on the laws pertaining to bicyclists could improve bicycle safety. Furthermore, extensive driver education campaigns that focus on driver compliance with bicyclist right-of-way laws and stricter enforcement could prevent bicycle crashes that were due to driver error.

CHAPTER 5
MACROSCOPIC ANALYSIS OF BICYCLE CRASHES

This chapter focuses on analyzing demographic and socio-economic factors affecting bicycle safety. It first introduces the spatial analysis framework, and then explains the Bayesian modeling approach developed to predict the relation between variables at the census block group level and bicycle crash frequencies in Florida. The chapter then discusses the demographic, socio-economic, roadway, traffic, and bicycle activity data preparation efforts. The model results along with detailed discussion are then provided.

5.1 Background

The relationship between crash occurrence and its contributing factors is investigated using crash frequency models. The models can be divided into two broad categories: micro-level or disaggregate models, and macro-level or aggregate models. In micro-level crash analysis, crashes are analyzed along the roadway segments, ramps, and intersections with an intent to determine geometric design features and traffic attributes contributing to crashes, identify hot spots, and suggest countermeasures to reduce crashes. On the other hand, in macro-level analysis, crashes are aggregated over some geographic areas and analyzed with an intent to identify socio-demographic, land use, infrastructure-related contributing factors, which can shape long-term planning and policy implications in improving safety within an area.

Analyzing bicycle crashes in the context of disaggregate modeling has the following issues: bicycle crashes are rare and often severe (e.g., bicyclists are more likely to be severely injured) compared to other motor-vehicle crashes; bicycle exposure is different from vehicle exposure and is difficult to quantify; and bicycle crash trends are quite distinctive and are dependent on land use, bicycle infrastructure, socio-economic and demographics factors, etc. Macro-level crash prediction models are therefore more popular in analyzing bicycle crashes (Amoh-Gyimah et al., 2016; Lee et al., 2015; Wedagama et al., 2006; Wei and Lovegrove, 2013). In this study, bicycle crash frequencies were analyzed at the macro-level.

Previous research on macro-level crash analysis used a wide array of areal units such as block groups (Abdel-Aty et al., 2013), census tracts (Abdel-Aty et al., 2013; Ukkusuri et al., 2011; Wang and Kockelman, 2013), cities (Moeinaddini et al., 2014), counties (Aguero-Valverde and Jovanis, 2006, Amoros et al., 2003; Huang et al., 2010; Noland and Oh, 2004), districts (Haynes et al., 2007), enumeration districts (Wedagama et al., 2006), local health areas (MacNab, 2004), statistical area level zones (Amoh-Gyimah et al., 2016), traffic analysis zones (Abdel-Aty et al., 2013; Ladron de Guevara et al., 2004; Lee et al., 2015; Siddiqui et al., 2012; Wei & Lovegrove (2013), traffic safety analysis zones (Lee et al., 2014b), uniform grid structures (Kim et al., 2006), wards (Quddus, 2008), and zip codes (Lee et al., 2014a). There is no single consensus on which neighborhood design should be adopted. In this study, analysis was conducted at the census block group level. A census block group is the smallest geographic entity for which the United States Census Bureau publishes data decennially (United States Census Bureau, 2012).

5.2 Methodology

The following approaches were undertaken in this study to analyze the presence and effect of spatial correlation in bicycle crashes among census block groups in Florida:

- Global Index of Spatial Autocorrelation
- Hierarchical Bayesian Analysis

5.2.1 Global Index of Spatial Correlation

A measure of global index assesses the spatial pattern of the data over the entire geographic area. The two most commonly used global indices to measure spatial correlation are Moran's *I,* and Geary's *C*, which are defined as follows (Serra-Sogas et al., 2008):

$$\text{Global Moran's } I: \quad I_G = \frac{n \sum_i \sum_j \omega_{ij} \left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{\sum_{i \neq j} \sum_j \omega_{ij} \sum_i \left(y_i - \bar{y}\right)^2} \tag{5-1}$$

$$\text{Global Geary's } C: \quad C_G = \frac{(n-1) \sum_i \sum_j \omega_{ij} \left(y_i - y_j\right)^2}{2 \sum_{i \neq j} \sum_j \omega_{ij} \sum_i \left(y_i - \bar{y}\right)^2} \tag{5-2}$$

where,

n	=	number of spatial units indexed by i and j,
ω_{ij}	=	weight assigned to the pair of spatial units i and j $(i \neq j)$ depending on spatial adjacency between the units; $\omega_{ij} = 1$ if spatial units i and j are neighbors (i.e., share a common boundary), $\omega_{ij} = 0$ for non-neighbors;
y_i, y_j	=	observed value of the variable y at spatial units i and j, respectively; and
$\bar{y}$	=	mean of the variable y.

The values of I_G typically range between -1 and 1. A positive value of I_G indicates a pattern of spatial clustering, a negative value of I_G indicates a pattern of spatial dispersion, and a value of I_G close to zero indicates no spatial association. On the other hand, the values of C_G range from 0 to 2, where values less than 1 imply positive correlation or a pattern of clustering, values greater than 1 imply negative association or a pattern of spatial dispersion, and values close to 1 indicate no spatial association (Serra-Sogas et al., 2008). The statistical significance test, irrespective of I_G or C_G, is based on the null hypothesis that the variable of interest has no spatial association over the geographic region of the study area.

The statistical significance of Moran's *I* and Geary's *C* was tested using the Monte Carlo simulation procedure in this study, as recommended by Banerjee et al. (2004). The Monte Carlo approach requires no pre-assumption about the distribution of data; rather it generates a reference distribution of I_G by computing its value a number of times by randomly permuting the observed values of the variable of interest around the spatial units. An empirical p-value is then determined by locating the actual I_G computed from the data as given (i.e., with no permutation) within the generated distribution of I_G under the null hypothesis of no spatial association. Note that the use of these indices must be restricted for preliminary assessment of spatial association (Banerjee et al., 2004).

5.2.2 Hierarchical Bayesian Modeling

Earlier studies (e.g., Noland and Quddus, 2004; Wedagama et al., 2006; Lovegrove and Sayed, 2006) applied traditional NB models to analyze macro-level bicycle crashes. NB regression is a widely used approach in developing crash frequency models as it accounts for overdispersion present in crash data. The regression is based on the assumption that observations are independent. In reality, crash aggregation over contiguous areas tends to introduce spatial autocorrelation between the observations. Spatial autocorrelation is said to exist when spatial units that are adjacent to one another in space have similar data values (Dale and Fortin, 2002). The assumption of full independence among the observations is thus violated in traditional NB models for macro-level crash analysis. In other words, ignoring the possible effect of spatial autocorrelation among neighborhoods in macro-level data might lead to inaccurate results. As a remedy, Aguero-Valverde and Jovanis (2006), Huang et al. (2010), Quddus (2008), Siddiqui et al. (2012), and Wang and Kockelman (2013) used hierarchical Bayesian model that is capable to capture the effects of spatial correlation and unobserved heterogeneity (i.e., overdispersion) in data.

Hierarchical Bayesian modeling is the most popular approach to take account of spatial correlation in the data. Bayesian inference provides a comprehensive and robust estimates of model parameters by a probability distribution rather than a point estimate provided by the classical regression model. Within a Bayesian framework, a data model is specified using a probability distribution such as $p(y|\Theta)$ that represents the likelihood of the observed data $y = (y_1, y_2, ..., y_n)$ given a set of unknown parameters $\Theta = (\Theta_1, \Theta_2, \dots, \Theta_k)$. Next, each of the parameters is specified with a probability distribution based on knowledge obtained from previous research or experience. Such a setting of probability distribution is known as prior distribution or simply prior. The prior, $p(\Theta|\lambda)$, is conditioned on hyperparameters λ. The posterior distribution of model parameters is then computed as follows (Saha et al., 2017):

$$p(\Theta|y, \lambda) = \frac{p(y|\Theta)p(\Theta|\lambda)}{\int p(y|\Theta)p(\Theta|\lambda)d\Theta} \tag{5-3}$$

In most cases, λ is unknown and an additional distribution about λ, known as hyperpriors $h(\lambda)$, is required. Equation 5-3 then takes the following form:

$$p(\Theta|y, \lambda) = \frac{p(y|\Theta)p(\Theta|\lambda)h(\lambda)}{\int p(y|\Theta)p(\Theta|\lambda)h(\lambda)d\Theta d\lambda} \tag{5-4}$$

A Poisson-lognormal model is typically employed in Bayesian hierarchical structure to replicate the underlying non-negative distribution of crash data in the NB model, while accounting for unobserved heterogeneity and spatial correlation. The specification of the Poisson-lognormal model for spatial analysis of bicycle crashes is as follows (Quddus, 2008; Siddiqui et al., 2012):

- The crash counts data by spatial units (e.g., census block groups), Y_i, are assumed to have a Poisson distribution with the mean parameter λ, also called risk of crash outcome y at the census block group i:

$$Y_i \sim \text{Poisson}(\lambda_i) \tag{5-5}$$

- The risk λ_i is modeled as a function of the intercept, the covariates, and random effects using a "log" link function:

$$\log(\lambda_i) = \beta_0 + \beta X_i + u_i + s_i \tag{5-6}$$

where, β_0 is the intercept, $\beta = (\beta_1, \beta_2, \ldots, \beta_K)$ is a vector of parameters associated with K covariates (e.g., demographic and socio-economic factors, traffic-related features, etc.), u_i and s_i are two random effects. Note that the parameters β are modeled as fixed effects. The random effect u_i is known as unobserved heterogeneity that accounts for extra-Poisson variability (i.e., overdispersion) in the data and varies globally, i.e., over the entire spatial area. On the other hand, s_i is the random effect for spatial correlation (i.e., correlated heterogeneity) that varies locally. In other words, it accounts for spatial association such that adjacent spatial units are likely to have similar outcomes.

- The following priors were assigned for the intercept β_0, the set of parameters β_k, and the random effect for unobserved heterogeneity u_i:

$$\beta_0 \sim \text{N}(0, 0) \tag{5-7}$$

$$\beta_k \sim \text{N}(0, 0.001) \; \textit{for } k = 1, 2, \cdots, K \tag{5-8}$$

$$u_i \sim \text{N}\left(0, \frac{1}{\tau_u}\right) \tag{5-9}$$

where τ_u is the precision. The prior distribution for spatial correlation u_i is specified by a conditional autoregressive (CAR) prior, as recommended by Besag (1974). Based on the conditional independence property of Markov random field, the CAR prior can be expressed as:

$$s_i | s_{-i} \sim \text{N}\left(\frac{1}{\sum_{i\sim j} w_{ij}} \sum_{i\sim j} w_{ij} s_j \, , \, \frac{1}{\tau_s \sum_{i\sim j} w_{ij}}\right) \tag{5-10}$$

where w_{ij} is the element of the adjacency matrix W and is equal to 1 if i and j are neighbors and is 0 otherwise, and τ_s is the precision.

- The following non-informative hyperpriors are specified for the hyperparameters τ_u and τ_s:

$$\tau_u \sim \text{Gamma}(0.001, 0.001) \tag{5-11}$$

$$\tau_s \sim \text{Gamma}(0.1, 0.1) \tag{5-12}$$

5.3 Data Preparation

The U.S. Census Bureau divided the state of Florida into 11,442 census block groups in its latest decennial census in 2010. Florida's census block groups data were obtained in GIS layers from the Florida Geographic Data Library (FGDL), which is a warehouse of geospatial data collected from local, state, federal, and private agencies. The dataset was scrutinized to make sure that census block groups met the following two criteria: (i) no census block groups should have zero population, and (ii) all the census block groups must have at least one neighbor. It was found that that several census block groups represent water body only, while several others have land area without any population. These census block groups were therefore excluded from analysis. To identify neighbors between census block groups, the common boundary definition of neighborhood was followed: if a pair of census block groups share a common boundary, they are called neighbors. Note that areas in contact with each other only at their corners were not considered neighbors. A single census block group was found to be in complete isolation from the rest of the census block groups and therefore, was excluded from analysis. Finally, a total of 11,355 census block groups were included in the analysis.

A square neighborhood matrix was formed based on the adjacency information, where each element c_{ij} has the value 1 if i and j are neighbors; otherwise, the value is zero including the diagonal elements c_{ii}.

Four years (2011-2014) of crash data were obtained in GIS layers from FDOT's Unified Basemap Repository (UBR) for both on-system and off-system roads in Florida. Bicycle crashes were identified from the binary variable FL_VRU_BIK; the value "Y" of this variable indicates that a bicyclist was involved in a crash. Bicycle crashes were then mapped to census block groups. An inherent problem of such mapping is associated with crashes those are located on the boundary between two or more neighboring areas, which may lead to over-counting of crashes (Fotheringham and Wegner, 2000; Lovegrove and Sayed, 2006). Another problem was associated with crash location errors when crashes were mapped outside the bordering census block groups (i.e., beyond the state boundary). To circumvent both issues, a near analysis was performed using ArcGIS tool. No radius was specific in the near analysis to assign crashes to the nearest census block group and thereby ensuring single as well as no omitted count of bicycle crashes. The number of bicycle-related crashes in each census block group was then counted for all crash severity levels. This study investigated census block group-level bicycle crashes for the following two injury levels: total crashes, and F+S crashes. Total crashes included crashes with severities reported as fatal, incapacitating injury, non-incapacitating injury, possible injury, property damage only, non-fatal traffic casualty, and unknown. F+S crashes were defined as those that resulted in either fatality (injury level = 5) or incapacitating injury (i.e., injury level = 4). Figures 5-1 and 5-2 show the spatial distribution of total and F+S bicycle crashes, respectively, at census block groups in Florida.

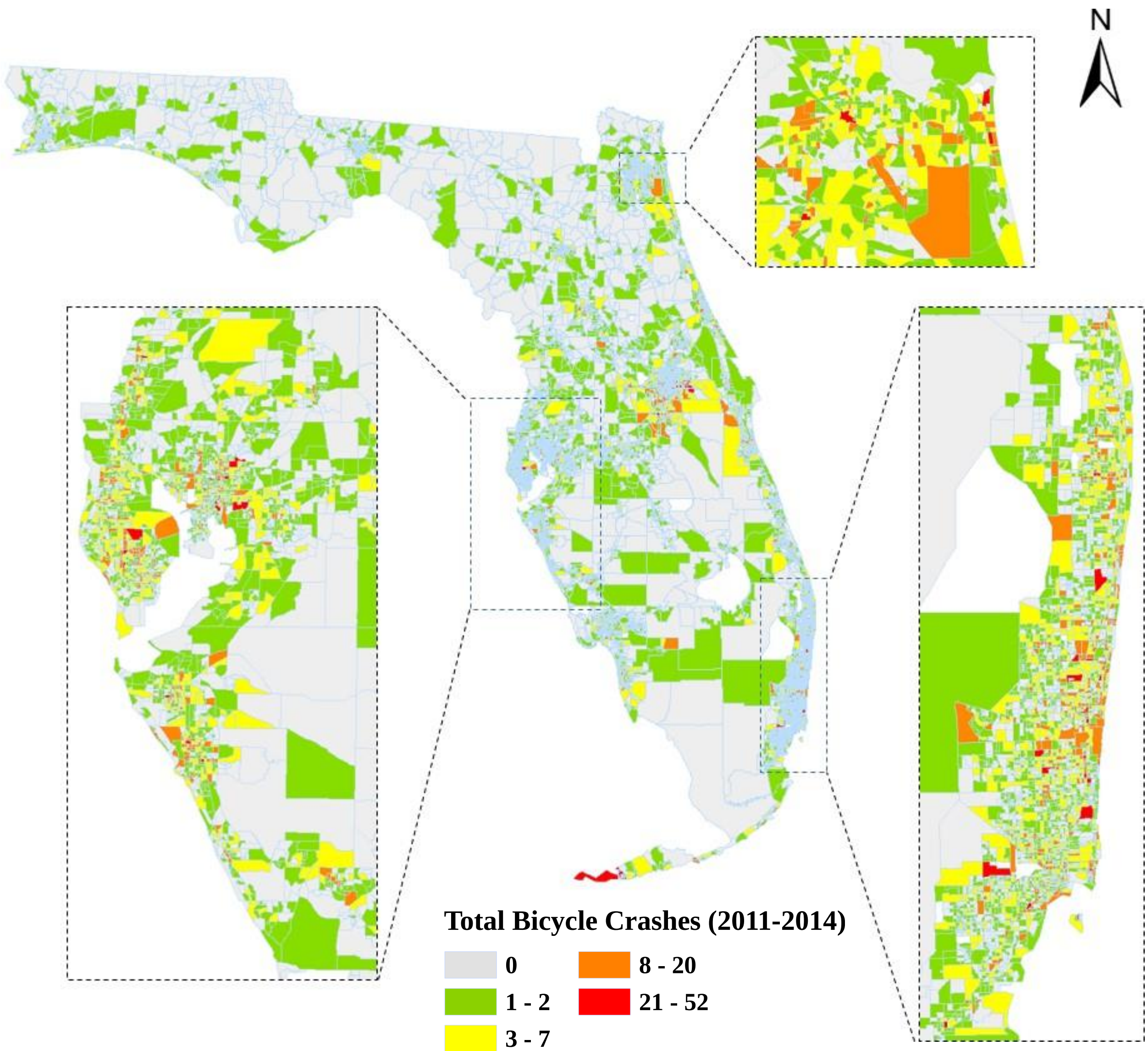


Figure 5-1: Spatial Distribution of Total Bicycle Crashes (2011-2014) at Census Block Groups in Florida

The explanatory variables considered in this study to perform spatial analysis of bicycle crashes could broadly be grouped into the following three categories (see Table 5-1):

- demographic and socio-economic characteristics,
- roadway and traffic characteristics, and
- *Strava* users' ride characteristics.

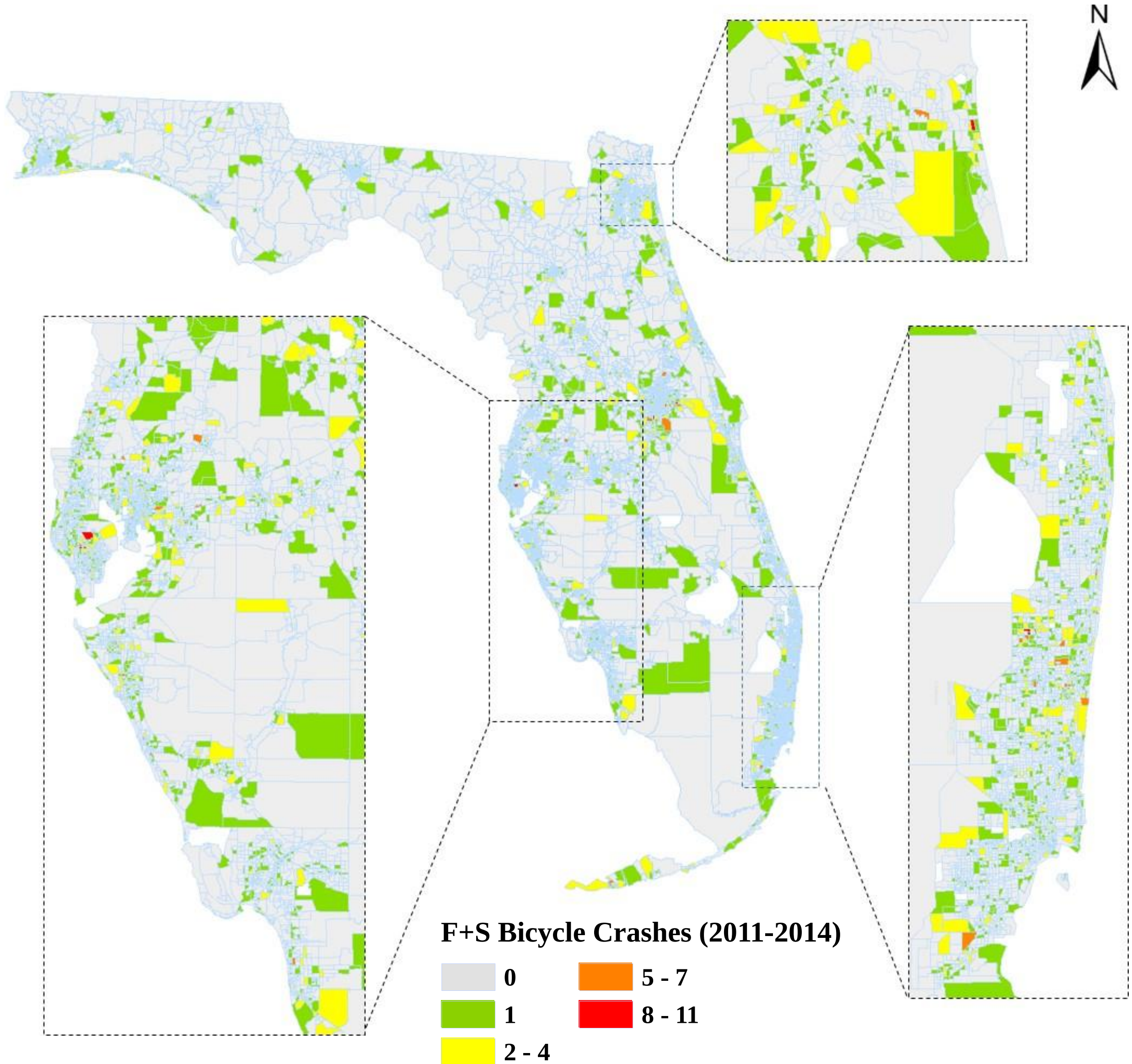


Figure 5-2: Spatial Distribution of Fatal and Severe Injury Bicycle Crashes (2011-2014) at Census Block Groups in Florida

5.3.1 Demographic and Socio-economic Characteristics

The demographic and socio-economic characteristics of census block groups for the state of Florida were obtained from the U.S. Census Bureau's 2010-2014 American Community Survey (ACS). The ACS data are released annually and reflect recent updates from the 2010 decennial census data. The 2014 ACS data were retrieved from the FGDL data library. The dataset contains more than 150 variables. Since it is not practical to consider all the 150 variables in developing models, only the variables that could potentially affect bicycle safety were extracted. Table 5-1 lists the variables considered in the analysis.

5.3.2 Roadway and Traffic Characteristics

The following roadway and traffic data variables were extracted from the 2014 RCI database (the name in the parentheses gives the description of the variable).

- FUNCLASS (functional classification)
- AADT (annual average daily traffic)
- AVGTFACT (section average truck factor)
- BIKELANE (presence of bicycle lane)
- BIKESLOT (presence of bicycle slot)

The 2014 RCI database included bicycle lane information for approximately 1,100 miles of road network. However, the GIS shapefile for bicycle lanes included this information for nearly 1,600 miles. Since the GIS shapefile provided a more complete inventory of the road network with bicycle lanes, the bicycle lane shapefile was used in the analysis. Similarly, since the GIS shapefile for bicycle slots provided a more complete information compared to the RCI database, GIS shapefile for bicycle slot was used in the analysis. Both the Bicycle Lanes and Bicycle Slots shapefiles were separately intersected with the census block group layer to estimate the miles of bicycle lanes and bicycle slots in each census block group. The combined length of bicycle facilities (i.e., bicycle lanes and bicycle slots) was obtained and included in the analysis.

Finally, only the functional classification, AADT, and truck factor variables were extracted from the 2014 RCI database. Since geographical coordinates of these features were not available, the following steps were performed to locate them within census block groups.

- *Step 1:* Functional Classification GIS shapefile for the year 2016 was downloaded from FDOT's GIS data library.

- *Step 2:* Segments that are part of rural and urban principal arterials - interstate, freeways, and expressways were excluded.

- *Step 3:* The generated non-freeway roadway segments layer was used to create routes for linear referencing. Individual RCI roadway features for the year 2014 were located along linearly referenced routes based on roadway ID, begin milepost, and end milepost. After performing linear referencing, each of the attributes was saved as layer files.

- *Step 4:* A geometric intersection between the individual roadway characteristics layer and the census block group layer was performed to locate features within census block groups. Note that because of proximity error near to the boundaries, a few road segments (< 0.5% of road network) could not be included in the analysis.

As shown in Table 5-1, rural arterials consist of roadway segments under rural principal arterial – other and rural minor arterial, rural collectors consist of rural major collector and rural minor collector roads, urban arterials consist of urban principal arterial – other and urban minor arterial, and urban collectors consist of urban major collector and urban minor collector. Roadway length is obtained by adding roadway lengths of rural arterials, rural collectors, rural local roads, urban arterials, urban collectors, and urban local roads.

Table 5-1: Descriptive Statistics per Census Block Group

Variable	Min	Max	Mean	Std. Dev.
Crash Characteristics				
Total number of bicycle crashes	0	52	2.45	3.71
Number of fatal and severe crashes involving bicyclists	0	11	0.38	0.86
Demographic and Socio-economic Characteristics				
Log of total population	1.95	10.48	7.25	0.63
Log of population density per sq. mi. of area	-5.17	11.81	7.54	1.57
Log of households	0	9.86	6.27	0.65
Log of households density per sq. mi. of area	-5.75	10.98	6.57	1.60
Household income in thousands	0	250	51.19	27.27
Proportion of population below poverty line	0	100	17.47	14.54
Proportion of households with no automobile	0	100	7.93	10.07
Proportion of households with one automobile	0	100	41.54	16.28
Proportion of male population	0	100	48.79	7.08
Non-Hispanic White population	0	100	59.58	30.87
Black or African American population	0	100	15.91	23.37
Hispanic or Latino population	0	100	21.02	24.53
Asian population	0	51.12	2.12	3.82
Proportion of population of other races: American Indian and Alaska Native, Native Hawaiian and Other Pacific Islander, Multiracial, and others	0	63.15	4.70	5.92
Proportion of population aged 5 - 17 years	0	52.35	13.92	7.59
Proportion of population aged 18 - 29 years	0	100	14.79	10.26
Proportion of population aged 30 - 39 years	0	100	11.45	6.60
Proportion of population aged 40 - 49 years	0	72.46	13.11	6.14
Proportion of population aged 50 - 64 years	0	100	20.93	7.96
Proportion of population aged 65 years and above	0	100	20.62	16.68
Proportion of population 16 years and above employed	0	100	42.53	12.45
Proportion of population 3 years and above enrolled in school	0	100	22.15	10.76
Proportion of population 25 years and above having no school diploma	0	89.73	14.11	11.76
Proportion of population 25 years and above having high school diploma only	0	100	30.07	11.94
Proportion of population 25 years and above having Associate's degree or attended some college with no degree achieved	0	100	29.57	9.53
Proportion of population 25 years and above having Bachelor's degree or higher	0	100	26.26	17.60
Roadway and Traffic Characteristics				
Density of rural arterials per sq. mi. of area	0	3.26	0.026	0.11
Density of rural collector roads per sq. mi. of area	0	2.42	0.03	0.12
Density of rural local roads per sq. mi. of area	0	13.09	0.02	0.202
Length of urban principal arterials per sq. mi. of area	0	17.16	1.11	1.51
Length of urban collector roads per sq. mi. of area	0	15.42	1.11	1.51
Length of urban local roads per sq. mi. of area	0	18.64	0.18	0.67
Density of all roads per sq. mi. of area	0	26.88	2.46	2.32
Density of bicycle lane and bicycle slot per sq. mi. of area	0	13.72	0.30	0.77
Log of daily vehicle miles traveled (DVMT) in thousands	-8.52	6.67	2.45	1.49
Log of number of bicycle commuters	0	5.77	0.53	1.18
Traffic intensity as DVMT in thousands /road length	0	82.0	14.42	11.59
Truck percentage	0	74.07	6.45	4.84
Strava Users' Ride Characteristics				
Bicycle trip miles from *Strava* data (number of bicycle trips × trip length in miles: Low [≤ 150], Medium [>150 & ≤ 1,000], and High [>1,000]	Low: 4,256 obs. Medium: 4,029 obs. High: 3,070 obs.			
Bicycle trip intensity (number of bicycle trips from *Strava* data /road length: Low [≤ 1,000], Medium [>1,000 & ≤ 10,000], and High [>10,000]	Low: 3,663 obs. Medium: 5,046 obs. High: 2,646 obs.			

Log of daily vehicle miles traveled (DVMT) for a census block group was estimated by taking a logarithmic function of the product of segment AADT and the corresponding segment length for those segments located in a census block group. Traffic intensity in the census block group was computed by a length-weighted average of AADT, as follows:

$$Traffic\ Intensity\ at\ a\ census\ block\ group = \frac{\sum_{i=1}^{n} AADT_i \times SL_i}{\sum_{i=1}^{n} SL_i} \tag{5-13}$$

where $AADT_i$ is AADT on segment i, SL_i is the length of segment i, and n is the number of segments in the particular census block group. Similarly, truck percentage was measured by multiplying truck factor with corresponding segment length and then normalizing for the total length of all segments within a census block group.

5.3.3 Strava Users' Ride Characteristics

Strava is a smartphone application to facilitate bicyclists keep track of their rides. *Strava* users' ride characteristics data for 2014 were obtained from FDOT's UBR system. *Strava* data were presented on a road network level, which included, among others, count of bicycle trips on a street segment. To locate the bicycle trips within a census block group, the Strava road layer shapefile was intersected with the census block group shapefile. Once the segments and associated bicycle trips on those segments within a census block group were identified, bicycle trip miles and bicycle trip intensity for each census block group were calculated as follows:

$$Bicycle\ trip\ miles\ at\ a\ census\ block\ group = \sum_{i=1}^{n} BT_i \times SL_i \tag{5-14}$$

$$Bicycle\ Intensity\ at\ a\ census\ block\ group = \frac{\sum_{i=1}^{n} BT_i \times SL_i}{\sum_{i=1}^{n} SL_i} \tag{5-15}$$

where BT_i is the count of bicycle trips on the street segment i regardless of the direction of travel, SL_i is the length of segment i, and n is the number of segments in the particular census block group. It was well understood that the variables do not represent the overall population of bicyclists, and therefore, just a sample of the bicyclists' data on roads. Therefore, the direct numeric values of these variables were not used in model development. Instead, the variables were categorized based on the distribution of their values (see Table 5-1).

5.4 Results and Discussions

5.4.1 Exploratory Analysis

Table 5-2 presents the results of Moran's I and Geary's C indices. The tests were based on 1,000 samples (i.e., 999 simulations and one given sample). Moran's I index for both total and F+S bicycle crashes were positive, indicating clustering of bicycle crashes at neighborhoods. Similarly, Geary's C index for both cases had values less than 1.0, indicating positive correlation and spatial clustering of bicycle crashes. Lower p-values in all the estimates indicate statistically significant results. In summary, spatial autocorrelation was found to be present in bicycle crash data at census block group level.

Table 5-2: Exploratory Analysis of Spatial Correlation for Bicycle Crashes

Index	Crash Type	Estimate	p-value	Spatial Correlation
I_G	Total bicycle crashes	0.3210	0.001	Clustered
	F+S bicycle crashes	0.1647	0.001	Clustered
C_G	Total bicycle crashes	0.8497	0.001	Clustered
	F+S bicycle crashes	0.9657	0.012	Clustered

5.4.2 Bayesian Inference

Prior to model development, correlations among variables were investigated to identify the highly correlated variables as their inclusion in models might yield biased results. Pearson's correlation coefficients were computed to determine the level of correlation present between variable pairs and then to select those variables that did not exhibit strong interdependence and multicollinearity. This also aids to reduce the number of explanatory variables in the models (MacNab, 2004). A value of Pearson's correlation coefficient equal to 0.5 was considered the threshold for strong correlation. This means that both variables of a pair that had a correlation coefficient greater than 0.50 were not included together in the models.

The models were fit using the Integrated Nested Laplace Approximation (INLA) algorithm proposed by Rue et al. (2009). This method provides accurate approximations (deterministic) of the posterior marginals of the parameters of interest of latent Gaussian models. Since spatial CAR models are incorporated into this class of latent Gaussian models, the INLA approach can be used for parameter estimations of the hierarchical Bayesian models. A major advantage of the INLA procedure is that it is computationally fast and it can be used through the ***R*** library INLA (Schrödle et al., 2010).

Bayesian inference is based on a density interval, commonly known as Bayesian credible interval (BCI), of the posterior distribution from which the credibility of a parameter could be determined. A 95% BCI is typically adopted; every point inside the 95% interval is more credible than any point outside it (Saha et al., 2017). Therefore, if the posterior distribution of the parameter does not include zero within its 95% density interval, the parameter is deemed credible. Table 5-3 presents the Bayesian estimation of model parameters for total and F+S bicycle crashes at census block groups in Florida. The results show that both the random factors, one measuring the effect of unobserved heterogeneity and the other measuring the effect of spatial autocorrelation, were credible.

As shown in Table 5-3, a total of 22 variables were credible in the total bicycle crash model and 17 variables were credible in the F+S bicycle crash model. The variables that were credible in the two models include:

- log of total population,
- log of daily vehicle miles traveled (DVMT),
- proportion of households with no automobile,

- proportion of households with one automobile,
- proportion of population aged 18-29 years,
- proportion of population 25 years and above having high school diploma only,
- proportion of population 25 years and above having Associate's degree or attended some college with no degree achieved,
- proportion of population 25 years and above having Bachelor's degree or higher,
- density of rural collector roads,
- density of rural local roads,
- density of urban arterials,
- density of bicycle facilities,
- truck percentage,
- bicycle trip miles, and
- bicycle trip intensity in a census block group.

Variables that were found to be credible only in the total bicycle crash model are:

- log of number of bicycle commuters,
- proportion of Black or African American population,
- proportion of Hispanic or Latino population,
- proportion of population aged 30-39 years,
- proportion of population aged 50-64 years,
- density of urban collector roads, and
- density of urban local roads.

Variables that were found to be credible only in the F+S bicycle crash model are:

- proportion of male population, and
- proportion of population aged 40-49 years.

The variables log of population, log of DVMT, and log of bicycle commuters can be considered as surrogate measures for bicycle exposure. All the three variables were found to be credible in the total bicycle crash model, while only log of population and log of DVMT were found to be credible in the F+S bicycle crash model. As expected, these variables had positive coefficients. These results were found to be consistent with previous studies (Amoh-Gyimah et al., 2016; and Lee et al., 2015).

The variables representing household vehicle ownership, including proportion of households with no automobile and proportion of households with one automobile, were found to have credible associations with both the total and F+S bicycle crash models. The positive coefficients of these variables imply that census block groups with growing proportion of households owning either zero or one automobile tend to experience more bicycle crashes. The effect of the proportion of households with no automobile was found to be approximately twice and 1.5 times the effect of the proportion of households with one automobile on total and F+S bicycle crashes, respectively. Household members who do not have any automobile are likely to use bicycle as one of the means of transportation and, therefore, have a greater probability to get involved in a crash. Again, one vehicle per household might not adequately serve all the members of the household, and therefore, some of the household members may use bicycles and have chances to get involved in a crash. Therefore, the risk of bicycle crashes was found to be credible in census block groups with high proportion of households with one automobile; intuitively, the risk will be lower than that for census block groups with high proportion of households with no automobile. Siddiqui et al. (2012) also reported credible and positive coefficients to describe the effect of households with no automobile and households with one automobile on bicycle crashes at TAZs.

Two ethnicity variables were found to be credible in the total bicycle crash model, while no ethnicity variable was found to be credible in the F+S bicycle crash model. The credible ethnicity variables, including proportion of Black or African American population and proportion of Hispanic or Latino population, had positive coefficients. The results indicate a higher propensity of bicycle crashes at census block groups with increasing population of these ethnic groups. The results are consistent with previous studies; for example, Yasmin and Eluru (2016) found positive coefficients for Hispanic population while investigating TAZ-level bicycle crashes in Montreal and Toronto in Canada.

The variables representing proportions of population aged 18-29 years, 30-39 years, and 50-64 years had credible positive associations with total bicycle crashes. In addition to the proportion of population aged 18-29 years, the variable representing proportion of population aged 40-49 years had credible and positive impact on F+S bicycle crashes. Population age cohorts, therefore, were found to have a significant impact on the occurrences of bicycle crashes at census block groups.

Among the other demographic and socio-economic variables, education related variables had shown credible impacts on the likelihood of bicycle crashes at census block groups. Population aged 25 years and above having at least a school diploma (i.e., consisting of population having a school diploma, an Associate's degree, some college education with no degree, a Bachelor's degree, a Master's degree, a Professional school degree, or a Doctoral degree) were found to have negative associations with both total and F+S bicycle crashes. This could be because educated people are more likely to learn about safety behaviors while riding bicyclists. Proportion of male population was the other demographic variable that was found to be credible in the F+S bicycle crash model. This suggests that census block groups with a greater proportion of males may experience a greater number of F+S bicycle crashes.

Several roadway characteristics variables were found to have credible associations with bicycle crashes at census block groups. In the total bicycle crash model, density of rural roads by functional class, including rural collector roads and rural local roads, had negative coefficients, and density of urban roads by functional class, including urban arterials, urban collector roads, and urban local roads, had positive coefficients. In the F+S bicycle crash model, density of rural collector roads and rural local roads were found to have negative coefficients, and density of urban arterials was found to have a positive coefficient. This indicates that census block groups with greater concentration of urban facilities are likely to experience more bicycle crashes, and those with greater concentration of rural facilities are likely to experience fewer bicycle crashes. This is expected since urban facilities have closely spaced intersections and driveways, which pose greater risk to bicyclists.

Density of bicycle facilities (bicycle lanes and bicycle slots) was found to be credible in both the total and F+S bicycle crash models. The coefficients for the density of bicycle facilities were found to have positive signs, which imply that census block groups with greater density of bicycle lanes and bicycle slots have high risk propensity of experiencing bicycle crashes. This is not surprising as bicycle lanes and bicycle slots along a roadway encourage more bicyclists to use the facilities, which in turn increases the bicyclists' exposure to motorized traffic, and hence, increase the likelihood of bicycle crashes.

Truck percentage had negative coefficients in both the crash models, which contradicts the results in Lee et al. (2015). One possible explanation could be that census block groups with high volume of truck traffic mostly represent rural areas, which generally experience fewer bicycle crashes.

The *Strava* user's ride characteristics variables, including bicycle trip miles and bicycle trip intensity, were found to be credible with positive coefficients for the total bicycle crash model. Census block groups with at least medium bicycle trip miles and medium bicycle trip intensity were found to have a higher propensity of bicycle crashes compared to the census block groups with low bicycle trip miles and low bicycle trip intensity. Similarly, for the F+S bicycle crash model, both bicycle trip miles and bicycle trip intensity were found to be credible. Medium and high bicycle trip intensity, and high bicycle trip miles were found to have positive association with F+S bicycle crashes.

5.5 Summary

This chapter presented a comprehensive analysis of bicycle crashes at the macro-level for the state of Florida. Data at the census block group level were used to investigate the impact of socio-economic and demographic, roadway environment and infrastructure, bicycle activity, and traffic characteristics on bicycle crash frequency. Separate models were developed for total bicycle crashes and F+S bicycle crashes. Based on the Moran's *I* index and the Geary's *C* index values, spatial autocorrelation was found to be present in bicycle crash data at census block group level.

A macro-level spatial analysis was conducted to determine the relation between bicycle crashes and independent variables, including demographic and socio-economic factors, roadway and traffic characteristics, and bicycle activity, while accounting for the effect of spatial correlation among census block groups. Table 5-4 summarizes the analysis results. It provides the association of the credible variables to total and F+S bicycle crashes.

Table 5-3: Bayesian Inference

Variable Description	Total Crashes				Fatal and Severe Crashes			
	Mean	SD	BCI		Mean	SD	BCI	
			2.5%	97.5%			2.5%	97.5%
Intercept	-4.2973	0.2116	-4.7134	-3.8828	-6.1026	0.3847	-6.8613	-5.3510
Log of total population	0.2632	0.0214	0.2213	0.3052	0.2847	0.0363	0.2137	0.3562
Log of DVMT	0.3174	0.0108	0.2963	0.3385	0.3831	0.0210	0.3420	0.4246
Log of number of bicycle commuters	0.0224	0.0087	0.0053	0.0394	--	--	--	--
Proportion of households with no automobile	0.0112	0.0013	0.0086	0.0137	0.3221	0.0104	0.0022	0.0060
Proportion of households with one automobile	0.0048	0.0008	0.0033	0.0063	-0.0046	0.0067	0.0014	0.0040
Proportion of male population	--	--	--	--	0.0061	0.0028	0.0005	0.0116
Proportion of Black or African American population	0.0037	0.0008	0.0021	0.0052	--	--	--	--
Proportion of Hispanic or Latino population	0.0048	0.0010	0.0029	0.0068	--	--	--	--
Proportion of population aged 18 - 29 years	0.0082	0.0013	0.0057	0.0107	0.0060	0.0021	0.0019	0.0101
Proportion of population aged 30 - 39 years	0.0064	0.0019	0.0027	0.0100	--	--	--	--
Proportion of population aged 40 - 49 years	--	--	--	--	0.0072	0.0035	0.0002	0.0142
Proportion of population aged 50 - 64 years	0.0047	0.0016	0.0016	0.0079	--	--	--	--
Proportion of population 25 years and above having high school diploma only	-0.0056	0.0016	-0.0088	-0.0024	-0.0084	0.0028	-0.0139	-0.0029
Proportion of population 25 years and above having Associate's degree or attended some college with no degree achieved	-0.0073	0.0016	-0.0103	-0.0042	-0.0130	0.0026	-0.0182	-0.0078
Proportion of population 25 years and above having Bachelor's degree or higher	-0.0097	0.0014	-0.0125	-0.0070	-0.0159	0.0022	-0.0202	-0.0115
Density of rural collector roads	-0.8646	0.1723	-1.2069	-0.5300	-0.7127	0.2811	-1.2783	-0.1736
Density of rural local roads	-0.8633	0.3315	-1.5428	-0.2400	-1.3880	0.6097	-2.6481	-0.2516
Length of urban principal arterials	0.0933	0.0088	0.0760	0.1107	0.0626	0.0155	0.0321	0.0930
Length of urban collector roads	0.0248	0.0079	0.0092	0.0403	--	--	--	--
Length of urban local roads	0.0391	0.0161	0.0074	0.0705	--	--	--	--
Density of bicycle lane and bicycle slot	0.0365	0.0138	0.0094	0.0636	0.0609	0.0231	0.0153	0.1060
Truck percentage	-0.0172	0.0037	-0.0244	-0.0100	-0.0143	0.0067	-0.0274	-0.0013
Bicycle trip miles: Medium	0.1155	0.0317	0.0533	0.1776	0.0933	0.0538	-0.0181	0.2049
Bicycle trip miles: High	0.2711	0.0455	0.1818	0.3603	0.2782	0.0799	0.1213	0.4351
Bicycle trip intensity: Medium	0.2095	0.0321	0.1466	0.2724	0.1228	0.0576	0.0099	0.2358
Bicycle trip intensity: High	0.5265	0.0454	0.4373	0.6157	0.3306	0.0833	0.1671	0.4942
τ_u	3.4710	0.2294	3.0439	3.9440	2.3980	0.2297	1.9813	2.8840
τ_s	1.0810	0.0769	0.9369	1.2390	1.1170	0.1330	0.8793	1.4010

Table 5-4: Summary of Results from the Macroscopic Spatial Analysis

Variable Description	Total Crash Model	F+S Crash Model
Demographic and Socio-economic Characteristics		
Log of total population	⇧	⇧
Proportion of households with no automobile	⇧	⇧
Proportion of households with one automobile	⇧	⇧
Proportion of male population	NC	⇧
Proportion of Black or African American population	⇧	NC
Proportion of Hispanic or Latino population	⇧	NC
Proportion of population aged 18 - 29 years	⇧	NC
Proportion of population aged 30 - 39 years	⇧	NC
Proportion of population aged 40 - 49 years	NC	⇧
Proportion of population aged 50 - 64 years	⇧	NC
Proportion of population 25 years and above having high school diploma only	⇩	⇩
Proportion of population 25 years and above having Associate's degree or attended some college with no degree achieved	⇩	⇩
Proportion of population 25 years and above having Associate's degree or attended some college with no degree achieved	⇩	⇩
Proportion of population 25 years and above having Bachelor's degree or higher	⇩	⇩
Roadway and Traffic Characteristics		
Density of rural collector roads per sq. mi. of area	⇩	⇩
Density of rural local roads per sq. mi. of area	⇩	⇩
Length of urban principal arterials per sq. mi. of area	⇧	⇧
Length of urban collector roads per sq. mi. of area	⇧	NC
Length of urban local roads per sq. mi. of area	⇧	NC
Density of bicycle lane and bicycle slot per sq. mi. of area	⇧	⇧
Log of daily vehicle miles traveled (DVMT) in thousands	⇧	⇧
Log of number of bicycle commuters	⇧	NC
Truck percentage	⇩	⇩
Strava Users' Ride Characteristics		
Bicycle trip miles: Medium	⇧	NC
Bicycle trip miles: High	⇧	⇧
Bicycle trip intensity: Medium	⇧	⇧
Bicycle trip intensity: High	⇧	⇧

Note: ⇧ indicates credible and increasing effect; ⇩ indicates credible and decreasing effect; NC is not credible.

CHAPTER 6
CRASH MODIFICATION FACTORS

This chapter presents the CMFs for bicycle crashes in Florida. It first discusses the segment, intersection, crash, and bicycle activity data preparation efforts. The approach used to develop CMFs is described next. The Florida-specific CMFs for different roadway segment and intersection facility types are then provided.

6.1 Data

6.1.1 Roadway Segment Data

The following data were used to develop CMFs:

- 2014 RCI data
- GIS shapefiles for:
  - Bicycle lane
  - Bicycle slot
  - Shared path
  - Sidewalk barrier
  - Sidewalk width and separation
  - State roads
  - Intersections

Detailed roadway characteristics information was extracted from the 2014 FDOT's RCI database. Of over 200 variables that are available in the RCI database, only those that could potentially affect bicycle safety were extracted. Table 6-1 lists these variables.

Table 6-1: RCI Variables Extracted for CMF Development

RCI Variable	RCI Code
Section Average Annual Daily Traffic	SECTADT
Number of Lanes	NOLANES
Median Width	MEDWIDTH
Bicycle Lane	BIKELNCD
Bicycle Slot	BIKSLTCD
Shared Path Width and Separation	SHARDPTH
Sidewalk Width and Separation	SIDWLKWD
Sidewalk Barrier	SDWLKBCD
Type of Road	TYPEROAD
Type of Parking	TYPEOP
Maximum Speed Limit	MAXSPEED
Pavement Surface Width	SURWIDTH
Type of Median	RDMEDIAN
Shoulder Type	SHLDTYPE
Functional Classification of Roadways	FUNCLASS

These variables are discussed below in detail.

- *Section AADT:* It is an estimate of the AADT traveled on the roadway section. The natural logarithm of AADT was considered in developing the regression models.

- *Number of Lanes:* Information on number of lanes was used to categorize segments into different facility types. When the roadway is divided, the RCI provides number of through lanes for each direction of travel. On the other hand, when the roadway is undivided, the RCI provides number of through lanes for both directions of travel combined. Since the total number of lanes for both directions of travel was considered for model fitting, the number of lanes information on undivided sections was used directly. However, when roadway is divided, the number of through lanes in each direction of travel was added to obtain the total number of through lanes along both directions of travel.

- *Median Width:* It denotes the width of the median in feet. The actual value of median width varied from 2 ft to over 100 ft. Since this level of detail is not required, the measured median width was rounded per the recommendations provided in the Highway Safety Manual (HSM). Table 6-2 presents the HSM guidance in rounding the median widths.

Table 6-2: HSM Recommended Rounded Median Widths (Source: AASHTO, 2010)

Measured Median Width	Rounded Median Width
1 to 14 ft	10 ft
15 to 24 ft	20 ft
25 to 34 ft	30 ft
35 to 44 ft	40 ft
45 to 54 ft	50 ft
55 to 64 ft	60 ft
65 to 74 ft	70 ft
75 to 84 ft	80 ft
85 to 94 ft	90 ft
95 ft or more	100 ft

- *Bicycle Lane:* The 2014 RCI database included bicycle lane information for approximately 1,100 miles of road network. However, the GIS shapefile for bicycle lanes included this information for nearly 1,600 miles. Since the GIS shapefile provided a more complete inventory of the road network with bicycle lanes, the bicycle lane shapefile was appended to the RCI database. Although the shapefile includes different categories for bicycle lanes such as designated, colored, etc., only presence or absence of bicycle lane was considered in the analysis.

- *Bicycle Slot:* Bicycle slot data was prepared in the same manner as the bicycle lane data. However, since bicycle slots are always located at or near intersections, this variable was considered only when analyzing intersections.

- *Shared Path Width and Separation:* Shared path width and separation provides information about the actual width of the shared path in feet. Because of lack of variability in this data, only the presence or absence of shared path was considered while developing the regression models. Similar to bicycle lane and bicycle slot data, this variable was extracted from FDOT's GIS shapefile.

- *Sidewalk Width and Separation:* Similar to shared path width and separation, only the presence or absence of sidewalk was considered in the analysis. Since the FDOT GIS shapefile has more complete information about sidewalks compared to the RCI, this variable was extracted from the FDOT's GIS shapefile.

- *Sidewalk Barrier:* Information on sidewalk barrier was also extracted from the GIS shapefile, and the presence or absence of sidewalk barrier was considered in developing the regression models.

- *Type of Road:* This variable denotes whether a roadway is undivided, divided, or one-way. The same classification was used to divide the road network into different facility types.

- *Type of Parking:* This variable includes the following information: no parking allowed, parking permitted on one side, and parking permitted on both sides. The same information was considered in developing the regression models.

- *Maximum Speed Limit:* Information on maximum speed limit was provided for each direction of travel on divided roads and for both directions of travel on undivided roads. If the maximum speed limit was different for each direction of travel, the highest value was taken as the maximum speed limit of the roadway. The maximum speed limit value was used directly for undivided sections.

- *Pavement Surface Width:* Surface width is the total width of all through lanes. For divided roadway segments, the surface widths on each direction of travel were summed up to obtain the total surface width of the roadway segment. The surface width for undivided segments was used directly. Note that lane width, instead of surface width, was considered in developing the regression models. Lane widths were calculated by dividing the total surface width with the total number of lanes for each roadway segment. Furthermore, the calculated lane widths were rounded per the recommendations provided in the HSM (see Table 6-3).

Table 6-3: HSM Recommended Rounded Lane Widths (Source: AASHTO, 2010)

Measured Lane Width	Rounded Lane Width
9.2 ft or less	9 ft or less
9.3 to 9.7 ft	9.5 ft
9.8 to 10.2 ft	10 ft
10.3 to 10.7 ft	10.5 ft
10.8 to 11.2 ft	11 ft
11.3 to 11.7 ft	11.5 ft
11.8 or more	12 ft or more

- *Type of Median:* Table 6-4 lists the different types of medians included in the RCI. The codes were redefined to yield longer and more homogeneous segments. The table also provides the modified median types considered in this analysis.

Table 6-4: Codes for Median Type

Highway Median Type	Original RCI Code	Modified Code
Paved	01	01
Raised Traffic Separator	02	02
Vegetation	08	08
Curb & Vegetation	17	17
Other	20	20
Counted Roundabout	41	20
Non-counted Roundabout	42	20
Counted Traffic Circle	43	20
Non-counted Traffic Circle	44	20
Non-counted Managed Lane	50	20

- *Shoulder Type:* The RCI includes information about three shoulder types based on offset direction (left, right, and both left and right): highway shoulder type, highway shoulder type2, and highway shoulder type3. Each type has ten different codes. The codes were also re-categorized to generate longer homogeneous segments. Table 6-5 presents both the original and the modified codes for shoulder type. Note that when the same segment has different codes for the three shoulder types (shoulder type, shoulder type2, and shoulder type3), the shoulder type was coded as "mixed".

Table 6-5: Codes for Shoulder Type, Shoulder Type2, and Shoulder Type3

RCI Code Description	Original RCI Code	Modified Code
Raised Curb	0	0
Paved (including paved parking and bicycle slots)	1	12
Paved with Warning Device (any device that serves to warn, guide, or regulate the motorist)	2	12
Lawn (number of feet to support roadbed)	3	345
Gravel/Marl	4	345
Valley Gutter (not a barrier)	5	345
Curb & Gutter	6	68
Other	7	7
Curb with Resurfaced Gutter	8	68

- *Functional Classification of Roadways:* Since bicyclists are not expected on limited-access facilitates, interstates, freeways, and expressways were excluded from the analysis. The following roadway functional classifications are included in this analysis. Note that the number in parentheses is the RCI code.

    - Rural – Principal Arterial – Other (04)
    - Rural – Minor Arterial (06)
    - Rural – Major Collector (07)
    - Rural – Minor Collector (08)

- Urban – Principal Arterial – Other (14)
- Urban – Minor Arterial (16)
- Urban – Major Collector (17)
- Urban – Minor Collector (18)

The entire road network was divided into the following facility types. Table 6-6 presents the descriptive statistics for these facility types.

- Urban Two-lane Divided Segments
- Urban Four-lane Divided Segments
- Urban Six-lane Divided Segments
- Urban Two-lane Undivided Segments
- Urban Three-lane Undivided Segments
- Urban Four-lane Undivided Segments
- Rural Two-lane Undivided Segments
- Rural Two-lane Divided Segments
- Rural Four-lane Divided Segments

Table 6-6: Descriptive Statistics of Segment Facility Types

Attribute	Attribute Category	Urban						Rural		
		Divided			Undivided			Divided		Undivided
		2L	4L	6L	2L	3L	4L	2L	4L	2L
Roadway Length (mi.)	--	509.2	2,328.9	1,209	1,050	85.3	107.6	234.5	1,029.4	3,771.5
Crash Freq. (2011-2014)	Total	215	1,764	2,049	262	108	135	14	44	46
	F+S	50	296	344	60	12	18	3	24	21
Roadway Length (mi.) with No Crashes	--	452.1	1,717.3	726.7	964.9	63.8	72.6	230.6	974.2	3,691.4
Section AADT (veh/day)[a]	Min	600	600	5,700	600	2,700	2,700	400	450	180
	Max	50,500	120,000	98,500	50,500	83,000	47,000	20,500	36,500	23,000
	Mean	11,704	24,545	42,085	10,046	14,594	16,868	6,352	10,837	4,610
	SD	5,474	10,290	13,303	5,576	7,488	7,922	3804.8	6,004	3,111
Bicycle Activity (total No. of trips per year)	Low (≤ 2,000)	132.5	525.6	271.1	264.3	22.6	30.8	108.3	444.1	1,858.3
	Medium (> 2,000 and ≤ 10,000)	149.2	828.2	454.8	298.8	19.9	31.3	64.5	263.2	1,110
	High (> 10,000)	227.3	975	482.9	486.8	42.8	45.4	61.6	322	803.2
No. of Lanes	--	2	4	6	2	3	4	2	4	2
Median Width (ft)[a]	Min	10	10	10	NA	NA	NA	10	10	NA
	Max	100	100	100				100	100	
	Mean	12.42	26.43	25.97				13	38.57	
	SD	8.12	15.14	11.28				9.54	18.3	
Bicycle Lane (mi.)[b]	No	383.4	1,715.2	831.8	880.9	67.7	102.8	222.9	939.2	3,662.2
	Yes	125.7	616.7	377.1	169.1	17.6	4.8	11.6	90.2	109.4
Shared Path (mi.)[b]	No	495.1	2,275.1	1,171.2	1,017.4	84.6	107.2	230.7	1,005	3,714.2
	Yes	14.06	53.8	37.7	32.6	0.6	0.3	3.7	24.3	57.3
Sidewalk (mi.)[b]	No	278.7	881.7	210.8	713.7	12.3	16.8	213.4	952.2	3,667.5
	Yes	230.4	1,447.2	998.2	336.3	73	90.8	21	77.1	104
Sidewalk Barrier (mi.)[b]	No	280.7	883.8	216.8	727.6	14.3	18.2	212.8	950.8	3,646.2
	Yes	228.5	1,445	992.2	322.4	71	89.3	21.6	78.5	125.3
Type of Road	Undivided	NA	NA	NA	934.9	7.2	98.4	NA	NA	3,766

Attribute	Attribute Category	Urban						Rural		
		Divided			Undivided			Divided		Undivided
		2L	4L	6L	2L	3L	4L	2L	4L	2L
(in miles)	Divided	509.2	2,328.9	1,209	NA	NA	NA	234.5	1029.4	NA
	One-way	NA	NA	NA	115.1	78.1	9.1	NA	NA	5.5
Type of Parking[b]	No	83.5	447.5	208.6	194.1	7.3	17	4.08	23.2	69.86
	One Side	1	5.8	0.9	7.6	0	2.2	0	0	0
	Both Side	10.6	52	11.22	41.4	1.7	2.5	0	0	2.03
	NULL	414	1,823.5	988.2	806.8	76.2	85.8	230.4	1,006.2	3,699.7
Maximum Speed Limit (mph)[a]	Min	--	--	--	--	--	--	--	--	--
	Max	60	65	65	60	55	50	60	65	60
	Mean	41.97	43.68	44.07	40.6	33.35	34.4	50.57	53.4	49.6
	SD	11.67	9.08	8.5	12.9	11.03	7.52	10.37	9.59	13.01
Pavement Surface Width (ft)[a]	Min	18	35	59	19	26	34	20	40	18
	Max	54	75	81	44	42	54	50	72	44
	Mean	24	47	69.5	24	34.5	44	24.5	48	24
	SD	2	2.5	3.5	2	2.5	3.5	2	1	1.5
Type of Median[b]	Paved	476.2	517.1	73.3				219.4	37.41	
	Raised Traffic Separator	9.7	181.2	256.2				2.49	3.98	
	Vegetation	4.5	927.7	78.4	NA	NA	NA	4.77	912.2	NA
	Curb & Vegetation	18.3	697.3	794.1				7.76	74.56	
	Other	0.4	5.4	6.8				0.04	1.27	
Shoulder Type[b]	Raised Curb	0	0	0	0	0	0	0	0	0
	Paved	0	0	0	0.3	0	0	0	0	0
	Lawn, Gravel /Marl, alley Gutter	0.5	5.9	0.9	29.8	0.3	0	0.11	0	14.2
	Curb & Gutter	0.4	0.9	0	14.8	14.7	5.8	0	0	1.56
	Mixed	507.9	2,322.1	1,208	1,002.6	70.3	101.8	233.9	1029.4	3,746.2
Functional Classification of Roadways	--	Principal Arterial, Minor Arterial, Major Collector, and Minor Collector						Principal Arterial, Minor Arterial, Major Collector, and Minor Collector		

Note: NA is not applicable; the sub-category lengths may not add up to facility length due to rounding issues; [a] numerical attribute; [b] categorical attribute.

6.1.2 Intersection Data

Intersection data were difficult to obtain directly from the existing FDOT databases. Therefore, intersection data collected for a recently completed FDOT project BDK80-977-37 titled "*Improved Processes for Meeting the Data Requirements for Implementing the Highway Safety Manual (HSM) and Safety Analyst in Florida*" were used to develop the models. The following intersection-related variables were included in the analysis:

- Major road AADT
- Minor road AADT
- Intersection skew angle
- Presence of lighting
- Number of bus stops within intersection influence area (i.e., within 1,000 ft of the intersection)
- Presence of schools within intersection influence area (i.e., within 1,000 ft of the intersection)

- Number of alcohol sales establishments within intersection influence area (i.e., within 1,000 ft of the intersection)
- Number of approaches with left-turn lanes
- Number of approaches with right-turn lanes
- Number of approaches with protected signal control
- Number of approaches with permitted signal control
- Number of approaches with protected-permitted signal control
- Number of approaches with no Right-Turn-on-Red
- Presence of red light running camera

In addition to the intersection data retrieved from project BDK80-977-37, GIS shapefiles for bicycle slot and bicycle lane were also included. If either bicycle slot or bicycle lane was located within 250 ft of an intersection, the intersection was considered to have a bicycle facility.

Due to sample size limitations, only urban four-leg signalized and urban three-leg stop-controlled intersections were analyzed. Table 6-7 presents the descriptive statistics for these two facility types.

Table 6-7: Descriptive Statistics of Intersection Facility Types

Attribute	Attribute Category	Urban Four-leg Signalized	Urban Three-leg Stop-controlled
Number of Sites	---	397	317
Total Bicycle Crashes (2011-2014)	---	380	71
Number of Sites with Zero Crashes	---	276	280
AADT on Major Road[a]	Minimum value	1,500	725
	Maximum value	74,500	61,750
	Average/Mean	31,829	19,268
	Standard deviation	14,214	12,655
AADT on Minor Road[a]	Minimum value	1,025	110
	Maximum value	55,250	30,000
	Average/Mean	18,532	3,486
	Standard deviation	11,708	3,176
Intersection Skew Angle[b]	No (No skew angle)	---	212
	Yes (Presence of skew angle)	---	105
Presence of Lighting[b]	No	27	96
	Yes	370	221
No. of Bus Stops within Intersection Influence Area[b]	0	127	257
	1-2	72	25
	≥ 3	198	35
Presence of Schools within Intersection Influence Area[b]	No	330	292
	Yes	67	25
No. of Alcohol Sales Establishments within Intersection Influence Area[b]	0	40	3
	1-8	355	112
	≥ 9	2	202
No. of Approaches with Left Turn Lanes[a]	0	2	114
	1	10	160
	2	20	43
	3	31	0
	4	334	---
	0	77	244
	1	95	68

Attribute	Attribute Category	Urban Four-leg Signalized	Urban Three-leg Stop-controlled
No. of Approaches with Right-Turn Lanes[a]	2	80	5
	3	77	0
	4	68	---
No. of Approaches with Protected Signal Control[a]	0	328	---
	1	28	
	2	23	
	3	10	
	4	8	
No. of Approaches with Permitted Signal Control[a]	0	159	---
	1	32	
	2	62	
	3	13	
	4	131	
No. of Approaches with Protected-Permitted Signal Control[a]	0	163	---
	1	28	
	2	70	
	3	31	
	4	105	
No. of Approaches with No Right-Turn-on-Red Sign[a]	0	387	---
	1	8	
	2	1	
	3	1	
	4	0	
Presence of Red Light Camera[b]	No	300	---
	Yes	97	
Presence of Bicycle Facility[b]	No	194	213
	Yes	203	104

--- Not Applicable; [a] numerical attribute; [b] categorical attribute.

6.1.3 Crash Data

Crash data for the years 2011-2014 were obtained from FDOT's CAR repository. The CAR database includes files for the following three data levels:

- crash level file,
- vehicle-driver-passenger level file, and
- non-motorist level file.

Crash level file includes crash related information such as crash number, roadway ID where the crash occurred, milepost of the crash location, crash severity, etc. The vehicle-driver-passenger file includes the road user related information for each crash record; thus it has information on crash number, all vehicles involved in the crash, all drivers and passengers involved in the crash, etc. Non-motorist level data file includes information about each non-motorist involved in a crash such as crash number, type of non-motorist, non-motorist location, non-motorist injury severity, etc.

As discussed in Section 3.1.1, bicycle crashes from 2011-2014 were identified first from the non-motorist level data file using the following codes for non-motorist type code variable (NON_MOTR_TYP_CD): 3 (bicyclist), and 4 (other cyclist).

Since multiple bicyclists could be involved in a single crash, only the information of the bicyclist with highest severity in each crash was retrieved, and included in the analysis. Once bicycle crashes were identified from the non-motorist data file, the records were linked to the crash level data file using crash number. The bicycle crash data were then merged with the roadway segment and intersection database such that each site had the total number of bicycle crashes that occurred during 2011-2014.

6.1.4 Bicycle Activity Data

The bicycle activity data were retrieved from the *2014 Strava* dataset which included distance of bicycle rides, time, pace, trail routes, and other geographic information data (collectively called "Activity Data"). This information was collected from the *Strava* smartphone application users who were biking in Florida. Since bicycle exposure provided in the *Strava* dataset is a sample and is dependent on the number of *Strava* smartphone application users in the area, the variables do not represent the overall population of bicyclists. Therefore, the raw *Strava* data representing the actual bicycle trips on each segment was processed to obtain a more representative bicycle exposure data. Bicycle volumes in each census block group were estimated by counting the number of bicycle trips made on the roadway segments in each census block group. The bicycle activity was then categorized into the following three classes. The roadway segments in each census block group were then assigned the bicycle activity of its census block group.

- Low Bicycle Activity (total bicycle trips per year ≤ 2,000)
- Medium Bicycle Activity (total bicycle trips per year > 2,000 and ≤ 10,000)
- High Bicycle Activity (total bicycle trips per year > 10,000)

6.2 Methodology

A CMF is a multiplicative factor which is used to compute the expected number of crashes when a particular countermeasure is implemented at a specific site. A CMF greater than 1.0 indicates an expected increase in crashes, while a CMF less than 1.0 indicates an expected reduction in crashes when a particular countermeasure is implemented. For example, a CMF of 0.8 indicates a 20% expected reduction in crashes, while a CMF of 1.1 indicates a 10% expected increase in crashes (Gross et al., 2010).

Cross-sectional analysis was used to develop CMFs for bicycle crashes in Florida. Cross-sectional studies are useful for CMF estimation when before-after studies cannot be conducted due to insufficient before and after crash data when a particular engineering countermeasure is implemented; or the date of the implemented treatment is unknown; or when it is difficult to distinguish the effect of a countermeasure from confounding factors. For example, there may be too few projects where lane width is reduced from 12 ft to 11 ft; but there may be many road segments with 11 ft lanes and 12 ft lanes. Before-after study might be impractical for credible results in such cases if enough before-after data are not available. Considering the datasets for this study, and the methodological pros and cons, cross-sectional study was identified as the best suited approach to develop CMFs.

In cross-sectional studies, crash experience at locations with and without a specific feature is studied; and then the difference in safety is attributed to that feature. The CMF can be estimated from the ratio of average crash frequency for sites with and without the treatment (or, countermeasure). To obtain reliable results from cross-sectional studies, it is critical that all locations are similar to each other in all other factors affecting crash risk. However, in practice, it is difficult to collect data for enough locations that are similar in all other factors affecting crash risk. Therefore, cross-sectional studies are often conducted through multivariate regression models.

The multivariate regression models attempt to address all the variables that have the potential for safety improvement. The models are developed using crash data from sites both with and without the treatment (or, countermeasure). The change in crashes from a unit change in a specific variable can be estimated from regression model. The CMFs are then deduced from the model parameters (Gross et al., 2010). This research used a generalized linear model (GLM) approach with NB distribution to develop the relevant multivariate regression models. The models have crash frequency as the dependent variable, i.e., response variable, and the roadway characteristics as independent variables, i.e., explanatory variables. Equation 6-1 illustrates the basic form of a multivariate regression model.

$$Y_i = exp\left(\beta_0 + \beta_1 \times ln\, AADT_i + \beta_2 \times LW_i + \beta_3 \times BL_i + \ldots + \beta_k \times X_{ik}\right) \qquad (6\text{-}1)$$

where,

Y_i	=	crash frequency on a road section *i* (crashes),
$AADT_i$	=	average annual daily traffic on a road section *i* (vehicle/day),
LW_i	=	lane width of a road section *i* (ft),
BL_i	=	presence of bicycle lane along a road section *i* (0 if absent, 1 if present),
X_{ik}	=	roadway characteristic *k* (i.e., countermeasure) of a road section *i*,
β_0	=	model intercept/constant, and
$\beta_1, \beta_2, \ldots, \beta_k$	=	model coefficients.

CMFs can be inferred from the estimated model parameters, i.e., coefficients; and as the model form is log-linear, the CMFs can be calculated as the exponent of the associated coefficient of the countermeasure variable as follows (Lord and Bonneson, 2007; Stamatiadis et al., 2009; Carter et al., 2012; Abdel-Aty et al., 2014):

$$CMF = exp\left(\beta_k \times (X_{kt} - X_{ku})\right) = exp\left(\beta_k\right) \qquad (6\text{-}2)$$

where X_{kt} is roadway characteristic *k* (i.e., countermeasure) of a treated site, and X_{ku} is roadway characteristic *k* (i.e., countermeasure) of an untreated site. For example, according to Equation 6-1, the CMF for increasing lane width (*LW*) by one foot is equal to *exp* (β_2).

The regression coefficients and over-dispersion parameter were estimated using the *glm.nb* function of MASS package in the statistical software ***R*** (R Core Team, 2016). An offset term was added to the regression equation to predict the crash frequency in crashes per mile per year, as shown in Equation 6-3.

$$Y_i = exp\left(\beta_0 + \beta_1 \times ln\, AADT_i + \beta_2 \times LW_i + \beta_3 \times BL_i + \cdots + \beta_k \times X_{ik} + OFFSET \right) \quad (6\text{-}3)$$

where,

Y_i	=	crash frequency on a road section *i*,
$AADT_i$	=	average annual daily traffic on a road section *i* (vehicle/day),
LW_i	=	lane width of a road section *i* (ft),
BL_i	=	presence of bicycle lane along a road section *i* (0 if absent, 1 if present),
X_{ik}	=	roadway characteristic *k* (i.e., countermeasure) of road section *i*,
β_0	=	model intercept/constant,
$\beta_1, \beta_2, \ldots, \beta_k$	=	model coefficients, and
$OFFSET_i$	=	ln(*4* × (section length of road section *i*, i.e., SL_i)) for segments and ln(*4*) for intersections. Note that the number *4* was used in the offset term because this study considered four years of crash data.

6.3 Crash Modification Factors for Roadway Segments

This section discusses the Florida-specific bicycle CMFs for total crashes and fatal and severe injury (F+S) crashes for the different segment facility types. As a first step in developing the CMFs, NB models for all roadway facilities were developed by considering all the following 12 variables:

1. section AADT,
2. median width,
3. bicycle lane,
4. shared path width and separation,
5. sidewalk width and separation,
6. sidewalk barrier,
7. type of road,
8. type of parking,
9. maximum speed limit,
10. lane width,
11. median type, and
12. shoulder type.

Only the variables that were significant at the 80% confidence interval in the initial model were used to develop the final models. The CMFs were estimated based on these final models. Table 6-8 lists the different segment facility types for which the NB regression models were developed for total and F+S bicycle crashes. The table also provides the reasons for not developing the models for some of the facility types.

Table 6-8: Overview of NB Models Developed for Different Segment Facility Types

Facility Type	NB Models for Total Bicycle Crashes	NB Models for F+S Bicycle Crashes
Urban Two-lane Divided	Yes	Yes
Urban Four-lane Divided	Yes	Yes
Urban Six-lane Divided	Yes	Yes
Urban Two-way Two-lane Undivided	No[1]	No[3]
Urban One-way Two-lane Undivided	No[1]	No[3]
Urban Two-way Three-lane Undivided	No[1]	No[1]
Urban One-way Three-lane Undivided	No[1]	Yes
Urban Two-way Four-lane Undivided	Yes	Yes
Urban One-way Four-lane Undivided	No[2]	No[2]
Rural Two-way Two-lane Undivided	Yes	No[4]
Rural One-way Two-lane Undivided	No[2]	No[2]
Rural Two-lane Divided	Yes	No[4]
Rural Four-lane Divided	No[3]	No[3]

[1] none of the variables were found significant; [2] inadequate sample size; [3] inadequate variability within the variables; [4] inadequate crash frequencies.

The following sections present the CMFs for total and F+S bicycle crashes for the different segment facility types. For each facility type, the data and model coefficients were reviewed closely to identify reliable CMFs. Note that the CMFs developed using small sample size are not considered to be reliable, and should be used with caution.

6.3.1 Urban Two-lane Divided Segments

Table 6-9 presents the model coefficients and CMFs for total bicycle crashes developed for urban two-lane divided roadways in Florida. The CMFs can be interpreted as one unit increase in the predictor variable results in an increase or decrease of certain percentage of bicycle crashes per mile per year. For example, Table 6-9 presents a CMF of 1.69 for the presence of bicycle lane; it can be inferred from this CMF that, the presence of bicycle lane increases the probability of bicycle crashes by 69% per year per mile on urban two-lane divided roadways in Florida. The reliable CMFs for total bicycle crashes for urban two-lane divided roadways in Florida are:

- Presence of sidewalk barrier increases the bicycle crash probability by 118%.
- Presence of parking on both sides increases the bicycle crash probability by 165% compared to the locations where parking is not allowed.
- One foot increase in lane width decreases the bicycle crash probability by 36%.
- Locations with raised traffic separator in the median increases the bicycle crash probability by 165% compared to the locations with paved medians.
- Locations with curb and vegetation in the median increases the bicycle crash probability by 143% compared to the locations with paved medians.
- Locations with medium bicycle activity decrease the bicycle crash probability by 49% compared to the locations with low bicycle activity.

- Locations with high bicycle activity decrease the bicycle crash probability by 27% compared to the locations with low bicycle activity.

Table 6-9: CMFs for Total Bicycle Crashes on Urban Two-lane Divided Segments

Variable	Coefficient	CMF
Intercept	-11.25582	Not Applicable
Section AADT	1.50264[a]	Not Applicable
Presence of Bicycle Lane	0.52859	1.69
Presence of Sidewalk Barrier	0.77943	2.18
Type of Parking (Permitted One Side)[b]	--	--
Type of Parking (Permitted Both Sides)[b]	0.97526	2.65
Maximum Speed Limit	-0.01784	0.98[e]
Lane Width	-0.43912	0.64
Type of Median (Raised Traffic Separator)[c]	0.97701	2.65
Type of Median (Vegetation)[c]	--	--
Type of Median (Curb & Vegetation)[c]	0.88938	2.43
Type of Median (Other)[c]	--	--
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[d]	-0.66810	0.51
High Bicycle Activity (Annual Trips > 10,000)[d]	-0.30984	0.73

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for type of parking is no parking allowed.
[c] The base condition for type of median is paved.
[d] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).
[e] The CMF is not reliable due to inadequate variability within the speed limit data.

Table 6-10 presents the model coefficients and CMFs for F+S bicycle crashes on urban two-lane divided roadways in Florida. The reliable CMFs for F+S bicycle crashes are:

- Presence of sidewalk decreases the F+S bicycle crash probability by 59%.
- Presence of sidewalk barrier increases the F+S bicycle crash probability by 320%.
- One foot increase in lane width decreases the F+S bicycle crash probability by 48%.
- Locations with medium bicycle activity decreases the F+S bicycle crash probability by 53% compared to the locations with low bicycle activity.

Table 6-10: CMFs for F+S Bicycle Crashes on Urban Two-lane Divided Segments

Variable	Coefficient	CMF
Intercept	-9.9291	Not Applicable
Section AADT	1.4228[a]	Not Applicable
Presence of Sidewalk	-0.9032	0.41
Presence of Sidewalk Barrier	1.4374	4.20
Type of Parking (Permitted One Side)[b]	--	--
Type of Parking (Permitted Both Sides)[b]	1.5318	4.62[c]
Lane Width	-0.6597	0.52
Type of Median (Raised Traffic Separator)[d]	1.7761	5.90[c]
Type of Median (Vegetation)[d]	--	--
Type of Median (Curb & Vegetation)[d]	--	--
Type of Median (Other)[d]	--	--
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[e]	-0.7459	0.47
High Bicycle Activity (Annual Trips > 10,000)[e]	--	--

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for type of parking is no parking allowed.
[c] The CMF is not reliable due to low sample size.
[d] The base condition for type of median is paved.
[e] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

6.3.2 Urban Four-lane Divided Segments

Table 6-11 presents the model coefficients and CMFs for total bicycle crashes developed for urban four-lane divided roadways in Florida. The reliable CMFs for total bicycle crashes are:

- One foot increase in median width decreases the probability of bicycle crashes by 1% per year per mile on urban four-lane divided roadways in Florida.
- Presence of bicycle lane decreases the bicycle crash probability by 14%.
- Presence of sidewalk increases the bicycle crash probability by 78%.
- One foot increase in lane width decreases the bicycle crash probability by 33%.
- Locations with raised traffic separator in the median increases the bicycle crash probability by 22% compared to the locations with paved medians.
- Locations with vegetation in the median decreases the bicycle crash probability by 38% compared to the locations with paved medians.
- Locations with curb and vegetation in the median decreases the bicycle crash probability by 15% compared to the locations with paved medians.

Table 6-12 presents the model coefficients and CMFs for F+S bicycle crashes developed for urban four-lane divided roadways in Florida. The reliable CMFs for F+S bicycle crashes are:

- One foot increase in median width decreases the F+S bicycle crash probability by 2%.
- Locations with curb and vegetation in the median decreases the F+S bicycle crash probability by 3% compared to the locations with paved medians.

- Locations with medium bicycle activity increases the F+S bicycle crash probability by 63% compared to the locations with low bicycle activity.
- Locations with high bicycle activity increases the F+S bicycle crash probability by 43% compared to the locations with low bicycle activity.

Table 6-11: CMFs for Total Bicycle Crashes on Urban Four-lane Divided Segments

Variable	Coefficient	CMF
Intercept	-5.593448	Not Applicable
Section AADT	0.836457[a]	Not Applicable
Median Width	-0.004565	0.99
Presence of Bicycle Lane	-0.152452	0.86
Presence of Sidewalk	0.578128	1.78
Type of Parking (Permitted One Side)[b]	-1.102343	0.33[c]
Type of Parking (Permitted Both Sides)[b]	--	--
Maximum Speed Limit	-0.036162	0.96[d]
Lane Width	-0.260731	0.77
Type of Median (Raised Traffic Separator)[e]	0.204150	1.22
Type of Median (Vegetation) [e]	-0.485550	0.62
Type of Median (Curb & Vegetation) [e]	-0.157041	0.85
Type of Median (Other) [e]	1.001926	2.72[f]

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for type of parking is no parking allowed.
[c] The CMF is not reliable due to low sample size.
[d] The CMF is not reliable due to inadequate variability within the speed limit data.
[e] The base condition for type of median is paved.
[f] The CMF is not meaningful because the "Other" category is not explicitly defined.

Table 6-12: CMFs for F+S Bicycle Crashes on Urban Four-lane Divided Segments

Variable	Coefficient	CMF
Intercept	-8.31560	Not Applicable
Section AADT	0.57413[a]	Not Applicable
Median Width	-0.01209	0.98
Maximum Speed Limit	-0.01831	0.98[b]
Type of Median (Raised Traffic Separator)[c]	--	--
Type of Median (Vegetation)[c]	--	--
Type of Median (Curb & Vegetation)[c]	-0.30456	0.97
Type of Median (Other)[c]	1.04973	2.85[d]
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[e]	0.48972	1.63
High Bicycle Activity (Annual Trips > 10,000)[e]	0.35828	1.43

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The CMF is not reliable due to inadequate variability within the speed limit data.
[c] The base condition for type of median is paved.
[d] The CMF is not meaningful because the "Other" category is not explicitly defined.
[e] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

6.3.3 Urban Six-lane Divided Segments

Table 6-13 presents the model coefficients and CMFs developed for urban six-lane divided roadways. The reliable CMFs for total bicycle crashes are:

- One foot increase in median width decreases the bicycle crash probability by 1%.
- Presence of shared path decreases the bicycle crash probability by 25%.
- Presence of sidewalk increases the bicycle crash probability by 87%.
- Presence of sidewalk barrier increases the bicycle crash probability by 99%.
- Presence of parking on both sides decreases the bicycle crash probability by 52% compared to the locations where parking is not allowed.
- One foot increase in lane width decreases the bicycle crash probability by 25%.
- Locations with vegetation in the median decreases the bicycle crash probability by 51% compared to the locations with paved medians.
- Locations with curb and vegetation in the median decreases the bicycle crash probability by 20% compared to the locations with paved medians.
- Locations with medium bicycle activity decrease the bicycle crash probability by 11% compared to the locations with low bicycle activity.
- Locations with high bicycle activity decrease the bicycle crash probability by 27% compared to the locations with low bicycle activity.

Table 6-13: CMFs for Total Bicycle Crashes on Urban Six-lane Divided Segments

Variable	Coefficient	CMF
Intercept	-4.399824	Not Applicable
Section AADT	0.804120[a]	Not Applicable
Median Width	-0.007534	0.99
Presence of Shared Path	-0.293190	0.75
Presence of Sidewalk	0.629530	1.87
Presence of Sidewalk Barrier	0.690807	1.99
Type of Parking (Permitted One Side)[b]	--	--
Type of Parking (Permitted Both Sides)[b]	-0.743806	0.48
Maximum Speed Limit	-0.010892	0.99[c]
Lane Width	-0.291003	0.75
Type of Median (Raised Traffic Separator)[d]	--	--
Type of Median (Vegetation)[d]	-0.722819	0.49
Type of Median (Curb & Vegetation)[d]	-0.219630	0.80
Type of Median (Other)[d]	-1.453537	0.23[e]
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[f]	-0.111178	0.89
High Bicycle Activity (Annual Trips > 10,000)[f]	-0.315020	0.73

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for type of parking is no parking allowed.
[c] The CMF is not reliable due to inadequate variability within the speed limit data.
[d] The base condition for type of median is paved.
[e] The CMF is not meaningful because the “Other” category is not explicitly defined.
[f] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

Table 6-14 presents the model coefficients and CMFs for F+S bicycle crashes developed for urban six-lane divided roadways in Florida. The reliable CMFs for F+S bicycle crashes are:

- Presence of sidewalk increases the F+S bicycle crash probability by 171%.
- One foot increase in lane width decreases the F+S bicycle crash probability by 21%.
- Locations with vegetation in the median decreases the F+S bicycle crash probability by 55% compared to the locations with paved medians.
- Locations with high bicycle activity decrease the F+S bicycle crash probability by 24% compared to the locations with low bicycle activity.

Table 6-14: CMFs for F+S Bicycle Crashes on Urban Six-lane Divided Segments

Variable	Coefficient	CMF
Intercept	-5.191890	Not Applicable
Section AADT	0.733848[a]	Not Applicable
Presence of Sidewalk	0.999177	2.71
Lane Width	-0.231726	0.79
Type of Median (Raised Traffic Separator)[b]	--	--
Type of Median (Vegetation)[b]	-0.803647	0.45
Type of Median (Curb & Vegetation)[b]	--	--
Type of Median (Other)[b]	-0.831556	0.44[c]
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[d]	--	--
High Bicycle Activity (Annual Trips > 10,000)[d]	-0.267017	0.76

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for type of median is paved.
[c] The CMF is not meaningful because the "Other" category is not explicitly defined.
[d] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

6.3.4 Urban One-way Three-Lane Undivided Segments

None of the model coefficients were found to be significant at 80% confidence level for total bicycle crashes on one-way three-lane undivided urban roadway segments. Table 6-15 presents the model coefficients and CMFs for F+S bicycle crashes for urban one-way three-lane undivided roadway segments. As can be observed from the table, one foot increase in lane width decreases the F+S bicycle crash probability by 76% for this facility type.

Table 6-15: CMFs for F+S Bicycle Crashes on Urban One-way Three-lane Undivided Segments

Variable	Coefficient	CMF
Intercept	-0.85734	Not Applicable
Section AADT	1.21122[a]	Not Applicable
Maximum Speed Limit	--	--
Lane Width	-1.40944	0.24

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).

6.3.5 Urban Two-way Four-lane Undivided Segments

Table 6-16 presents the model coefficients and CMFs for total bicycle crashes on urban four-lane undivided roadway segments. Similarly, Table 6-17 presents the model coefficients and CMFs for F+S bicycle crashes. The reliable CMFs for bicycle crashes are:

- Presence of bicycle lane increases the total bicycle crash probability by 124%
- Presence of sidewalk barrier decreases the total bicycle crash probability by 67%, and the F+S bicycle crash probability by 64%.

Table 6-16: CMFs for Total Bicycle Crashes on Urban Two-way Four-lane Undivided Segments

Variable	Coefficient	CMF
Intercept	-8.8486	Not Applicable
Section AADT	0.5883[a]	Not Applicable
Presence of Bicycle Lane	0.8098	2.24
Presence of Sidewalk	3.0935	--
Presence of Sidewalk Barrier	-1.1183	0.33

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).

Table 6-17: CMFs for F+S Bicycle Crashes on Urban Two-way Four-lane Undivided Segments

Variable	Coefficient	CMF
Intercept	-9.04834	Not Applicable
Section AADT	0.60829[a]	Not Applicable
Presence of Sidewalk	2.92332	--
Presence of Sidewalk Barrier	-1.00935	0.36
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[b]	--	--
High Bicycle Activity (Annual Trips > 10,000)[b]	--	--

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

6.3.6 Rural Two-way Two-lane Undivided Segments

Tables 6-18 presents the model coefficients and CMFs developed for rural two-way two-lane undivided roadway segments for total bicycle crashes. Note that CMFs were not developed for F+S bicycle crashes as there were very few F+S crashes on these facilities.

Table 6-18: CMFs for Total Bicycle Crashes on Rural Two-way Two-lane Undivided Segments

Variable	Coefficient	CMF
Intercept	-13.80986	Not Applicable
Section AADT	1.07412[a]	Not Applicable
Maximum Speed Limit	-0.02111	0.98[b]
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[c]	0.55784	1.74[d]
High Bicycle Activity (Annual Trips > 10,000)[c]	--	--

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The CMF is not reliable due to inadequate variability within the speed limit data.
[c] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).
[d] The CMF is not reliable due to inadequate variability within bicycle activity data.

6.3.7 Rural Two-lane Divided Segments

Table 6-19 presents the model coefficients and CMFs developed for total bicycle crashes on rural two-lane divided roadway segments. One foot increase in median width was found to decrease the bicycle crash probability by 16% on this roadway facility. Note that CMFs were not developed for F+S bicycle crashes as there were very few F+S crashes on these facilities.

Table 6-19: CMFs for Total Bicycle Crashes on Rural Two-lane Divided Segments

Variable	Coefficient	CMF
Intercept	-9.0403	Not Applicable
Section AADT	0.7153[a]	Not Applicable
Median Width	-0.1753	0.84
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[b]	--	--
High Bicycle Activity (Annual Trips > 10,000)[b]	1.2522	3.5[c]

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).
[c] The CMF is not reliable due to inadequate variability within bicycle activity data.

6.4 Crash Modification Factors for Intersections

This section discusses the Florida-specific CMFs for the urban four-leg signalized and urban three-leg stop-controlled intersections. As discussed in Section 6.3, the NB models for intersections were first developed by considering all the variables listed in Table 6-7. Only the variables significant at the 80% confidence interval in the first model were used to develop the final models. These final models were then used to estimate the CMFs. The following sections present the CMFs for urban four-leg signalized and urban three-leg stop-controlled intersections. For each facility type, the data and model coefficients were reviewed closely to identify reliable CMFs. Note that the CMFs developed using small sample size are not considered to be reliable, and should be used with caution.

6.4.1 Urban Four-leg Signalized Intersections

Table 6-20 presents the model coefficients and CMFs for total bicycle crashes on urban four-leg signalized intersections in Florida. The reliable CMFs are:

- Presence of three or more bus stops within intersection influence area increases the probability of bicycle crashes by 90%.
- Presence of up to eight alcohol sales establishments within intersection influence area increases the probability of bicycle crashes by 53%.
- Presence of bicycle facilities (i.e., either bicycle lane, or bicycle slot, or both) at intersections increases the probability of bicycle crashes by 27%.

Table 6-20: CMFs for Total Bicycle Crashes on Urban Four-leg Signalized Intersections

Variable	Coefficient	CMF
Intercept	-13.02980	Not Applicable
AADT on Major Road	1.03716[a]	Not Applicable
1-2 Bus Stops within Intersection Influence Area[b]	0.05416	--
≥ 3 Bus Stops within Intersection Influence Area[b]	0.64057	1.90
1-8 Alcohol Sales Establishment within Intersection Influence Area[c]	0.42557	1.53
≥ 9 Alcohol Sales Establishment within Intersection Influence Area[c]	0.78981	--
No. of Approaches with Right-Turn Lanes	-0.05595	--
Presence of Bicycle Facilities	0.24263	1.27

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The base condition for bus stops is absence of bus stops within intersection influence area.
[c] The base condition for alcohol sales establishments is absence of alcohol sales establishments within intersection influence area.

Table 6-21 presents the model coefficients and CMFs for F+S bicycle crashes on urban four-leg signalized intersections in Florida. The reliable CMFs for F+S bicycle crashes are:

- Presence of a right-turn lane on an approach reduces the F+S bicycle crash probability by 18%.
- Presence of bicycle facilities at intersections increases the probability of F+S bicycle crashes by 71%.

Table 6-21: CMFs for F+S Bicycle Crashes on Urban Four-leg Signalized Intersections

Variable	Coefficient	CMF
Intercept	-20.7679	Not Applicable
AADT on Major Road	1.0046[a]	Not Applicable
AADT on Minor Road	0.6716[a]	Not Applicable
1-8 Alcohol Sales Establishment within Intersection Influence Area	0.4279	--
≥ 9 Alcohol Sales Establishment within Intersection Influence Area	1.9535	7.05[b]
No. of Approaches with Right-Turn Lanes	-0.1951	0.82
No. of Approaches with No-Right-Turn-on-Red	0.8113	2.25[c]
Presence of Bicycle Facilities	0.5368	1.71

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).
[b] The CMF is not reliable because the data are skewed.
[c] The CMF is not reliable due to low sample size.

6.4.2 Urban Three-leg Stop-controlled Intersections

Table 6-22 presents the model coefficients and CMFs for total bicycle crashes developed for urban three-leg stop-controlled intersections in Florida. Presence of bicycle facilities at three-leg stop-controlled urban intersections increases the probability of bicycle crashes by 36%. Note that CMFs were not developed for F+S bicycle crashes because none of the variables except AADT on major road were found to be significant at 80% confidence level.

Table 6-22: CMFs for Total Bicycle Crashes on Urban Three-leg Stop-controlled Intersections

Variable	Coefficient	CMF
Intercept	-18.3443	Not Applicable
AADT on Major Road	1.5402[a]	Not Applicable
Presence of Bicycle Facilities	0.3077	1.36

-- Not significant at 80% confidence level; [a] The coefficient is for ln (Section AADT).

6.5 Summary

Tables 6-23 and 6-24 summarize Florida-specific CMFs developed for total bicycle crashes for different roadway segment and intersection facility types, respectively. Similarly, Tables 6-25 and 6-26 summarize Florida-specific CMFs developed for F+S bicycle crashes for different roadway segment and intersection facility types, respectively.

Table 6-23: Summary of CMFs for Total Bicycle Crashes for Segment Facility Types

Variable	Urban								Rural		
	Divided			Undivided					Divided		Undiv.
	2L	4L	6L	2L2[a]	2L1[b]	3L2[c]	3L1[d]	4L2[e]	2L	4L	2L2[f]
Median Width	--	0.99	0.99	NA	NA	NA	NA	NA	0.84	--	NA
Presence of Bicycle Lane	1.69	0.86	--	--	--	--	--	2.24	--	--	--
Presence of Shared Path	--	--	0.75	--	--	--	--	--	--	--	--
Presence of Sidewalk	--	1.78	1.87	--	--	--	--	--	--	--	--
Presence of Sidewalk Barrier	2.18	--	1.99	--	--	--	--	0.33	--	--	--
Type of Parking (One Side)[g]	--	--	--	--	--	--	--	--	--	--	--
Type of Parking (Both Sides)[g]	2.65	--	0.48	--	--	--	--	--	--	--	--
Lane Width	0.64	0.77	0.75	--	--	--	--	--	--	--	--
Type of Median (Raised Traffic Separator)[h]	2.65	1.22	--						--	--	
Type of Median (Vegetation)[h]	--	0.62	0.49	NA	NA	NA	NA	NA	--	--	NA
Type of Median (Curb & Vegetation)[h]	2.43	0.85	0.80						--	--	
Shoulder Type (Paved)[i]	--	--	--	--	--	--	--	--	--	--	--
Shoulder Type (Lawn, Gravel/Marl, Valley Gutter)[i]	--	--	--	--	--	--	--	--	--	--	--
Shoulder Type (Curb & Gutter)[i]	--	--	--	--	--	--	--	--	--	--	--
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[j]	0.51	--	0.89	--	--	--	--	--	--	--	--
High Bicycle Activity (Annual Trips > 10,000)[j]	0.73	--	0.73	--	--	--	--	--	--	--	--

-- Not significant; NA is not applicable.
[a] Urban 2-Lane Undivided Two-way Road; [b] Urban 2-Lane Undivided One-way Road;
[c] Urban 3-Lane Undivided Two-way Road; [d] Urban 3-Lane Undivided One-way Road;
[e] Urban 4-Lane Undivided Two-way Road; [f] Rural 2-Lane Undivided Two-way Road.
[g] The base condition for type of parking is no parking allowed.
[h] The base condition for type of median is paved.
[i] The base condition for shoulder type is raised curb.
[j] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

Table 6-24: Summary of CMFs for Total Bicycle Crashes for Intersection Facility Types

Variables	Urban 4-Leg Signalized	Urban 3-Leg Stop-controlled
Skew Angle of the Intersection	--	--
Presence of Lighting	--	--
1-2 Bus Stops within Intersection Influence Area[a]	--	×
≥ 3 Bus Stops within Intersection Influence Area[a]	1.90	×
Presence of Schools within Intersection Influence Area	--	×
1-8 Alcohol Sales within Intersection Influence Area[b]	1.53	×
≥ 9 Alcohol Sales within Intersection Influence Area[b]	--	×
No. of Approaches with Left-Turn Lanes	--	--
No. of Approaches with Right-Turn Lanes	--	--
No. of Approaches with Protected Signal Control	--	×
No. of Approaches with Permitted Signal Control	--	×
No. of Approaches with Protected-Permitted Signal Control	--	×
No. of Approaches with No-Right-Turn-on-Red Sign	--	×
Presence of Red Light Camera	--	×
Presence of Bicycle Facilities	1.27	1.36

-- Not significant; × Excluded from modeling.

[a] The base condition for bus stops is absence of bus stops within intersection influence area.

[b] The base condition for alcohol sales establishments is absence of alcohol sales establishments within intersection influence area.

Table 6-25: Summary of CMFs for F+S Bicycle Crashes for Segment Facility Types

Variable	Urban								Rural		
	Divided			Undivided					Divided		Undiv.
	2L	4L	6L	2L2[a]	2L1[b]	3L2[c]	3L1[d]	4L2[e]	2L	4L	2L2[f]
Median Width	--	0.98	--	NA	NA	NA	NA	NA	--	--	NA
Presence of Bicycle Lane	--	--	--	--	--	--	--	--	--	--	--
Presence of Shared Path	--	--	--	--	--	--	--	--	--	--	--
Presence of Sidewalk	0.41	--	2.71	--	--	--	--	--	--	--	--
Presence of Sidewalk Barrier	4.20	--	--	3.96	--	--	--	0.36	--	--	--
Type of Parking (One Side)[g]	--	--	--	--	--	--	--	--	--	--	--
Type of Parking (Both Sides)[g]	4.62	--	--	--	--	--	--	--	--	--	--
Lane Width	0.52	--	0.79	0.42	--	--	0.24	--	--	--	--
Type of Median (Raised Traffic Separator)[h]	5.9	--	--	--					--	--	
Type of Median (Vegetation)[h]	--	--	0.45	--	NA	NA	NA	NA	--	--	NA
Type of Median (Curb & Vegetation)[h]	--	0.97	--	--					--	--	
Shoulder Type (Paved)[i]	--	--	--	--	--	--	--	--	--	--	--
Shoulder Type (Lawn, Gravel/Marl, Valley Gutter)[i]	--	--	--	--	--	--	--	--	--	--	--
Shoulder Type (Curb & Gutter)[i]	--	--	--	--	--	--	--	--	--	--	--
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[j]	0.47	1.63	--	--	--	--	--	--	--	--	--
High Bicycle Activity (Annual Trips > 10,000)[j]	--	1.43	0.76	--	--	--	--	--	--	--	--

-- Not significant; NA is not applicable.
[a] Urban 2-Lane Undivided Two-way Road; [b] Urban 2-Lane Undivided One-way Road;
[c] Urban 3-Lane Undivided Two-way Road; [d] Urban 3-Lane Undivided One-way Road;
[e] Urban 4-Lane Undivided Two-way Road; [f] Rural 2-Lane Undivided Two-way Road.
[g] The base condition for type of parking is no parking allowed.
[h] The base condition for type of median is paved.
[i] The base condition for shoulder type is raised curb.
[j] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

Table 6-26: Summary of CMFs for F+S Bicycle Crashes for Intersection Facility Types

Variable	Urban 4-Leg Signalized	Urban 3-Leg Stop-controlled
Skew Angle of the Intersection	--	--
Presence of Lighting	--	--
1-2 Bus Stops within Intersection Influence Area[a]	--	×
≥ 3 Bus Stops within Intersection Influence Area[a]	--	×
Presence of Schools within Intersection Influence Area	--	×
1-8 Alcohol Sales within Intersection Influence Area[b]	--	×
≥ 9 Alcohol Sales within Intersection Influence Area[b]	--	×
No. of Approaches with Left-Turn Lanes	--	--
No. of Approaches with Right-Turn Lanes	0.82	--
No. of Approaches with Protected Signal Control	--	×
No. of Approaches with Permitted Signal Control	--	×
No. of Approaches with Protected-Permitted Signal Control	--	×
No. of Approaches with No-Right-Turn-on-Red Sign	--	×
Presence of Red Light Camera	--	×
Presence of Bicycle Facilities	1.71	--

-- Not significant; × Excluded from modeling.

[a] The base condition for bus stops is absence of bus stops within intersection influence area.

[b] The base condition for alcohol sales establishments is absence of alcohol sales establishments within intersection influence area.

CHAPTER 7
SUMMARY AND CONCLUSIONS

The goal of this research project was to conduct a comprehensive study to improve bicycle safety in Florida. The objective is achieved through a detailed analysis of the roadway, behavioral, and spatial factors associated with bicycle crashes. An extensive literature review was first conducted. The review focuses on the methods to identify bicycle hot spots and findings on bicycle crash causes, crash contributing factors, and potential countermeasures. A descriptive trend analysis was then performed based on a total of 26,036 bicycle crashes that occurred during 2011-2014. A spatial analysis using ArcGIS was then performed to identify the top five bicycle crash hot spots in each Florida Department of Transportation (FDOT) district. These hot spots together experienced a total of 2,954 bicycle crashes during the four-year analysis period. Police reports of these bicycle crashes were reviewed in detail to identify specific bicycle crash types, their crash contributing factors and potential countermeasures. Macroscopic spatial analysis was performed to model the relation between demographic, socio-economic, roadway, traffic, and bicycle activity data at the census block group level and bicycle crash frequencies in Florida. Finally, a cross-sectional analysis was performed to develop Florida-specific Crash Modification Factors (CMFs) for bicycle crashes for different roadway segment and intersection facility types.

7.1 Literature Review

The review summarized existing studies in the following four areas: (1) risk factors that affect the frequency and severity of bicycle crashes; (2) bicycle crash causes, patterns, and contributing factors; (3) network screening methods used to identify and prioritize bicycle hot spots; and (4) safety performance of the most commonly implemented engineering countermeasures.

Researchers preferred to differentiate the risk factors affecting bicycle safety for intersections and mid-block locations due to the obvious variability in the operational characteristics. Traffic, geometric, and socio-economic variables were investigated to determine their impact on bicycle crash frequency and severity. Spatial analysis, especially the use of ArcGIS, has evolved as an effective tool to better understand and model bicycle crash frequencies. Moreover, spatial analysis using ArcGIS was found to be the most commonly used network screening approach. Several studies however used a combination of different methods to identify and rank bicycle high crash locations.

In addition to the typical bicycle infrastructure such as bicycle lanes and bicycle slots, researchers have investigated the impact of several other roadway characteristics including shared path width and separation, shoulder type, shoulder width, etc. on bicycle safety. One of the main challenges observed in improving bicycle safety is the lack of bicycle exposure data. Unlike traffic volumes, bicycle volumes are scarcely available, if at all. Researchers addressed this limitation by using surrogate measures of bicycle exposure such as number of transit stops in a region, population, etc.

7.2 Statewide Bicycle Crash Causes and Patterns

Statewide bicycle crash patterns and causes were identified based on a total of 26,036 bicycle crashes that occurred during 2011-2014. The descriptive trend analysis was based on temporal, environmental, bicyclist-related, crash location-related, and vehicle-related factors. The effect of roadway geometric features on the frequency and severity of bicycle crashes was also studied using data from 9,884.3 miles of non-limited-access state roads in Florida, which experienced a total of 10,546 bicycle crashes during the four-year analysis period. Some of the key findings include:

- Bicycle fatal crashes accounted for 5.6% of all traffic fatal crashes, while they constituted only 1.9% of total crashes.
- The majority of bicycle crashes occurred on urban roadways; only 1.2% of all crashes that occurred on state roads occurred in rural areas. In terms of crash severity, 16.9% of all bicycle crashes that occurred on rural facilities resulted in fatalities while only 2.5% of those that occurred on urban facilities resulted in fatalities.
- Nighttime bicycle crashes resulted in more fatalities compared to daytime crashes.
- Crashes involving elder bicyclists (≥ 65 years) resulted in more fatalities compared to crashes involving younger bicyclists (< 65 years).
- Crashes involving male bicyclists resulted in more fatalities compared to crashes involving female bicyclists.
- Over 10% of all bicyclists involved in crashes who were under the influence of alcohol were killed, and a high 27.6% of all bicyclists involved in crashes who were under the influence of drugs were killed.
- Crashes involving bicyclists using helmets or protective pads were less severe compared to those involving bicyclists using reflective clothing or lighting.
- Although bicyclists were frequently hit while cycling on the sidewalk, these crashes resulted in very few fatalities.
- Crashes involving bicyclists cycling along the roadway against traffic were found to be more severe compared to those involving bicyclists cycling along the roadway with traffic.
- In terms of bicyclist's action at the time of the crash, failure to yield right-of-way was the most frequent contributing cause, resulting in about 15% of total crashes.
- Among all types of vehicles, passenger cars were found to result in relatively less severe crashes. Medium and heavy trucks resulted in more severe crashes; a relatively high 14.5% of all crashes involving medium and heavy trucks were fatal.

7.3 Bicycle Crash Patterns at Hot Spots

Spatial analysis in ArcGIS was used to identify top five bicycle hot spots in each FDOT district. Police reports of all the 2,954 bicycle crashes that occurred at these hotspots were reviewed in detail to identify specific bicycle crash types and patterns. Some of the key findings from the police report review include:

- Drivers were at-fault in 45.7% of the crashes, while bicyclists were at-fault in 30.2% of the crashes.
- Crashes involving at-fault bicyclists resulted in a greater percentage of fatal crashes compared to those involving at-fault drivers.
- Signalized intersections experienced a greater proportion of bicycle crashes compared to unsignalized locations.
- Locations with bicycle lanes experienced a smaller proportion of fatal crashes compared to locations without bicycle lanes.

- Crossing the street was found to result in a greater proportion of fatal crashes compared to riding along the roadway.
- Crashes involving bicyclists riding along the roadway facing traffic resulted in a greater proportion of fatal crashes compared to crashes involving bicyclists riding along with vehicles.
- Crosswalk locations, although experienced a high frequency of bicycle crashes, experienced a relatively low proportion of fatal crashes.

The crash pattern analysis identified the following four major bicycle crash types:

- Motorist turns right while bicyclist is crossing the street
- Motorist turns left facing bicyclist
- Bicyclist rides out at intersection
- Motorist drives out at stop sign

In addition to these crash types, the following bicycle crash contributing factors and scenarios were also found to be more frequent:

- Inadequate street lighting
- Unconventional intersection geometry
- Traffic violations
- Bicyclists sideswipe vehicles
- Driveways near intersections
- U-turn maneuvers by bicyclists and motorists
- Bicyclists hit the door of parked vehicle
- Bicyclists ride opposite to the traffic

Several engineering and education countermeasures were recommended for these crash types and scenarios. Engineering countermeasures, including signal optimization, turn restrictions, and sign and pavement marking improvements, could improve the overall safety situation for bicyclists. Agency-wide education campaigns on the laws pertaining to bicyclists and extensive driver education campaigns that focus on driver compliance with bicyclist right-of-way laws and stricter enforcement could improve bicycle safety.

7.4 Macroscopic Analysis of Bicycle Crashes

Bicycle crash trends are quite distinctive and are dependent on land use, existing bicycle infrastructure, socio-economic factors, etc. The impact of these factors on bicycle crash frequencies was therefore studied using spatial analysis. The preliminary analysis with Moran's *I* and Geary' *C*, two measures of Global index of spatial correlation, indicated that spatial clustering of bicycle crashes was prevalent among census block groups. A macro-level spatial analysis was conducted to determine the relation between bicycle crashes and independent variables, including demographic and socio-economic factors, roadway and traffic characteristics, and bicycle activity, while accounting for the effect of spatial correlation among census block groups. Separate models were developed for total bicycle crashes and F+S bicycle crashes.

Table 7-1 provides a quick overview of the impact of different demographic and socio-economic, roadway and traffic, and bicycle activity data on total and F+S bicycle crash models.

Table 7-1: Impact of Variables on Bicycle Crash Models at Census Block Group Level

Variable Description	Total Crash Model	F+S Crash Model
Demographic and Socio-economic Characteristics		
Log of total population	⇧	⇧
Proportion of households with no automobile	⇧	⇧
Proportion of households with one automobile	⇧	⇧
Proportion of male population	NC	⇧
Proportion of Black or African American population	⇧	NC
Proportion of Hispanic or Latino population	⇧	NC
Proportion of population aged 18 - 29 years	⇧	NC
Proportion of population aged 30 - 39 years	⇧	NC
Proportion of population aged 40 - 49 years	NC	⇧
Proportion of population aged 50 - 64 years	⇧	NC
Proportion of population ≥ 25 years having high school diploma only	⇩	⇩
Proportion of population ≥ 25 years having Associate's degree or attended some college with no degree achieved	⇩	⇩
Proportion of population ≥ 25 years having Associate's degree or attended some college with no degree achieved	⇩	⇩
Proportion of population ≥ 25 years having Bachelor's degree or higher	⇩	⇩
Roadway and Traffic Characteristics		
Density of rural collector roads per sq. mi. of area	⇩	⇩
Density of rural local roads per sq. mi. of area	⇩	⇩
Length of urban principal arterials per sq. mi. of area	⇧	⇧
Length of urban collector roads per sq. mi. of area	⇧	NC
Length of urban local roads per sq. mi. of area	⇧	NC
Density of bicycle lane and bicycle slot per sq. mi. of area	⇧	⇧
Log of daily vehicle miles traveled (DVMT) in thousands	⇧	⇧
Log of number of bicycle commuters	⇧	NC
Truck percentage	⇩	⇩
Strava Users' Ride Characteristics		
Bicycle trip miles: Medium	⇧	NC
Bicycle trip miles: High	⇧	⇧
Bicycle trip intensity: Medium	⇧	⇧
Bicycle trip intensity: High	⇧	⇧

Note: ⇧ indicates credible and increasing effect; ⇩ indicates credible and decreasing effect; NC is not credible.

7.5 Florida-Specific CMFs

Cross-sectional analysis was conducted to develop Florida-specific CMFs for bicycle crashes. Multivariate regression models were developed using a generalized linear model (GLM) approach with negative binomial (NB) distribution. Only the variables that were significant at the 80% confidence interval in the initial model were used to develop the final models. Finally, the CMFs were estimated based on these final models. For each facility type, the data and model coefficients were reviewed closely to identify reliable CMFs. Table 7-2 and 7-3 provide the Florida-specific CMFs developed for total bicycle crashes for different roadway segment and intersection facility types, respectively. Similarly, Tables 7-4 and 7-5 list the Florida-specific CMFs developed for F+S bicycle crashes for different roadway segment and intersection facility types, respectively.

Table 7-2: Florida-Specific CMFs for Total Bicycle Crashes for Segment Facility Types

Variable	Urban				Rural
	Divided			Undivided	Divided
	2L[a]	4L[b]	6L[c]	4L2[d]	2L[e]
Median Width	--	0.99	0.99	NA	0.84
Presence of Bicycle Lane	1.69	0.86	--	2.24	--
Presence of Shared Path	--	--	0.75	--	--
Presence of Sidewalk	--	1.78	1.87	--	--
Presence of Sidewalk Barrier	2.18	--	1.99	0.33	--
Type of Parking (One Side)[f]	--	--	--	--	--
Type of Parking (Both Sides)[f]	2.65	--	0.48	--	--
Lane Width	0.64	0.77	0.75	--	--
Type of Median (Raised Traffic Separator)[g]	2.65	1.22	--		--
Type of Median (Vegetation)[g]	--	0.62	0.49	NA	--
Type of Median (Curb & Vegetation)[g]	2.43	0.85	0.80		--
Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[h]	0.51	--	0.89	--	--
High Bicycle Activity (Annual Trips > 10,000)[h]	0.73	--	0.73	--	--

-- Not significant; NA is not applicable.
[a] Urban 2-Lane Divided Two-way Road; [b] Urban 4-Lane Divided Two-way Road;
[c] Urban 6-Lane Divided Two-way Road; [d] Urban 4-Lane Undivided Two-way Road;
[e] Rural 2-Lane Divided Two-way Road.
[f] The base condition for type of parking is no parking allowed.
[g] The base condition for type of median is paved.
[h] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

Table 7-3: Florida-Specific CMFs for Total Bicycle Crashes for Intersection Facility Types

Variables	Urban 4-Leg Signalized	Urban 3-Leg Stop-controlled
1-2 Bus Stops within Intersection Influence Area[a]	--	×
≥ 3 Bus Stops within Intersection Influence Area[a]	1.90	×
1-8 Alcohol Sales within Intersection Influence Area[b]	1.53	×
≥ 9 Alcohol Sales within Intersection Influence Area[b]	--	×
Presence of Bicycle Facilities	1.27	1.36

-- Not significant; × Excluded from modeling.
[a] The base condition for bus stops is absence of bus stops within intersection influence area.
[b] The base condition for alcohol sales establishments is absence of alcohol sales establishments within intersection influence area.

Table 7-4: Florida-Specific CMFs for F+S Bicycle Crashes for Segment Facility Types

<table>
<tr><th rowspan="3">Variable</th><th colspan="6">Urban</th></tr>
<tr><th colspan="3">Divided</th><th colspan="3">Undivided</th></tr>
<tr><th>2L[a]</th><th>4L[b]</th><th>6L[c]</th><th>2L2[d]</th><th>3L1[e]</th><th>4L2[f]</th></tr>
<tr><td>Median Width</td><td>--</td><td>0.98</td><td>--</td><td>NA</td><td>NA</td><td>NA</td></tr>
<tr><td>Presence of Sidewalk</td><td>0.41</td><td>--</td><td>2.71</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Presence of Sidewalk Barrier</td><td>4.20</td><td>--</td><td>--</td><td>3.96</td><td>--</td><td>0.36</td></tr>
<tr><td>Type of Parking (One Side)[g]</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Type of Parking (Both Sides)[g]</td><td>4.62</td><td>--</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>Lane Width</td><td>0.52</td><td>--</td><td>0.79</td><td>0.42</td><td>0.24</td><td>--</td></tr>
<tr><td>Type of Median (Raised Traffic Separator)[h]</td><td>5.9</td><td>--</td><td>--</td><td rowspan="3">NA</td><td rowspan="3">NA</td><td rowspan="3">NA</td></tr>
<tr><td>Type of Median (Vegetation)[h]</td><td>--</td><td>--</td><td>0.45</td></tr>
<tr><td>Type of Median (Curb & Vegetation)[h]</td><td>--</td><td>0.97</td><td>--</td></tr>
<tr><td>Medium Bicycle Activity (Annual Trips > 2,000 and ≤ 10,000)[i]</td><td>0.47</td><td>1.63</td><td>--</td><td>--</td><td>--</td><td>--</td></tr>
<tr><td>High Bicycle Activity (Annual Trips > 10,000)[i]</td><td>--</td><td>1.43</td><td>0.76</td><td>--</td><td>--</td><td>--</td></tr>
</table>

-- Not significant; NA is not applicable;
[a] Urban 2-Lane Divided Two-way Road; [b] Urban 4-Lane Divided Two-way Road;
[c] Urban 6-Lane Divided Two-way Road; [d] Urban 2-Lane Undivided Two-way Road;
[e] Urban 3-Lane Undivided One-way Road; [f] Urban 4-Lane Undivided Two-way Road.
[g] The base condition for type of parking is no parking allowed.
[h] The base condition for type of median is paved.
[i] The base condition for bicycle exposure is low bicycle activity (Annual Trips ≤ 2,000).

Table 7-5: Florida-Specific CMFs for F+S Bicycle Crashes for Intersection Facility Types

Variable	Urban 4-Leg Signalized Intersection
No. of Approaches with Right-Turn Lanes	0.82
Presence of Bicycle Facilities	1.71

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APPENDIX A:
SATELLITE IMAGES OF BICYCLE HOT SPOTS IN EACH DISTRICT

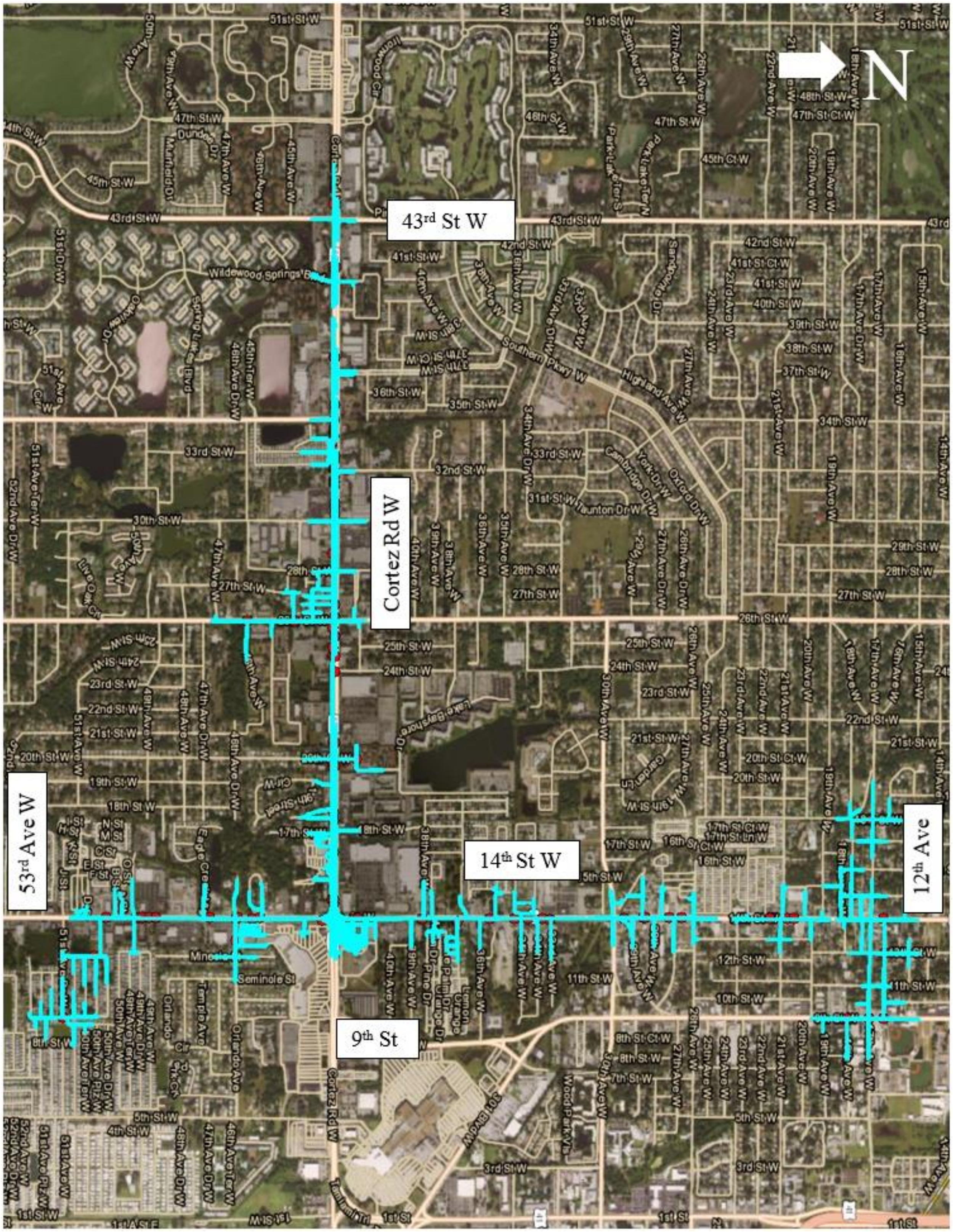

Figure A-1: Hot Spot 1 in District 1 (Total Crashes: 92) (Map)

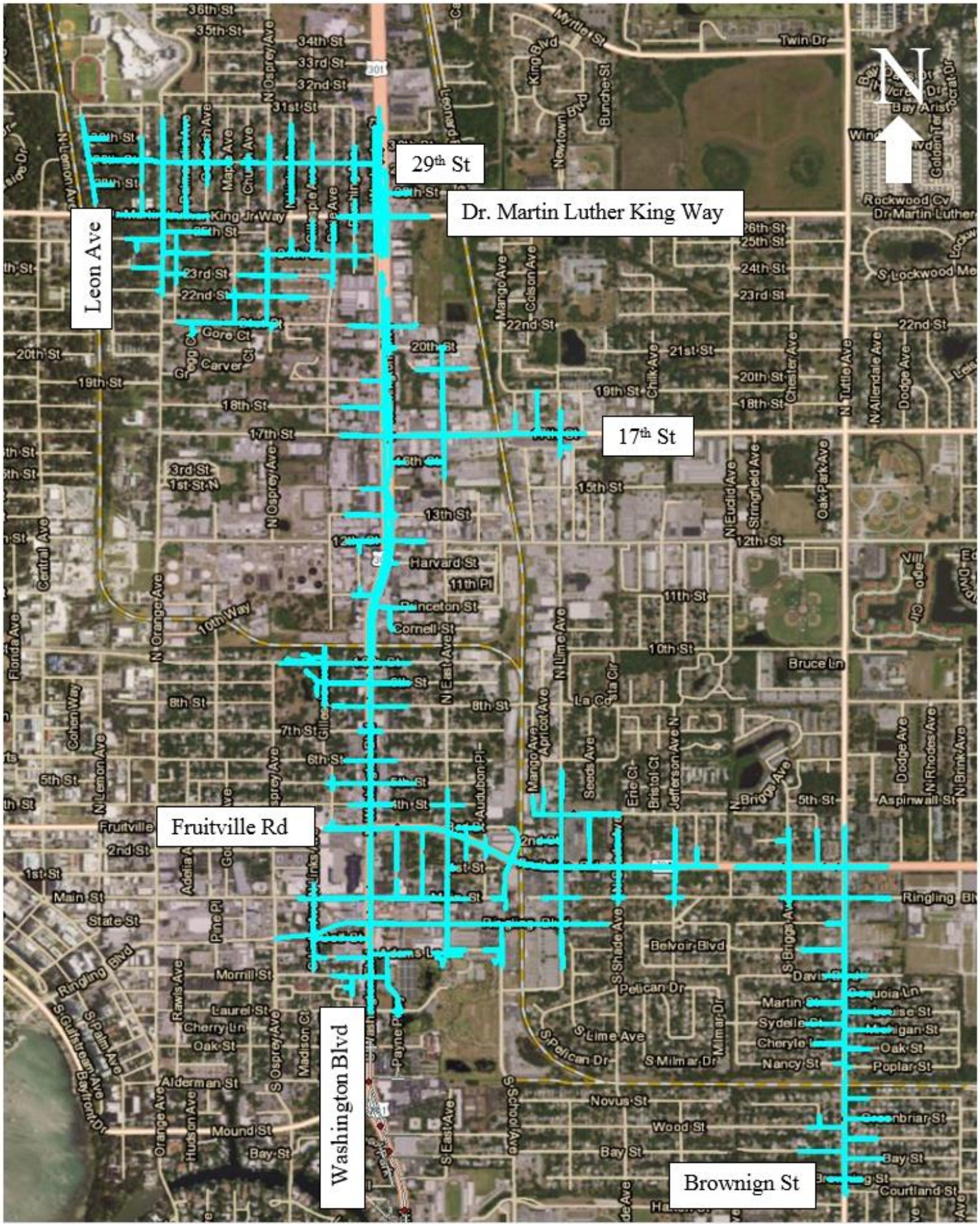

Figure A-2: Hot Spot 2 in District 1 (Total Crashes: 90) (Map)

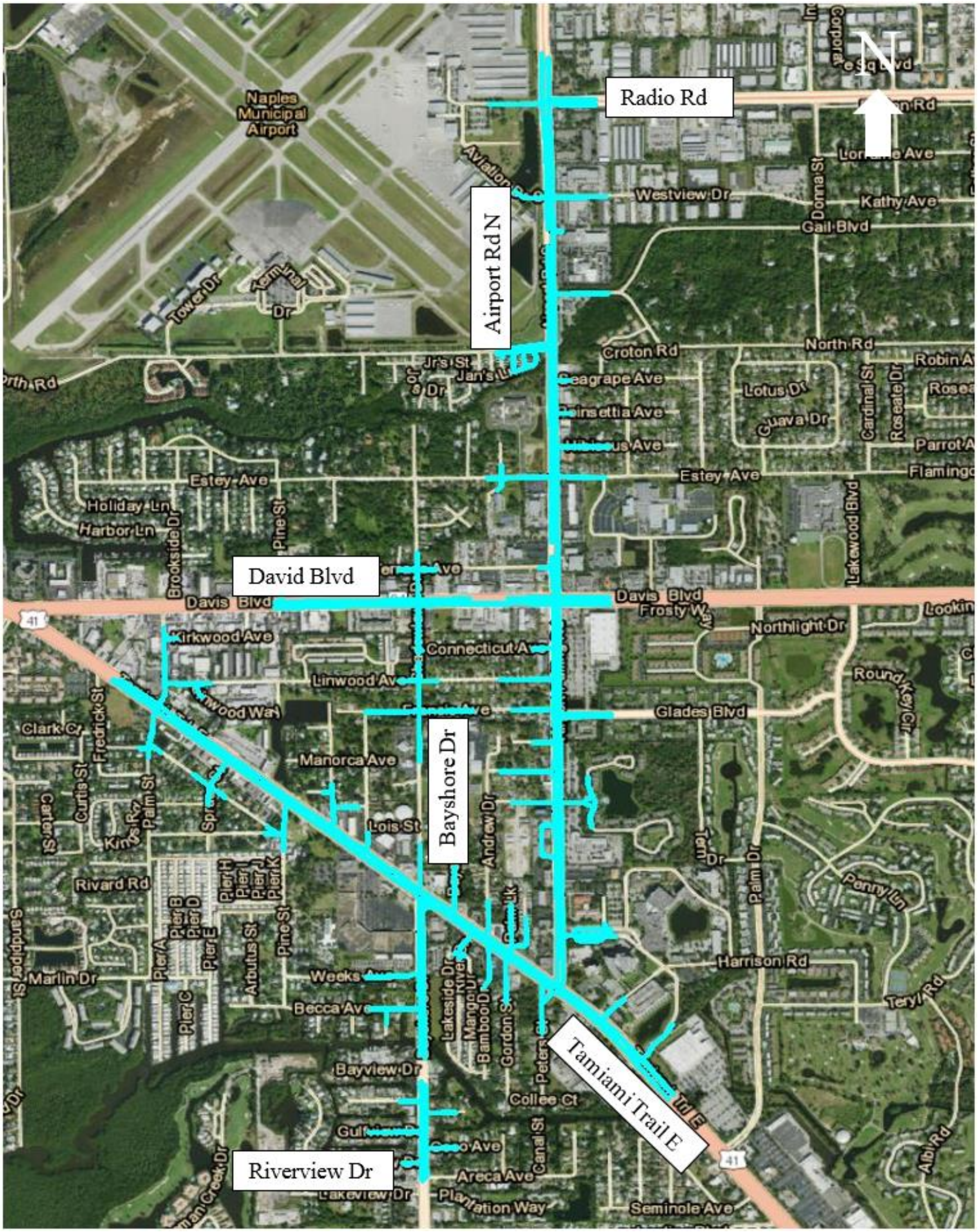

Figure A-3: Hot Spot 3 in District 1 (Total Crashes: 81) ([Map](Map))

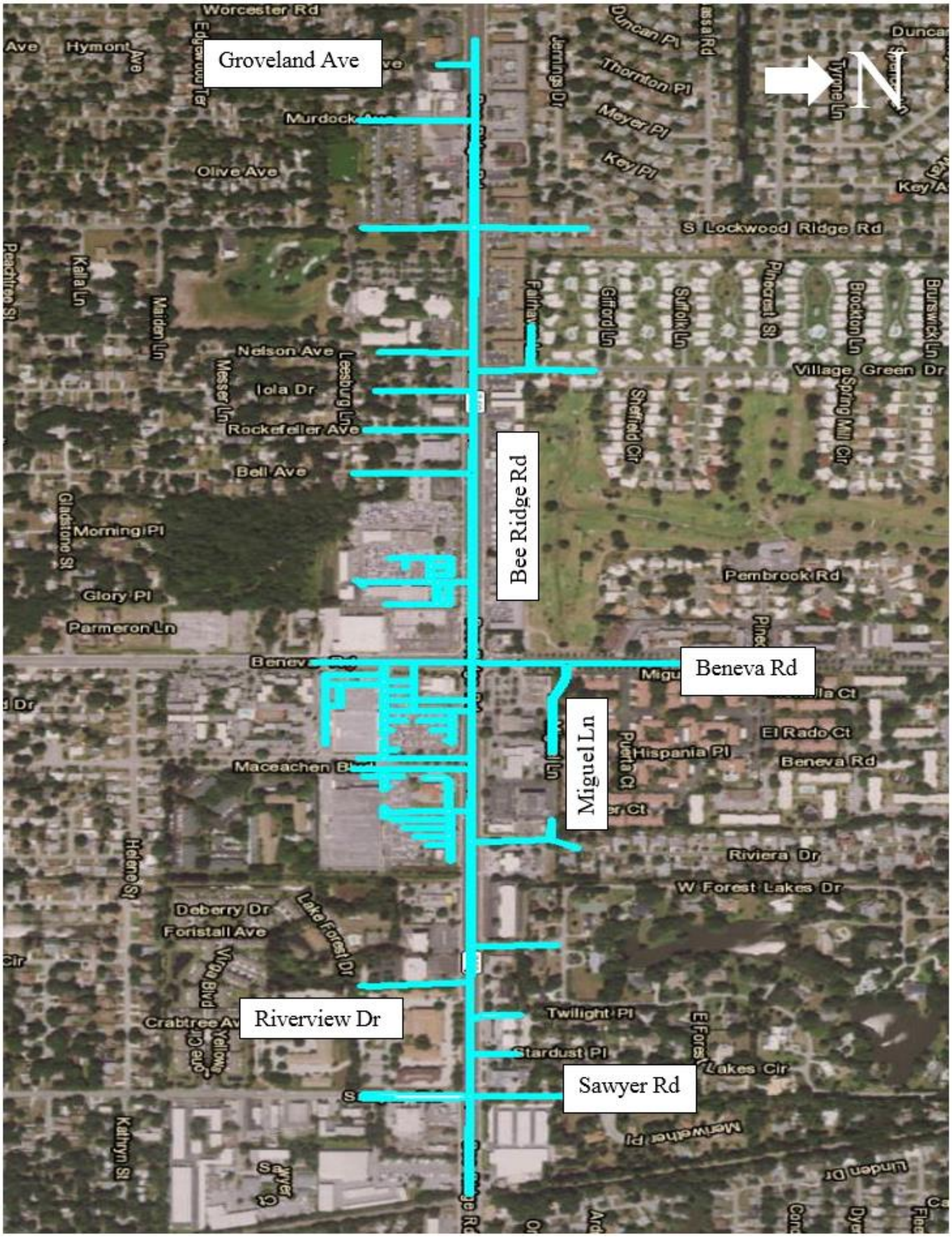

Figure A-4: Hot Spot 4 in District 1 (Total Crashes: 32) ([Map])

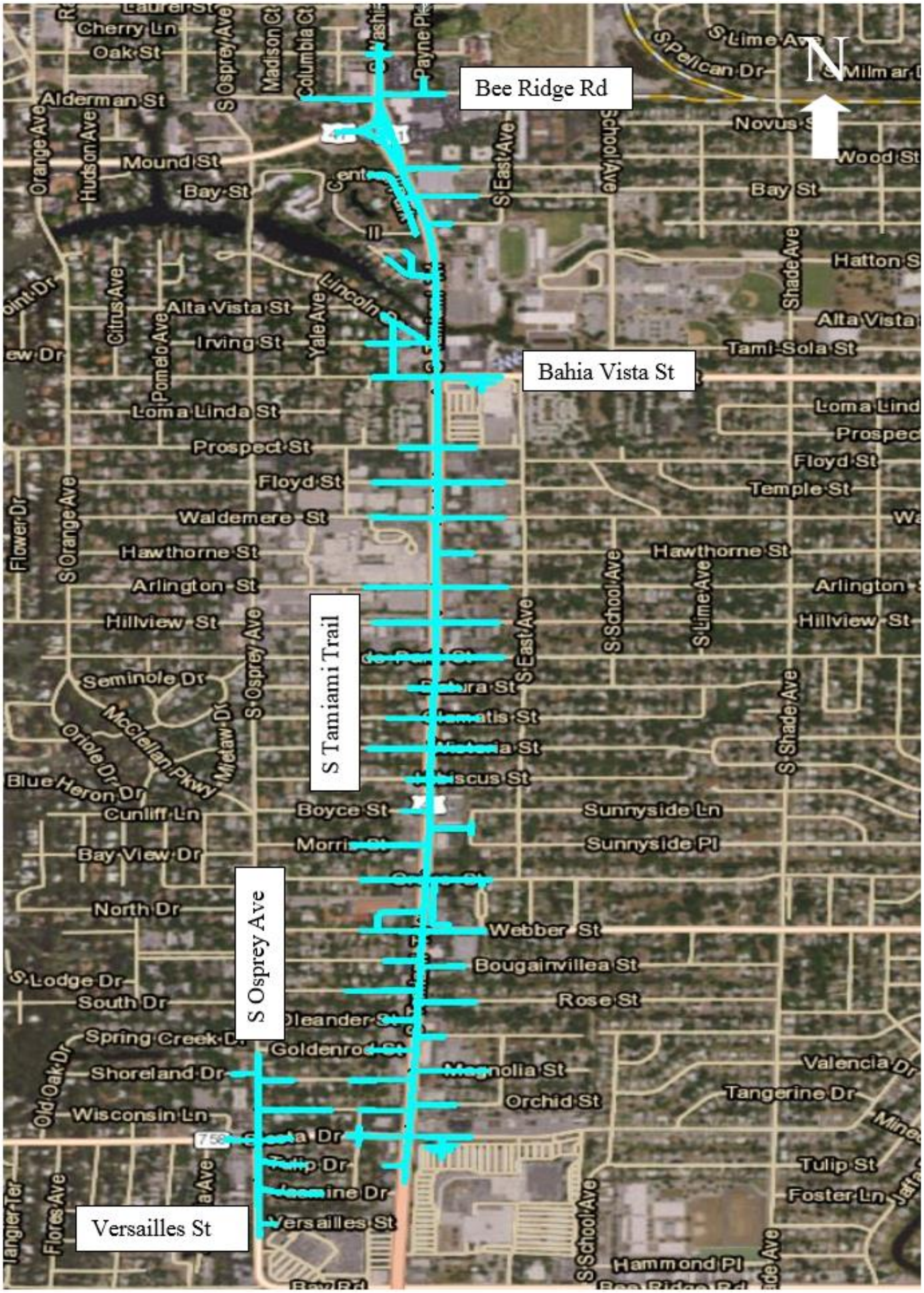

Figure A-5: Hot Spot 5 in District 1 (Total Crashes: 29) ([Map](#))

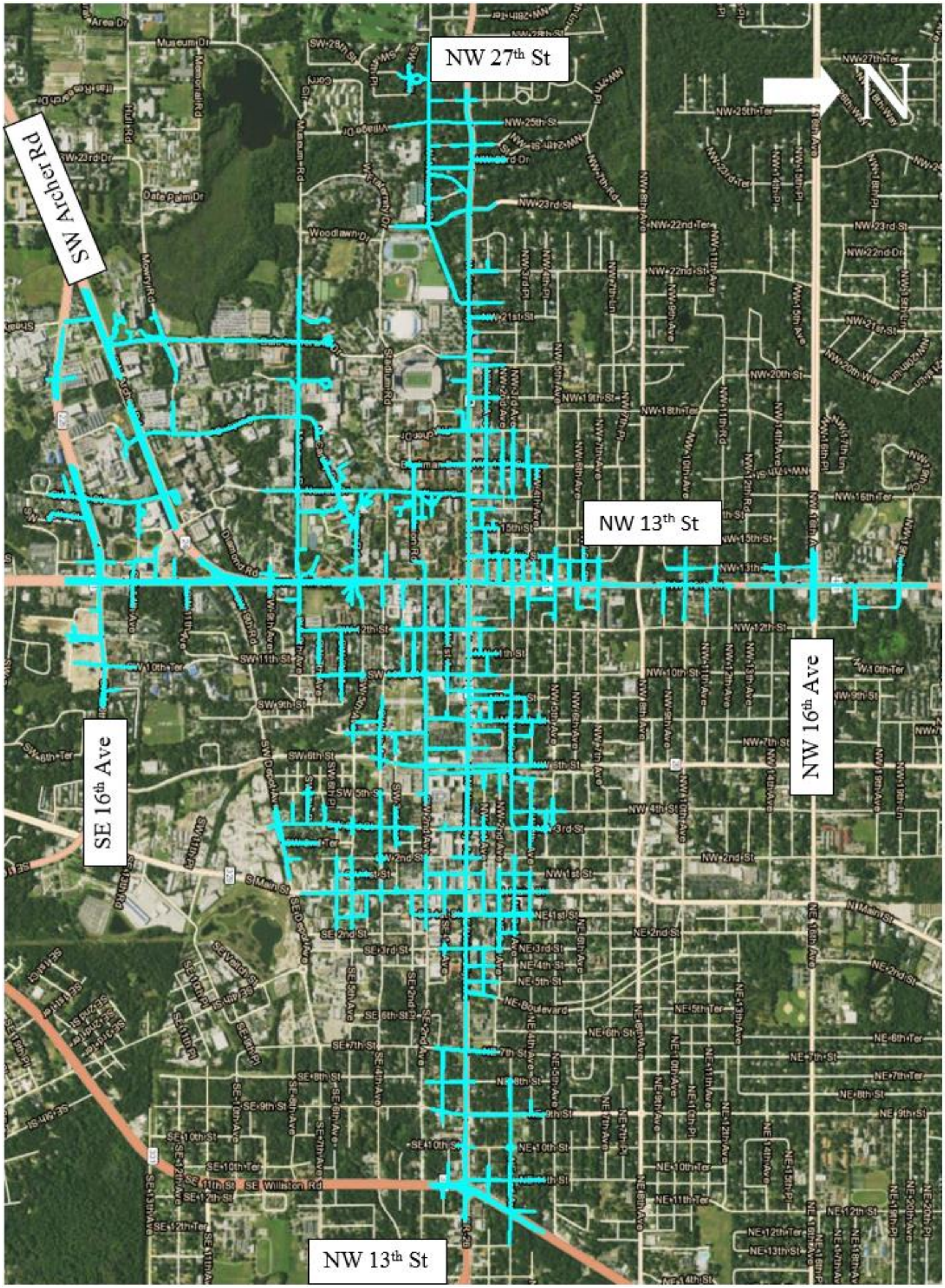

Figure A-6: Hot Spot 1 in District 2 (Total Crashes: 199) ([Map](#))

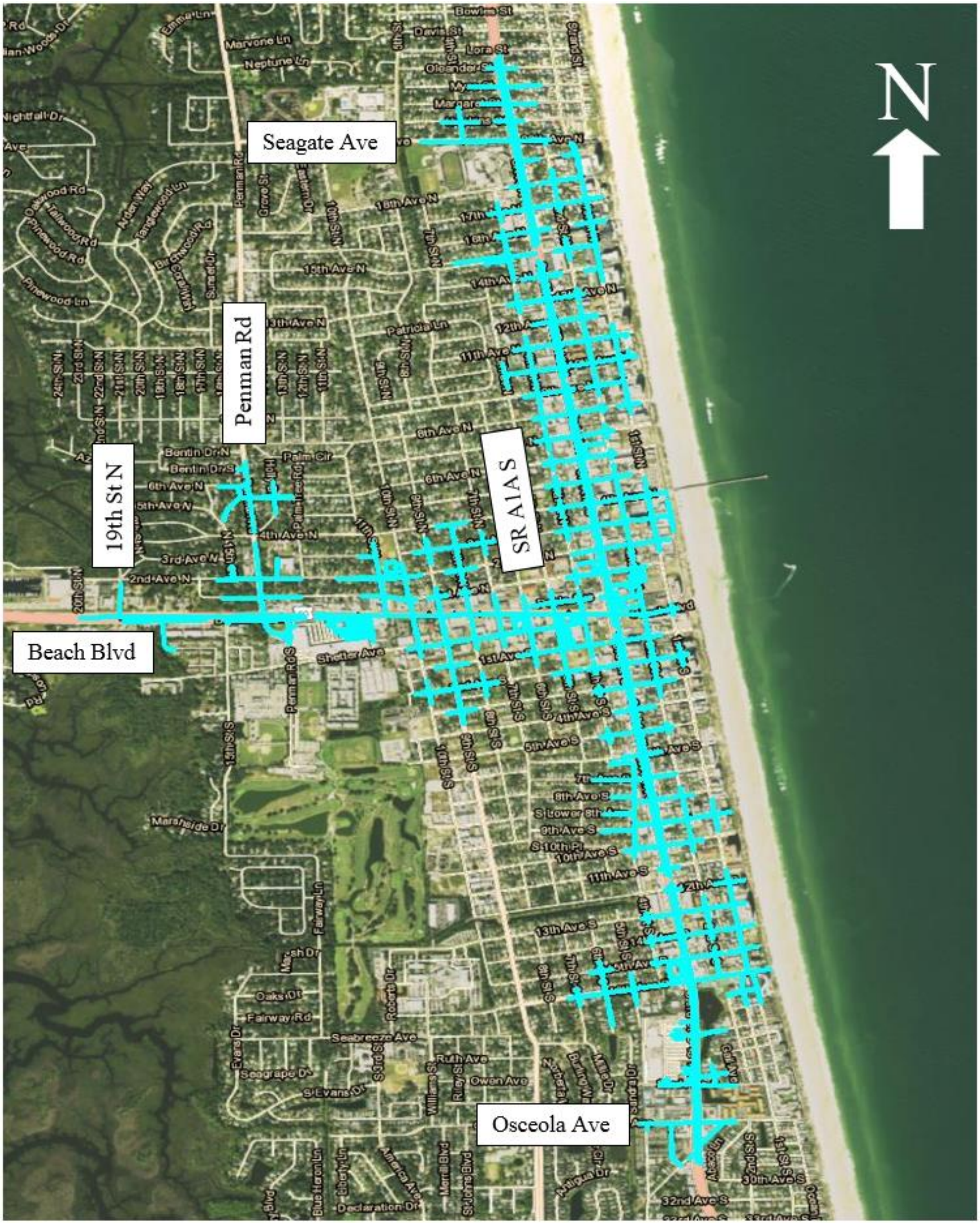

Figure A-7: Hot Spot 2 in District 2 (Total Crashes: 74) ([Map](Map))

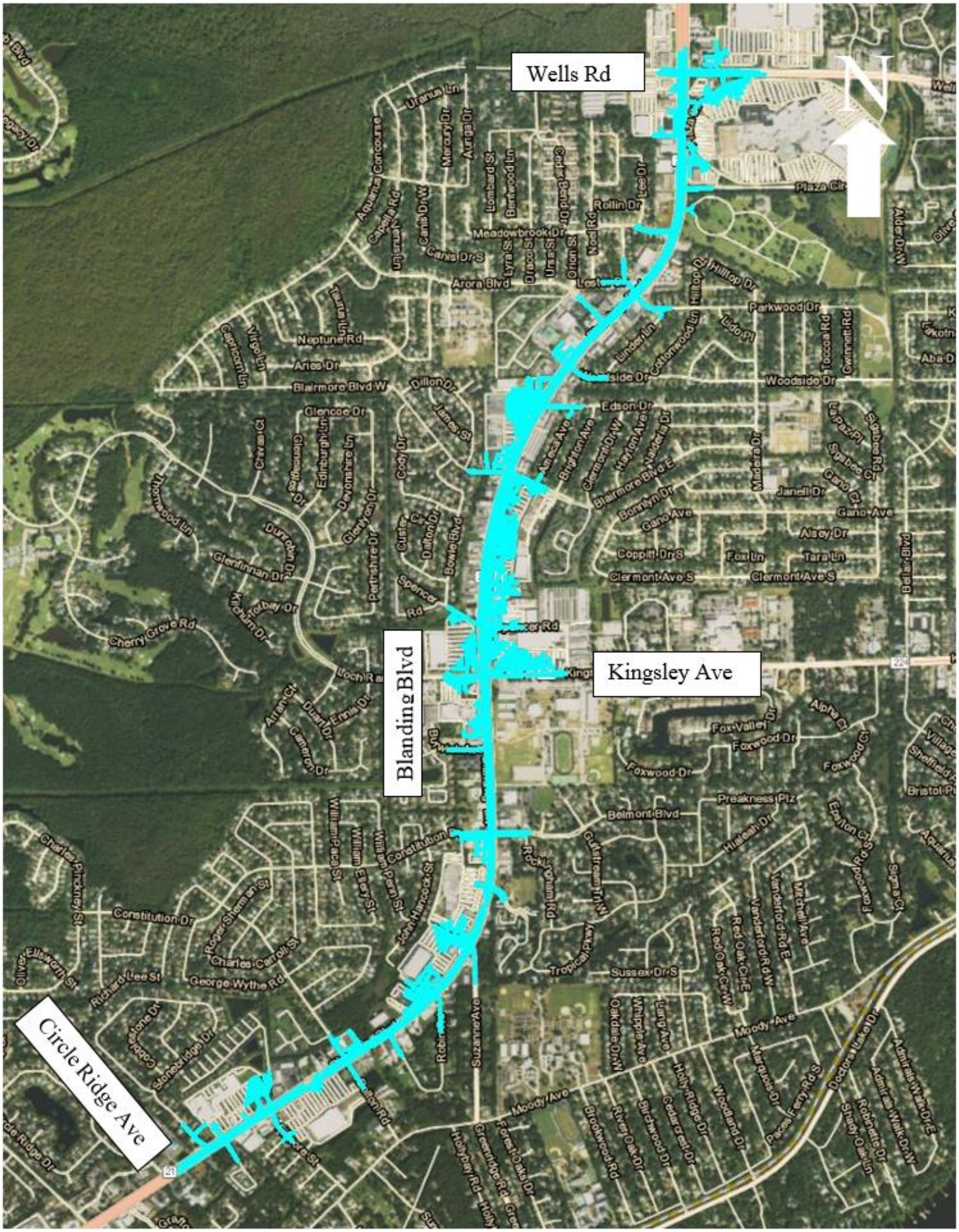

Figure A-8: Hot Spot 3 in District 2 (Total Crashes: 55) (Map)

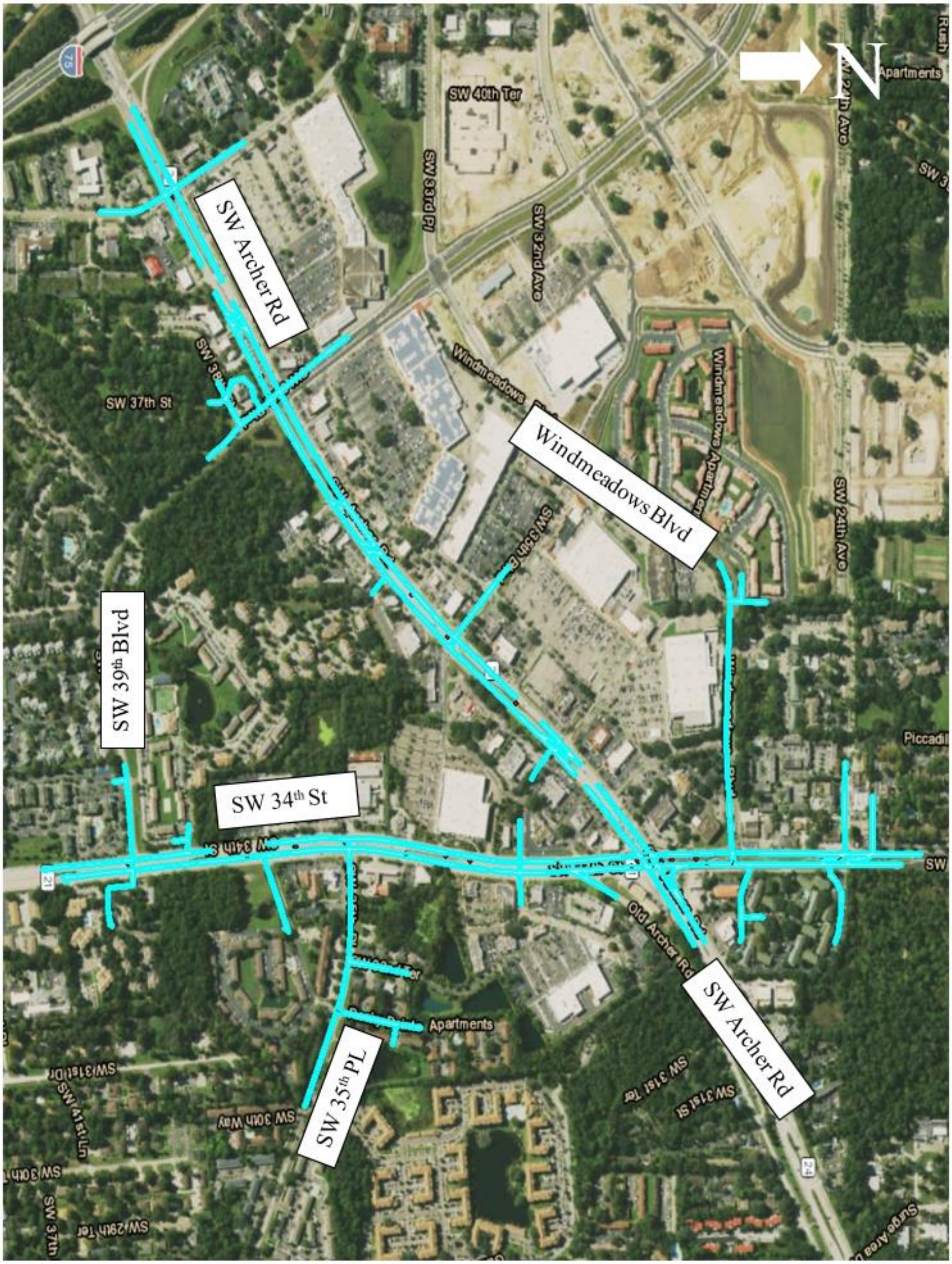

Figure A-9: Hot Spot 4 in District 2 (Total Crashes: 35) ([Map](#))

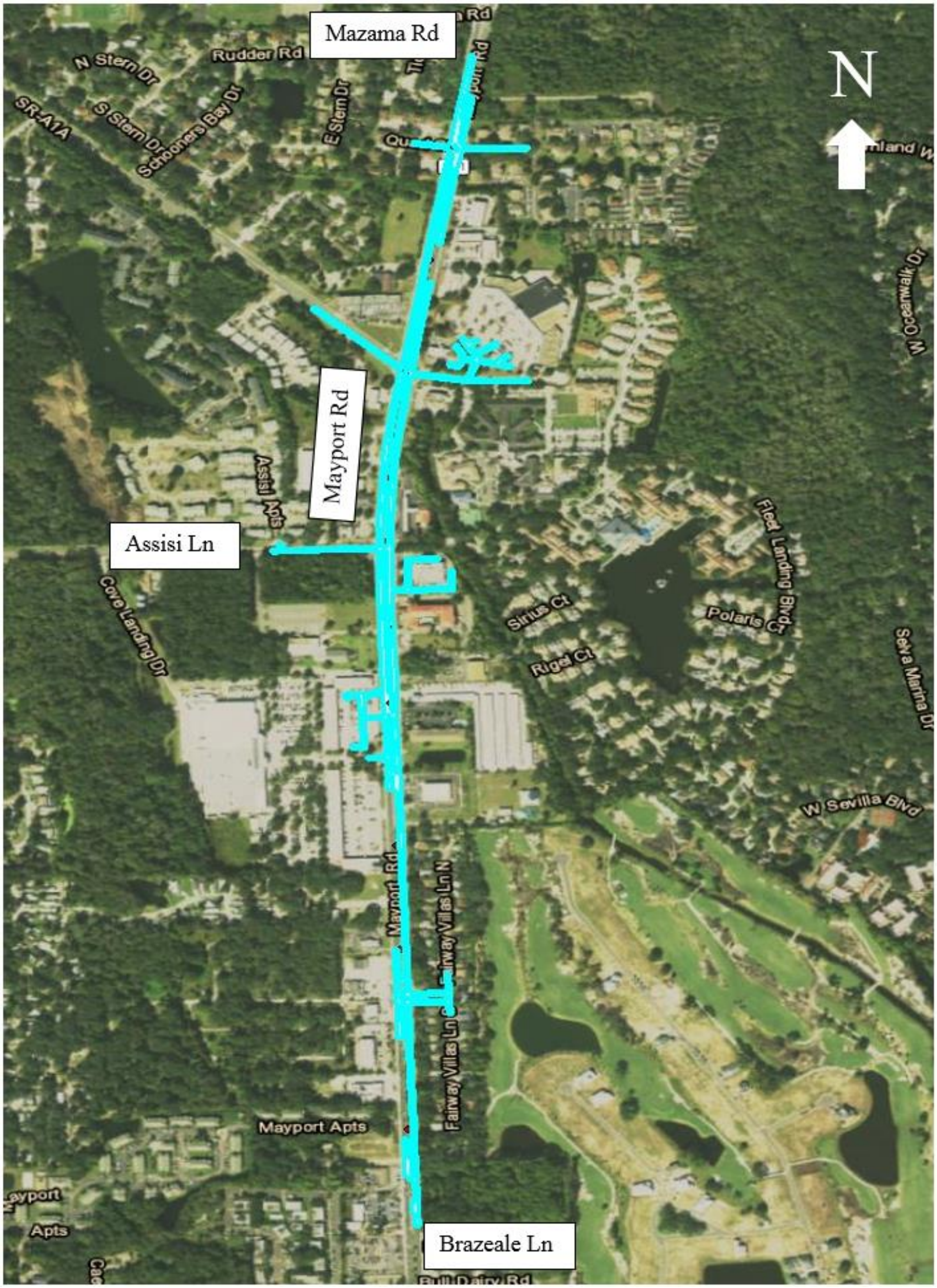

Figure A-10: Hot Spot 5 in District 2 (Total Crashes: 20) (Map)

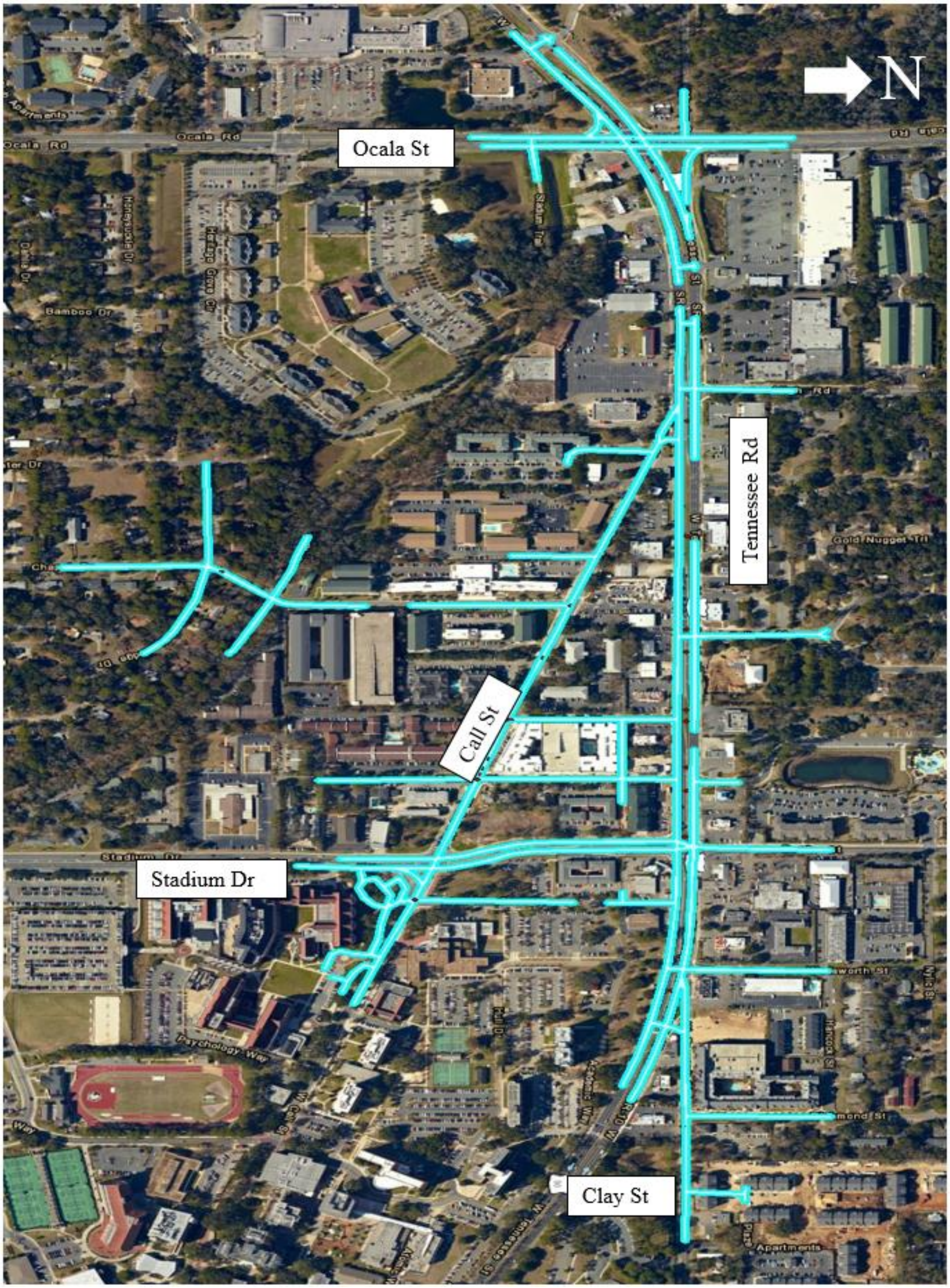

Figure A-11: Hot Spot 1 in District 3 (Total Crashes: 32) ([Map])

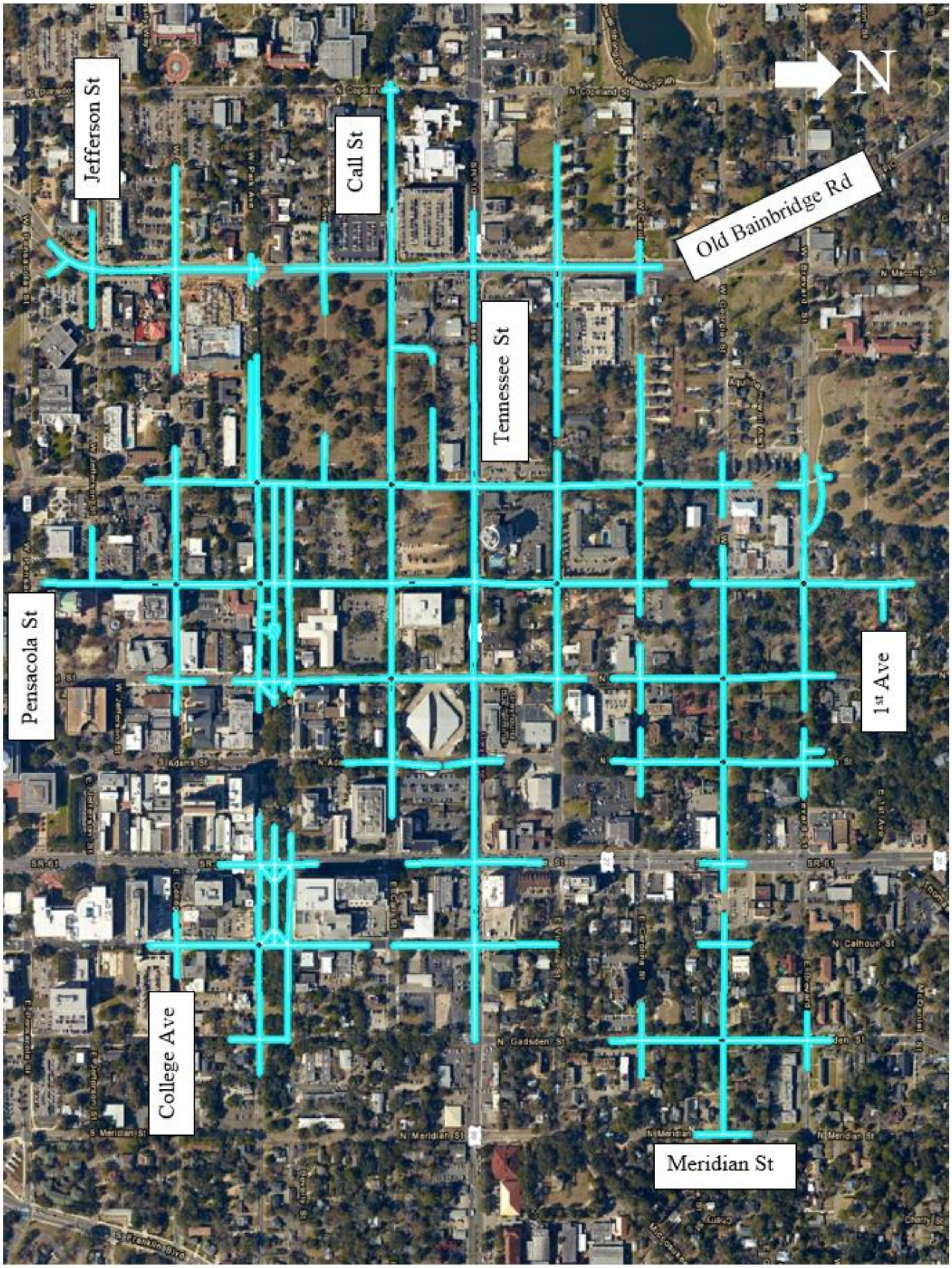

Figure A-12: Hot Spot 2 in District 3 (Total Crashes: 27) ([Map])

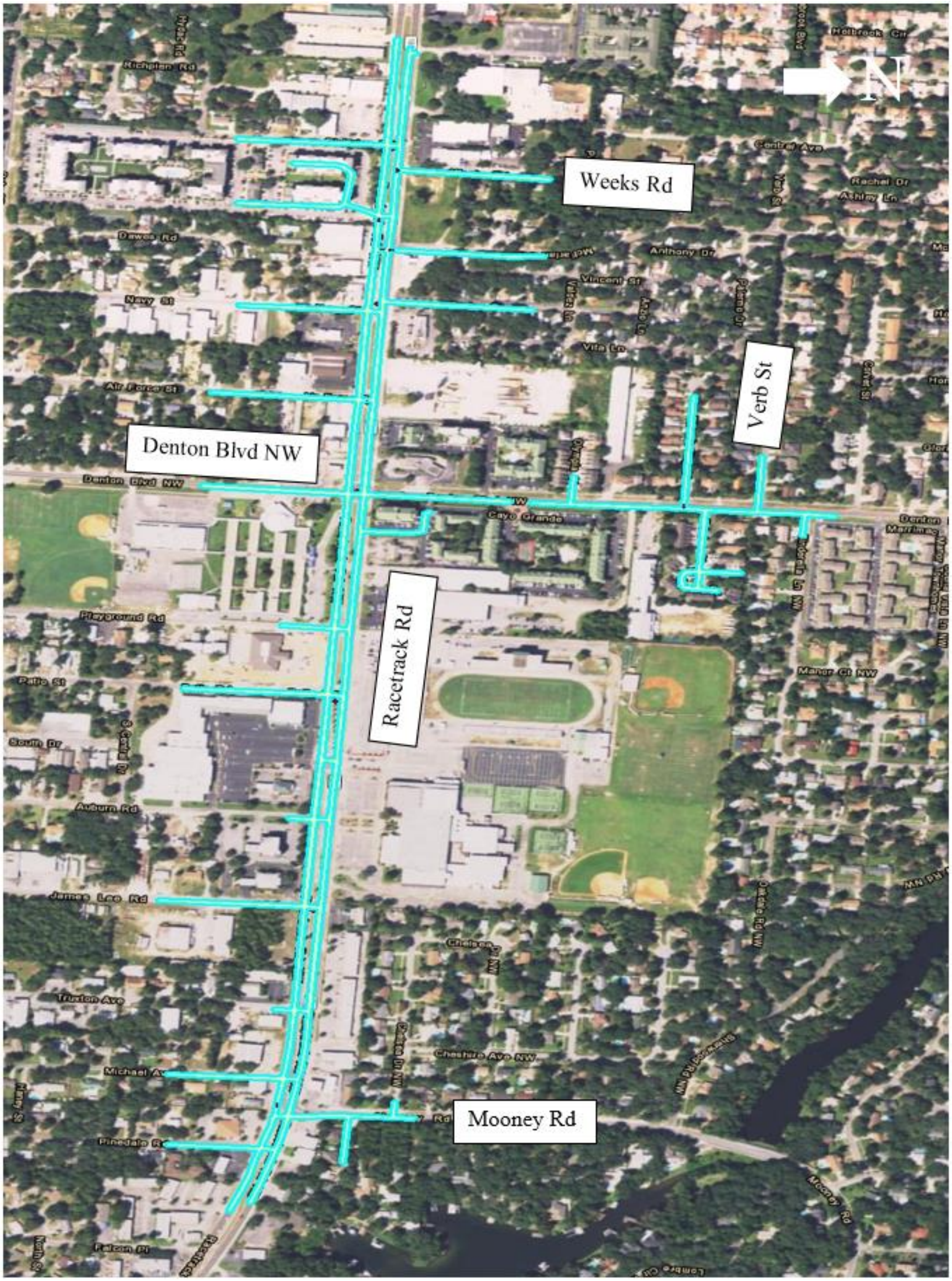

Figure A-13: Hot Spot 3 in District 3 (Total Crashes: 13) (Map)

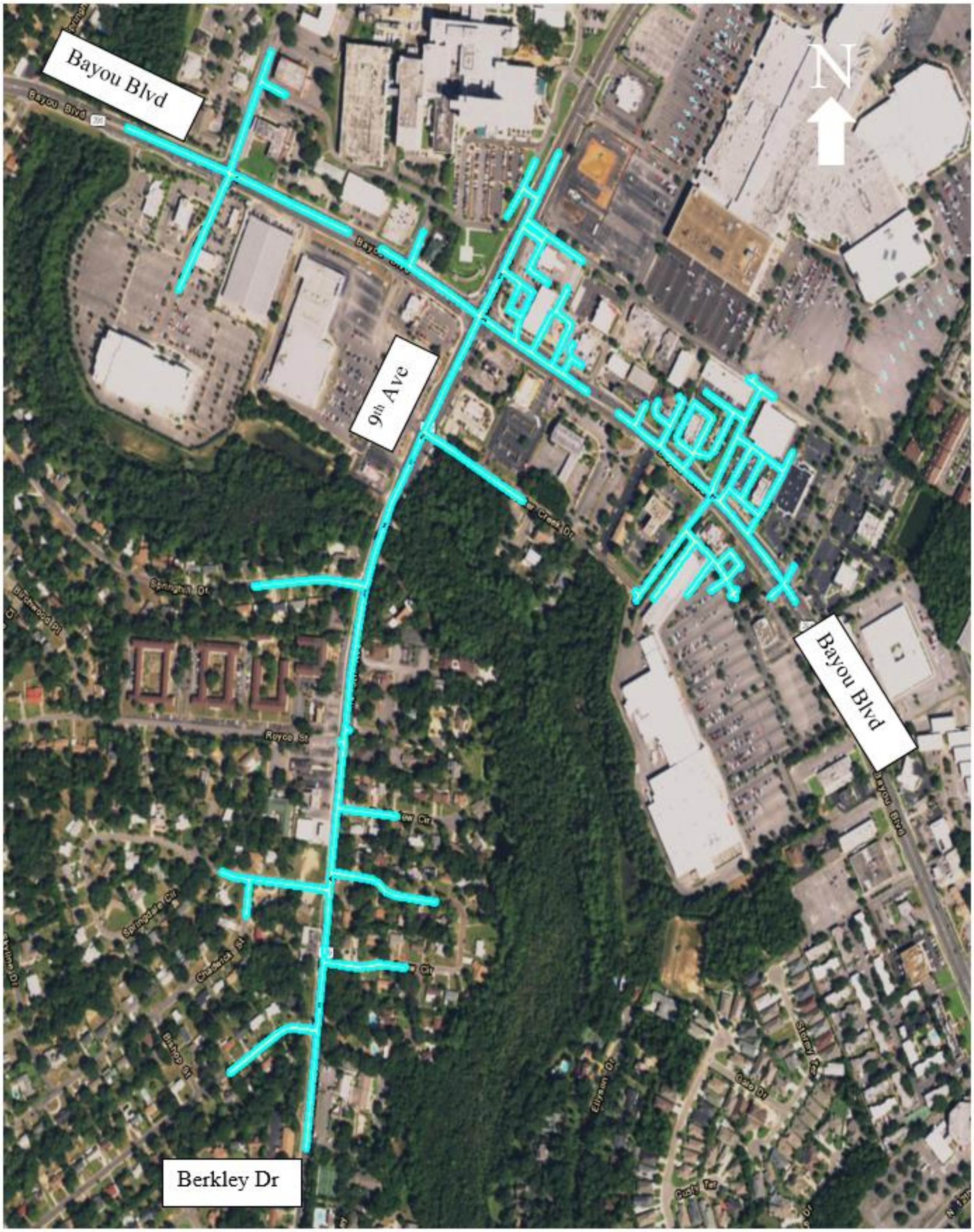

Figure A-14: Hot Spot 4 in District 3 (Total Crashes: 13) (Map)

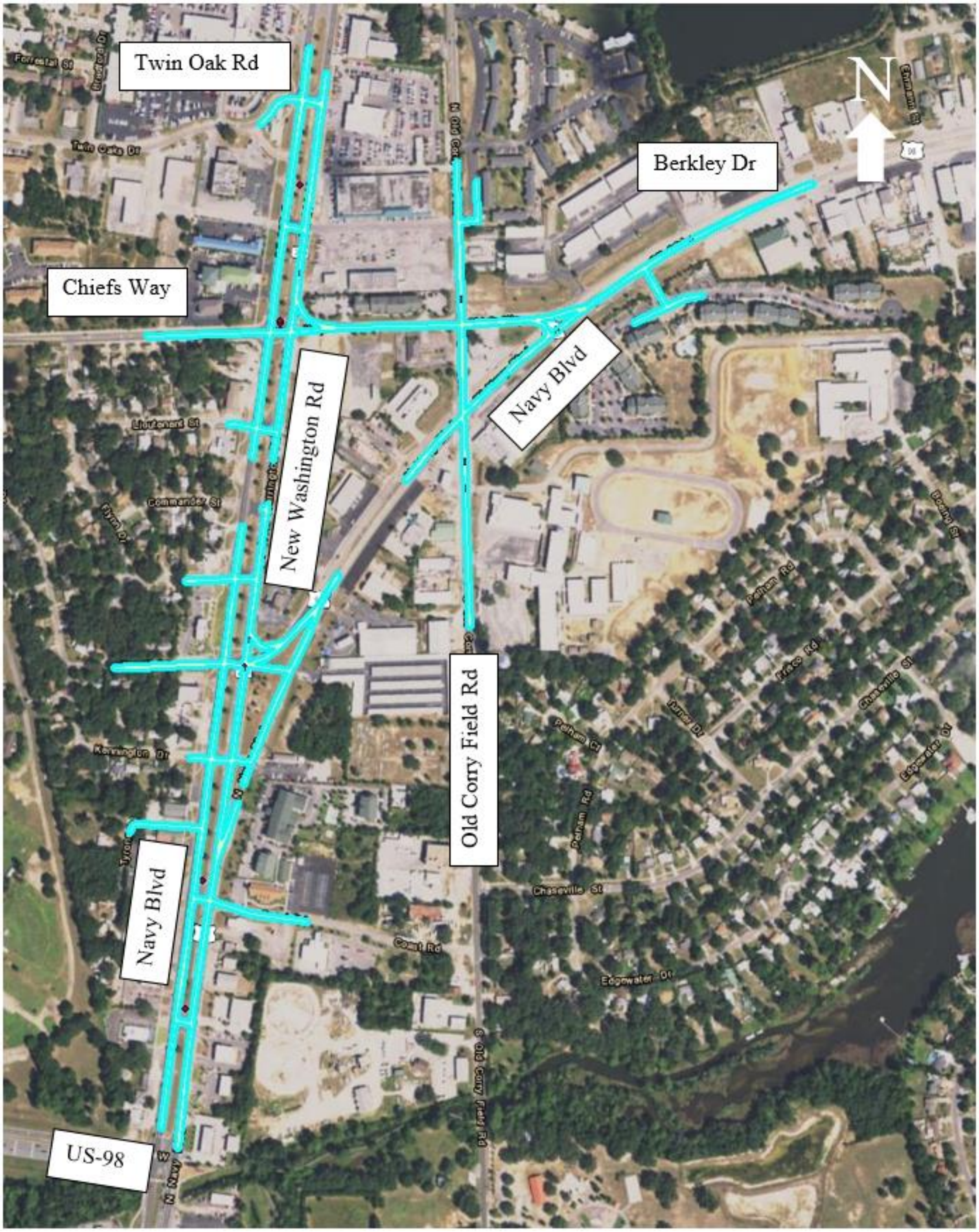

Figure A-15: Hot Spot 5 in District 3 (Total Crashes: 13) (Map)

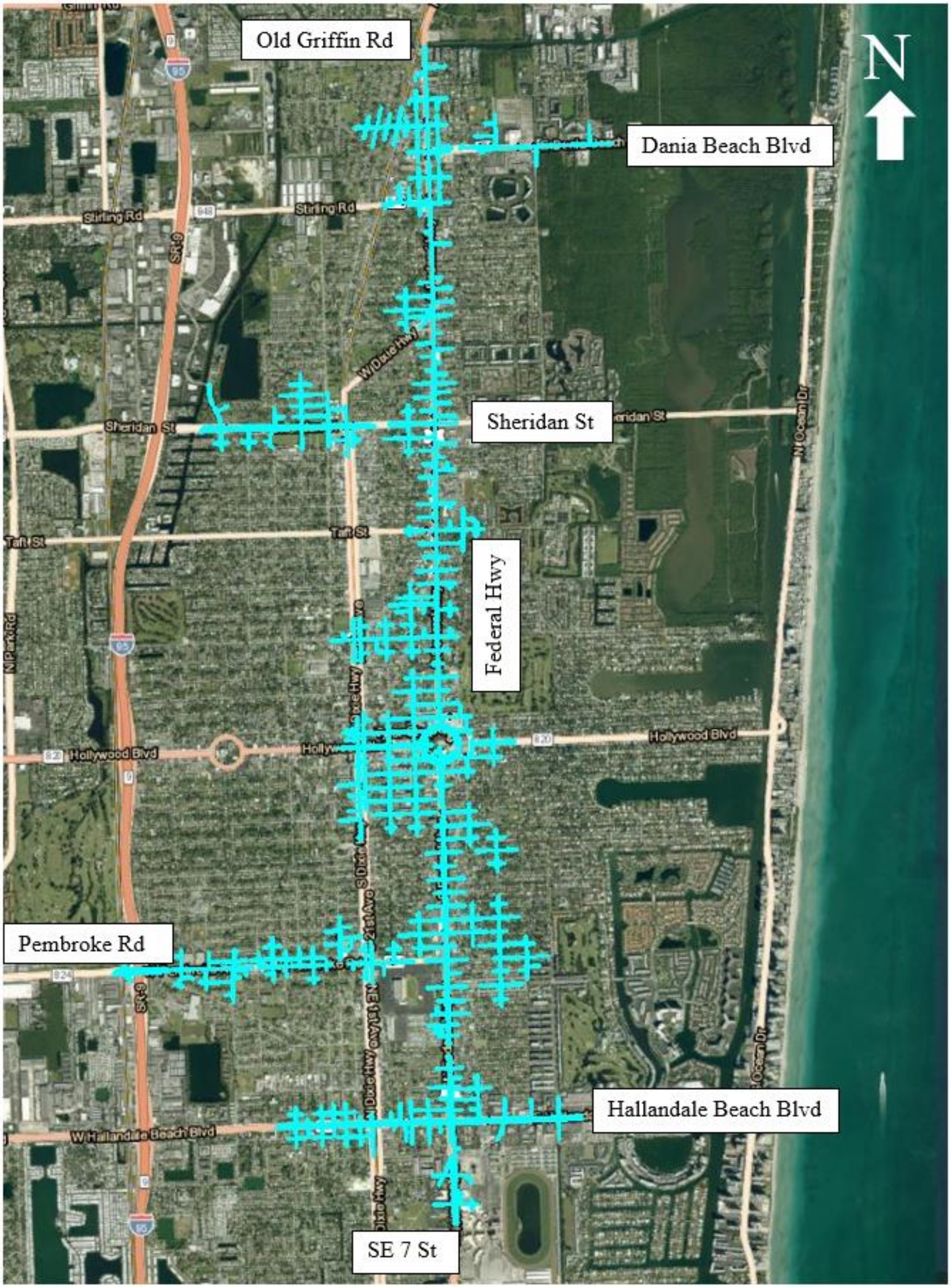

Figure A-16: Hot Spot 1 in District 4 (Total Crashes: 232) ([Map](#))

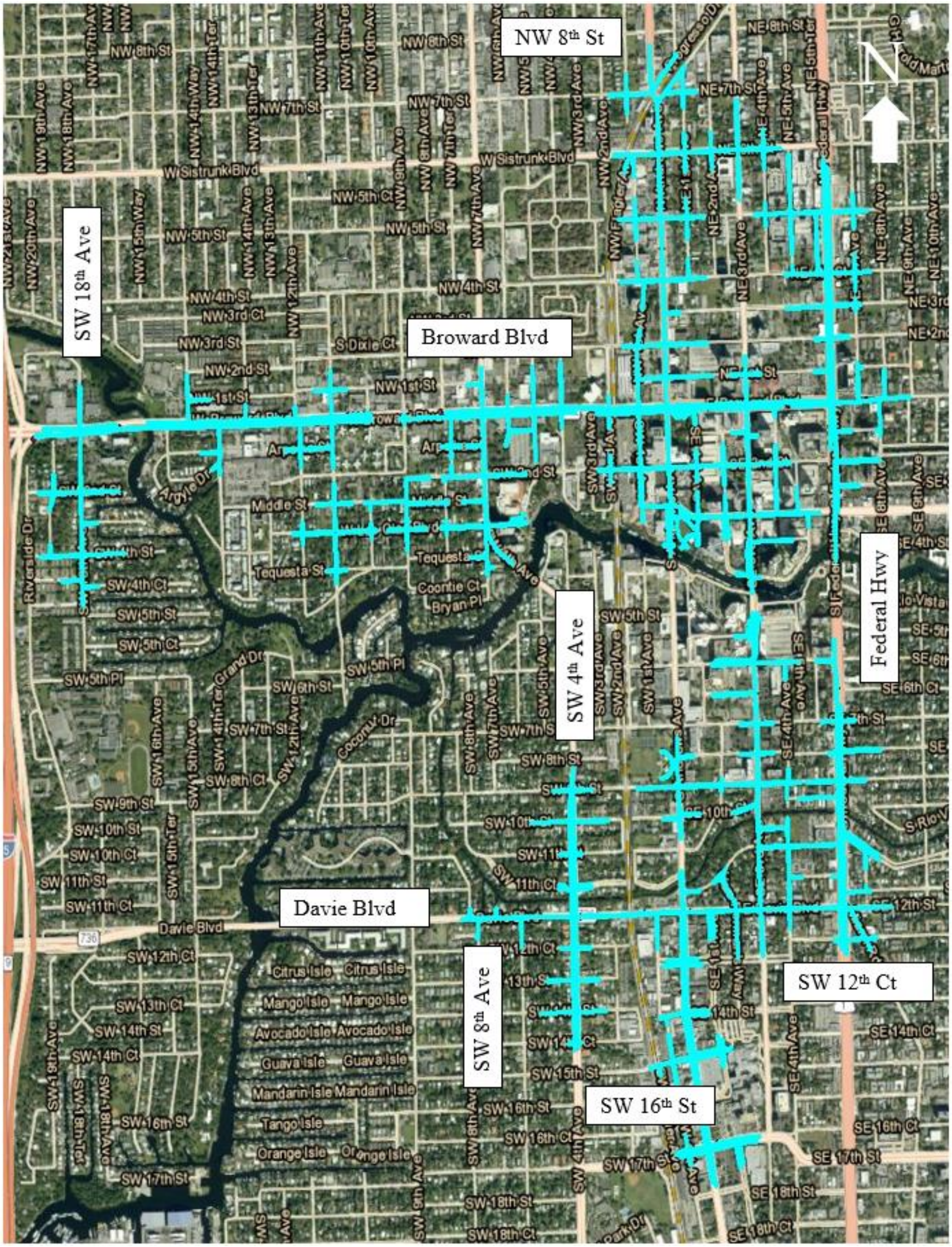

Figure A-17: Hot Spot 2 in District 4 (Total Crashes: 104) ([Map](#))

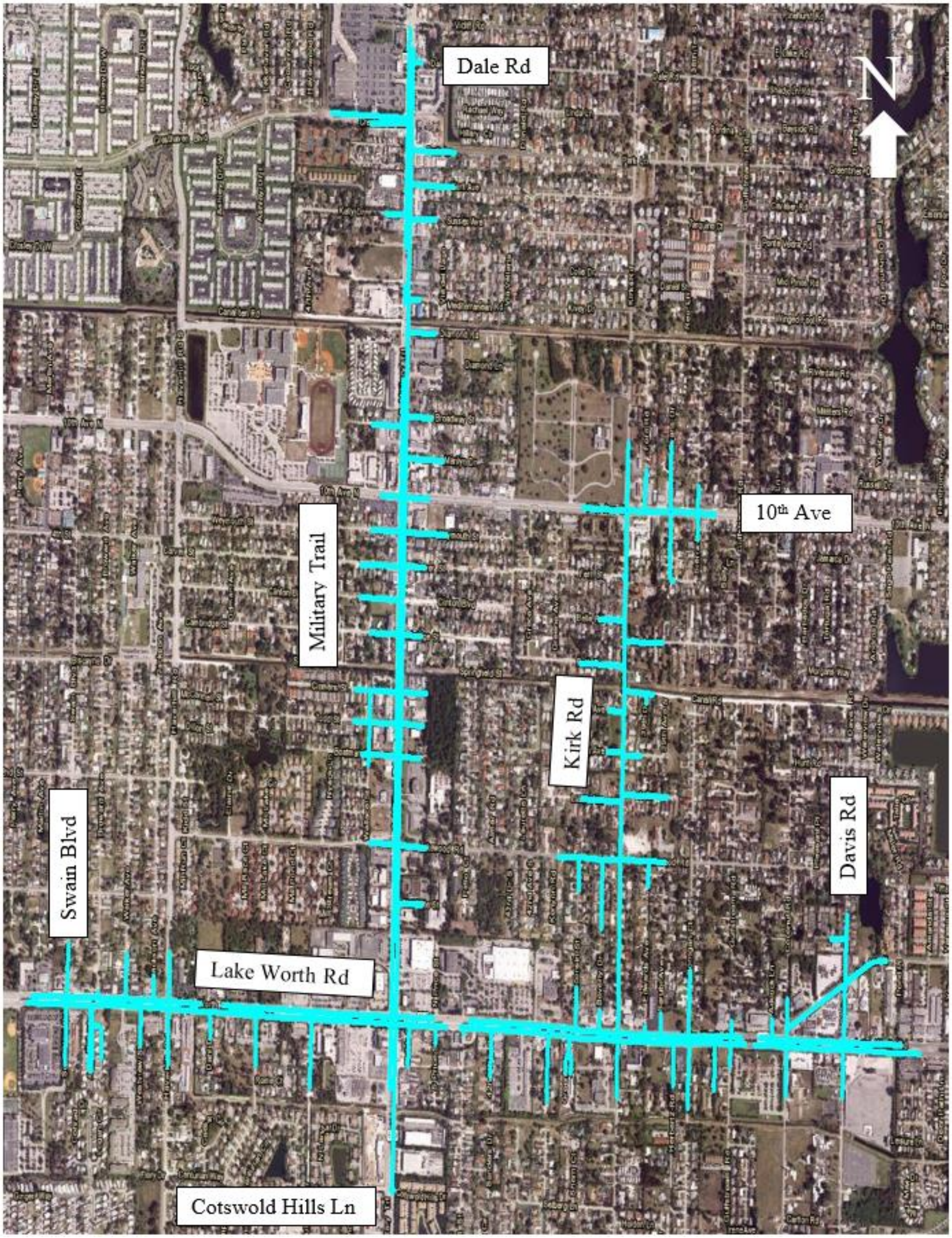

Figure A-18: Hot Spot 3 in District 4 (Total Crashes: 85) ([Map](#))

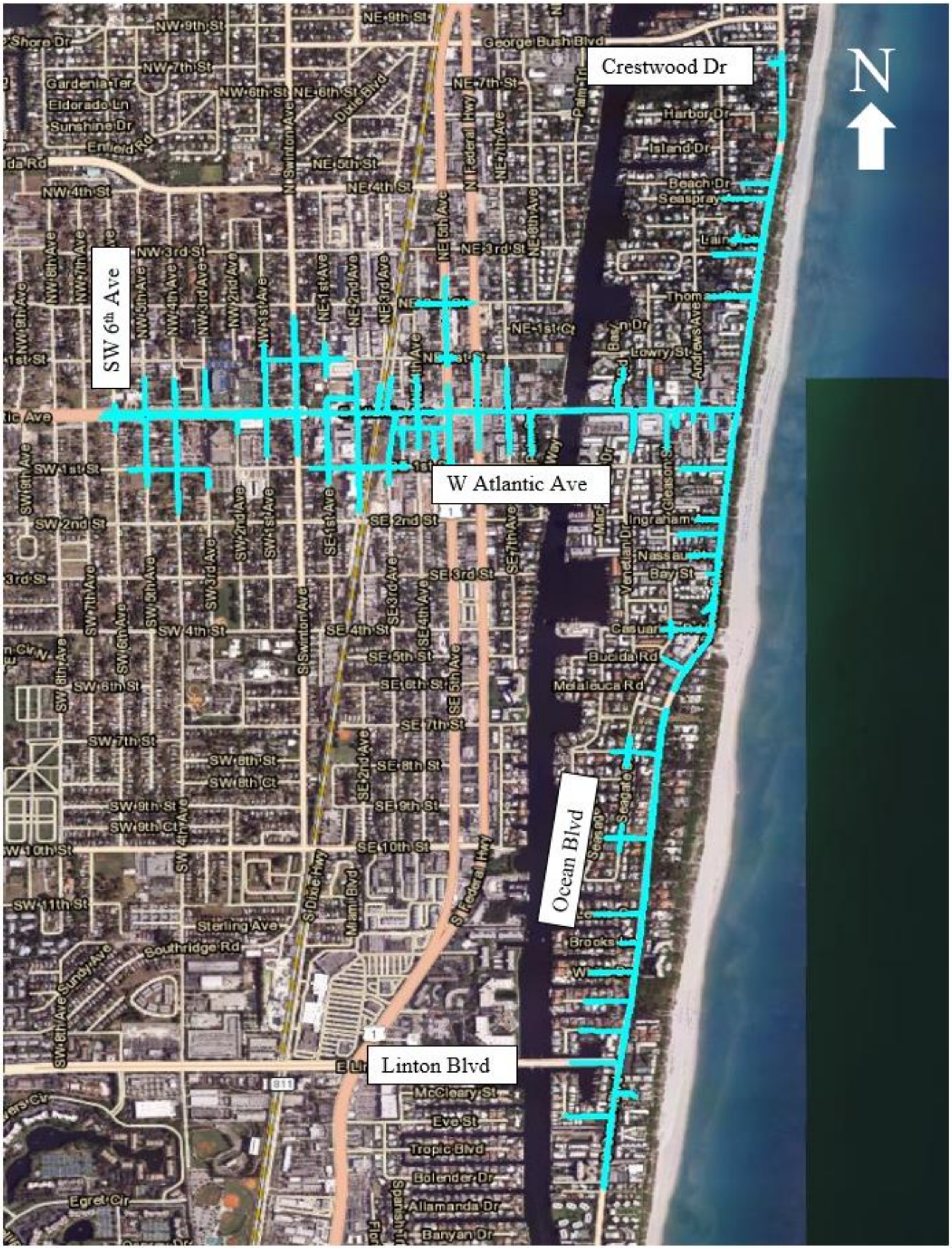

Figure A-19: Hot Spot 4 in District 4 (Total Crashes: 71) ([Map](Map))

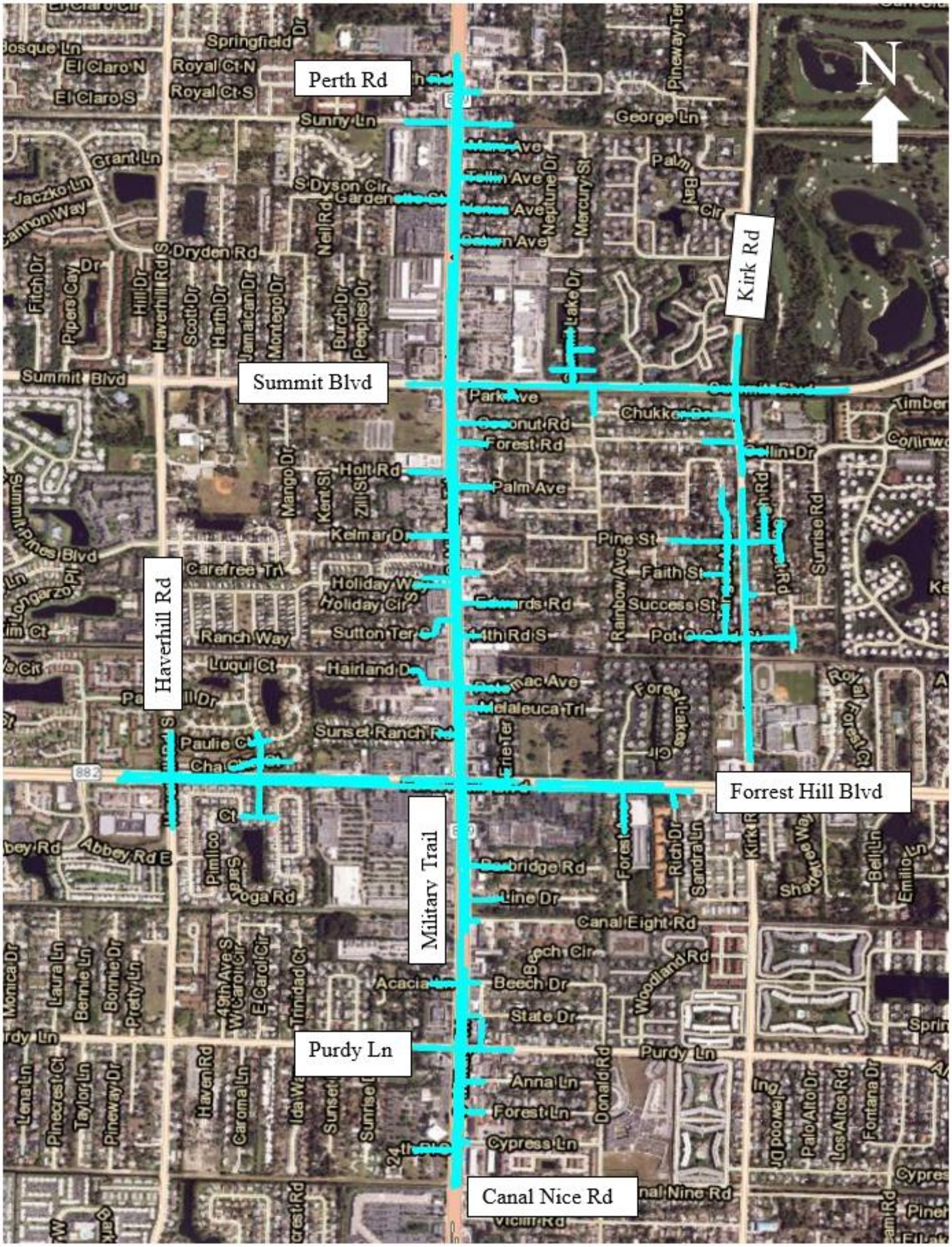

Figure A-20: Hot Spot 5 in District 4 (Total Crashes: 65) ([Map])

Figure A-21: Hot Spot 1 in District 5 (Total Crashes: 91) ([Map])

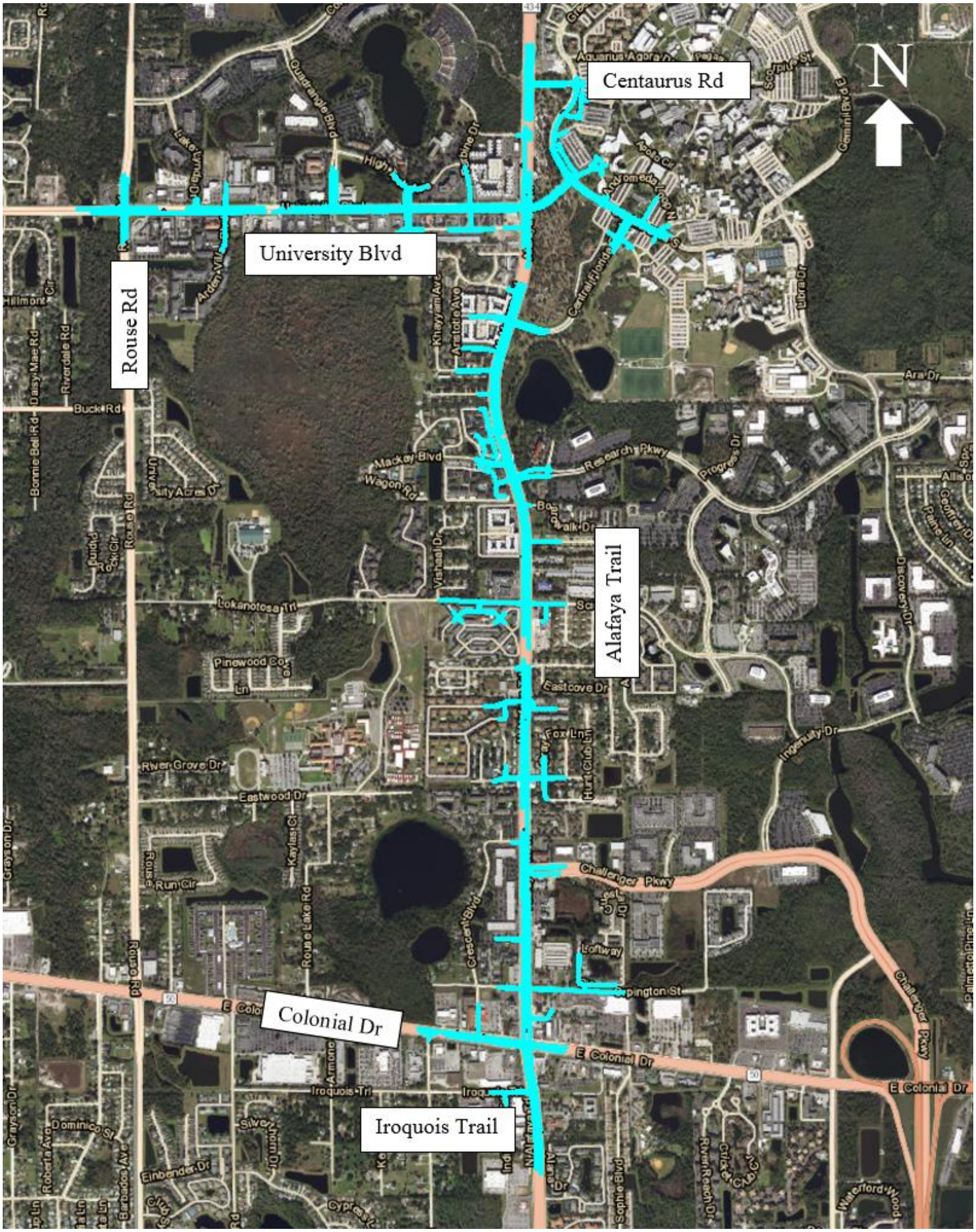

Figure A-22: Hot Spot 2 in District 5 (Total Crashes: 87) ([Map](#))

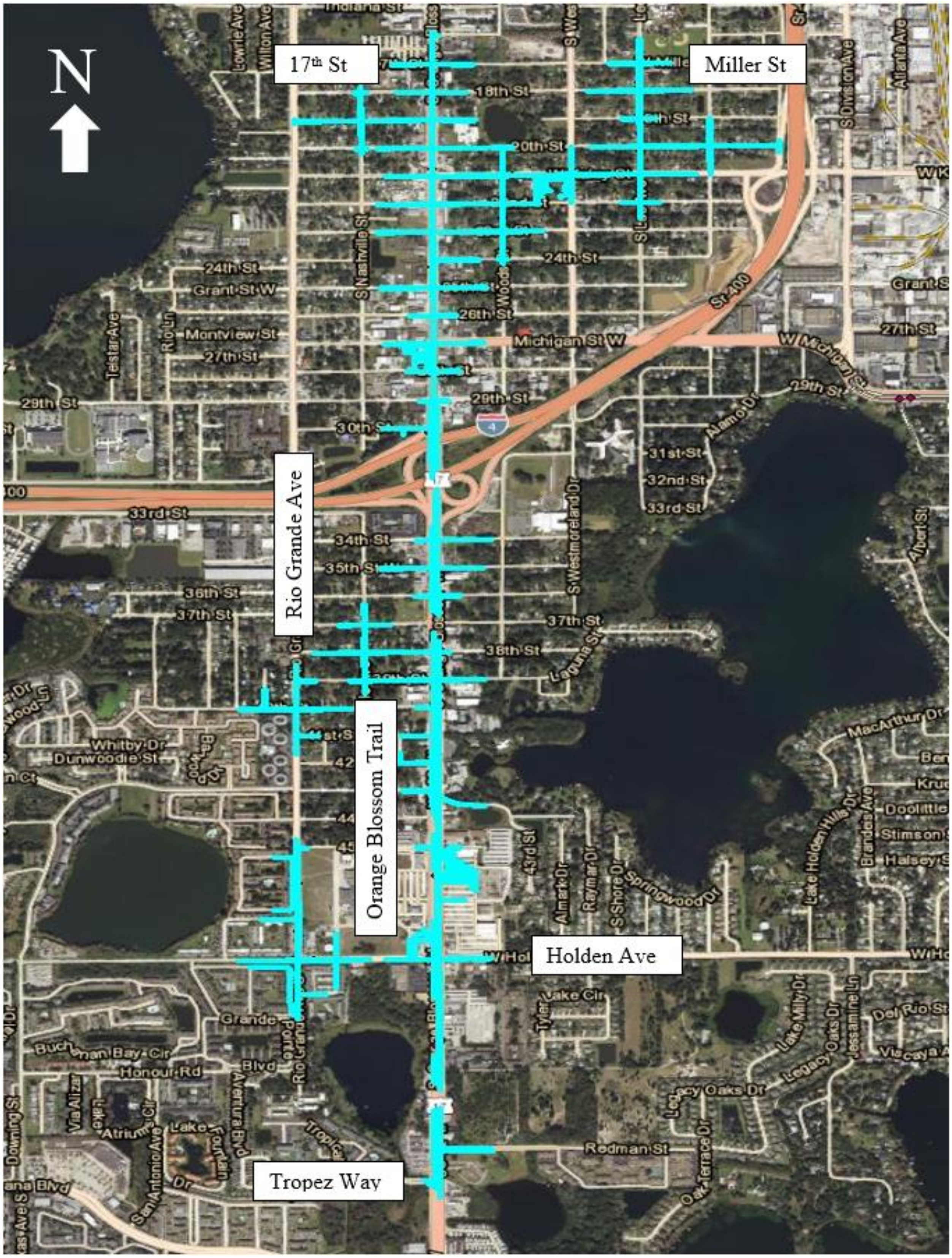

Figure A-23: Hot Spot 3 in District 5 (Total Crashes: 49) (Map)

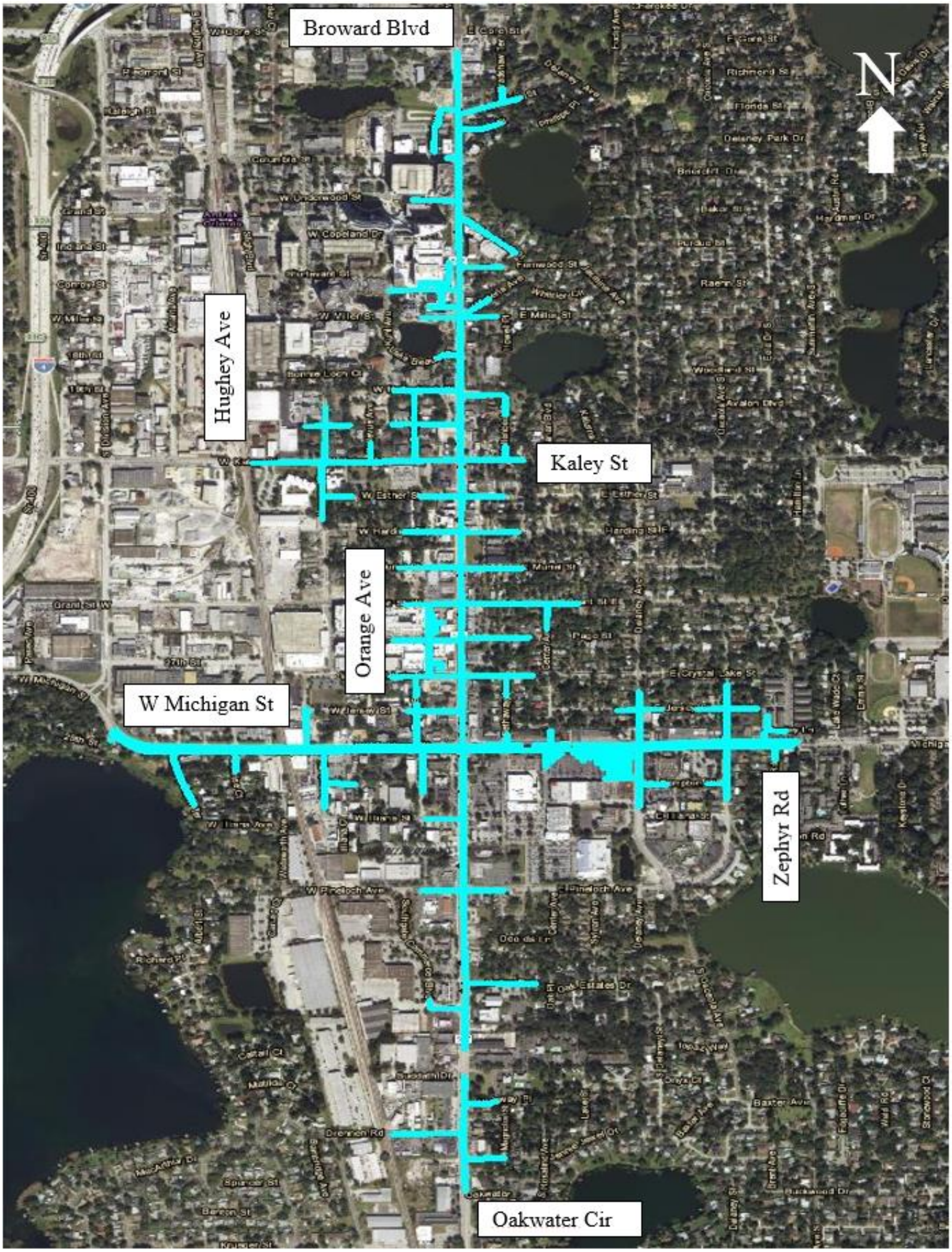

Figure A-24: Hot Spot 4 in District 5 (Total Crashes: 37) (Map)

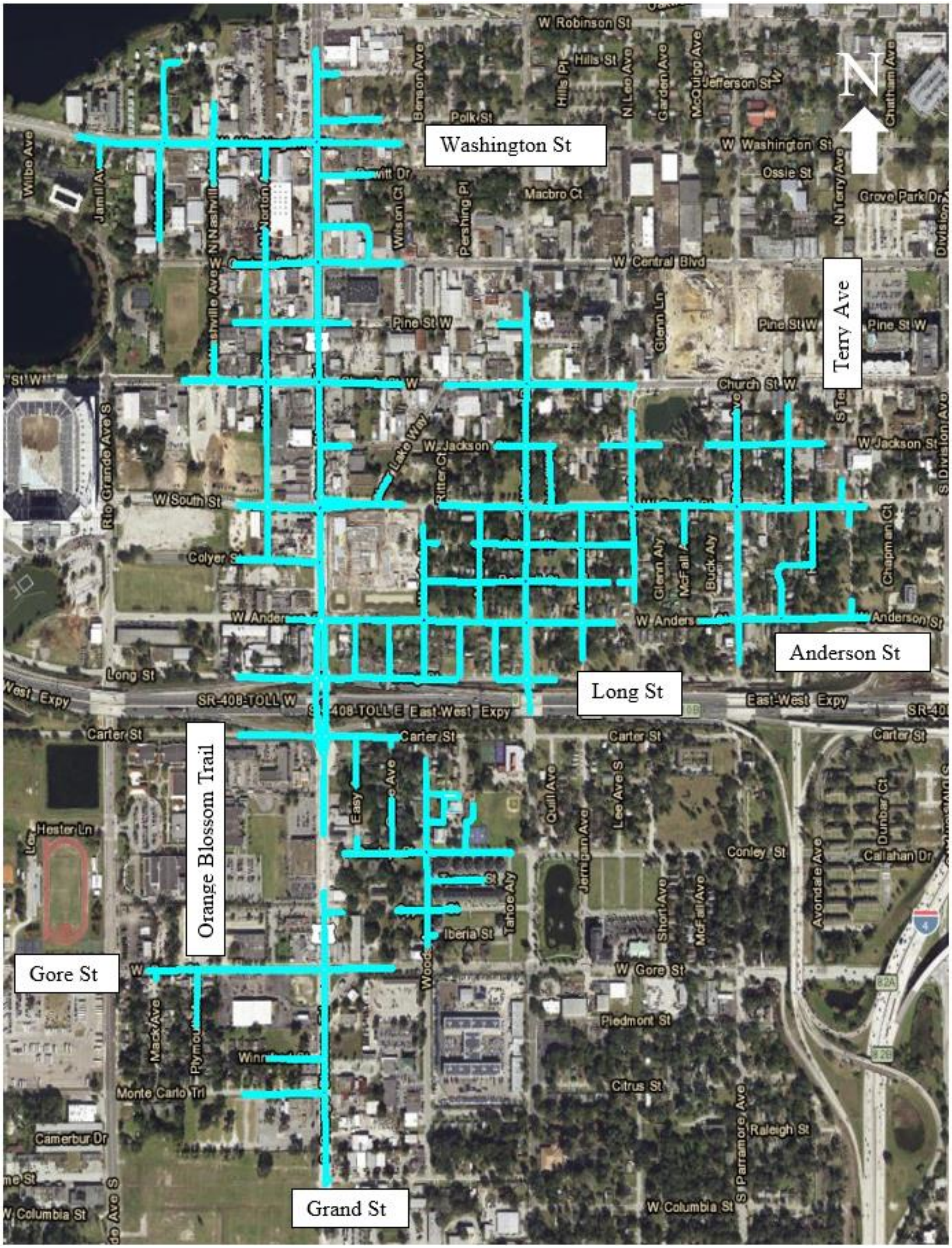

Figure A-25: Hot Spot 5 in District 5 (Total Crashes: 32) ([Map](#))

Figure A-26: Hot Spot 1 in District 6 (Total Crashes: 327) ([Map])

Figure A-27: Hot Spot 2 in District 6 (Total Crashes: 262) ([Map])

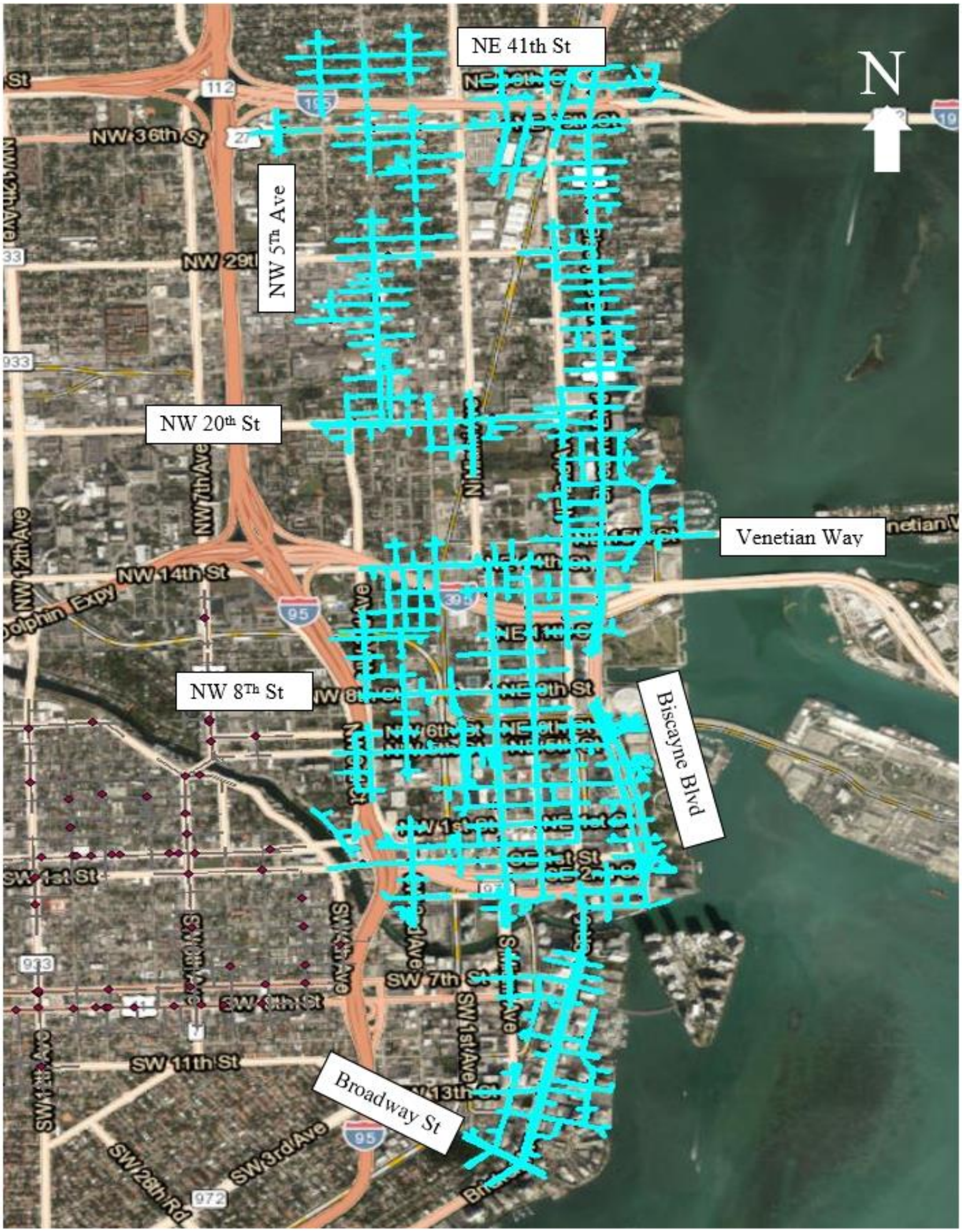

Figure A-28: Hot Spot 3 in District 6 (Total Crashes: 179) ([Map](#))

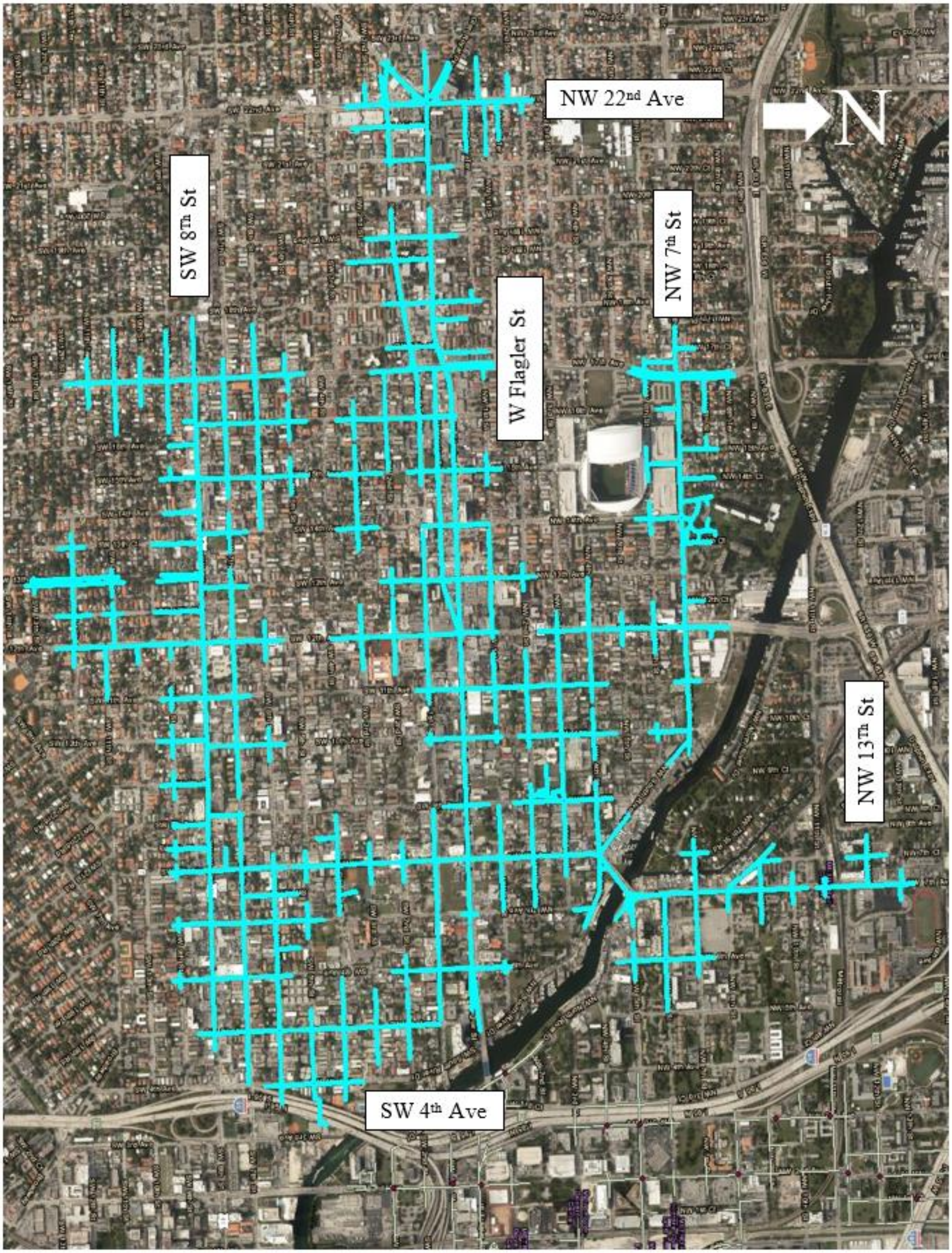

Figure A-29: Hot Spot 4 in District 6 (Total Crashes: 115) ([Map](Map))

Figure A-30: Hot Spot 5 in District 6 (Total Crashes: 68) (Map)

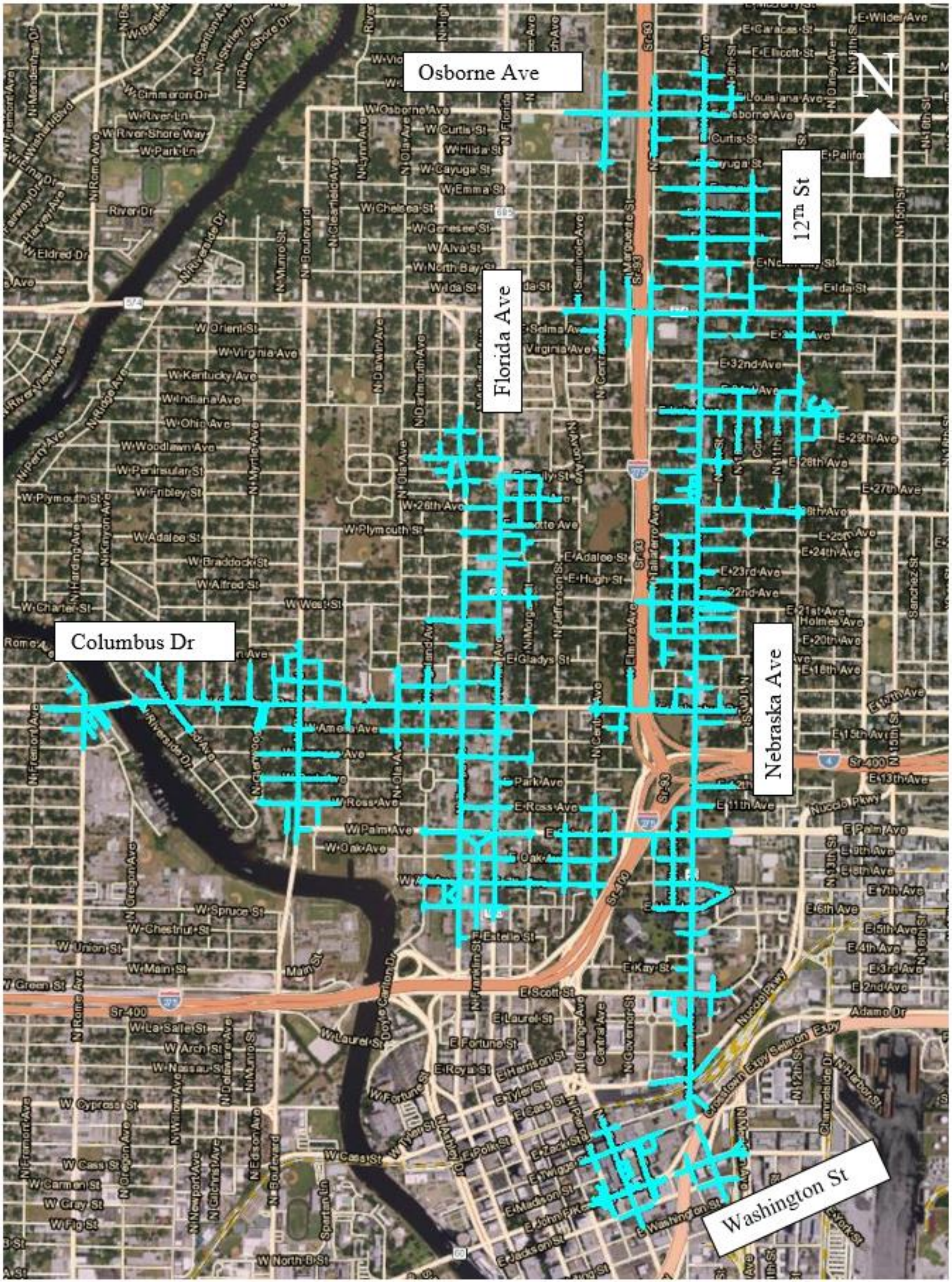

Figure A-31: Hot Spot 1 in District 7 (Total Crashes: 95) ([Map])

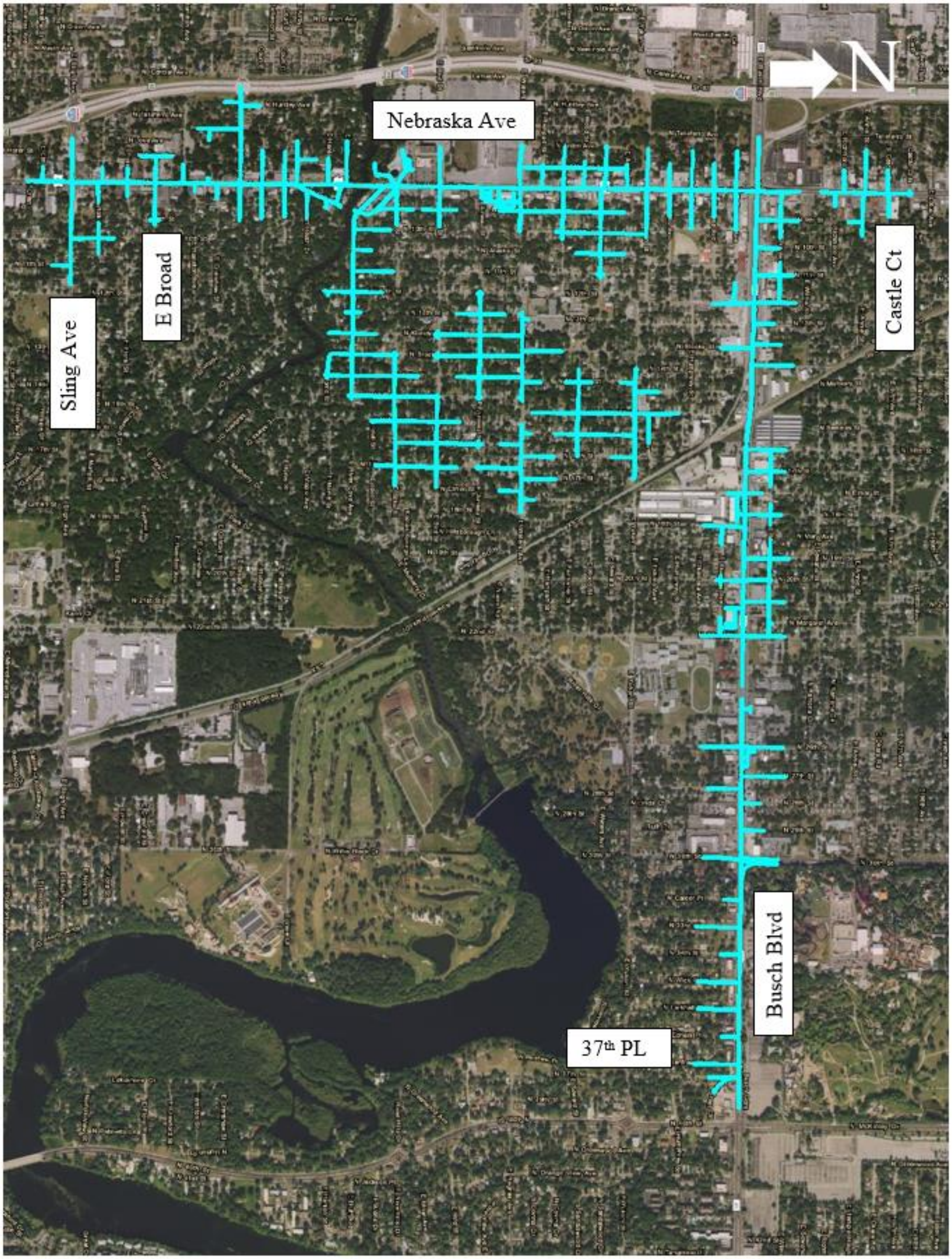

Figure A-32: Hot Spot 2 in District 7 (Total Crashes: 71) ([Map])

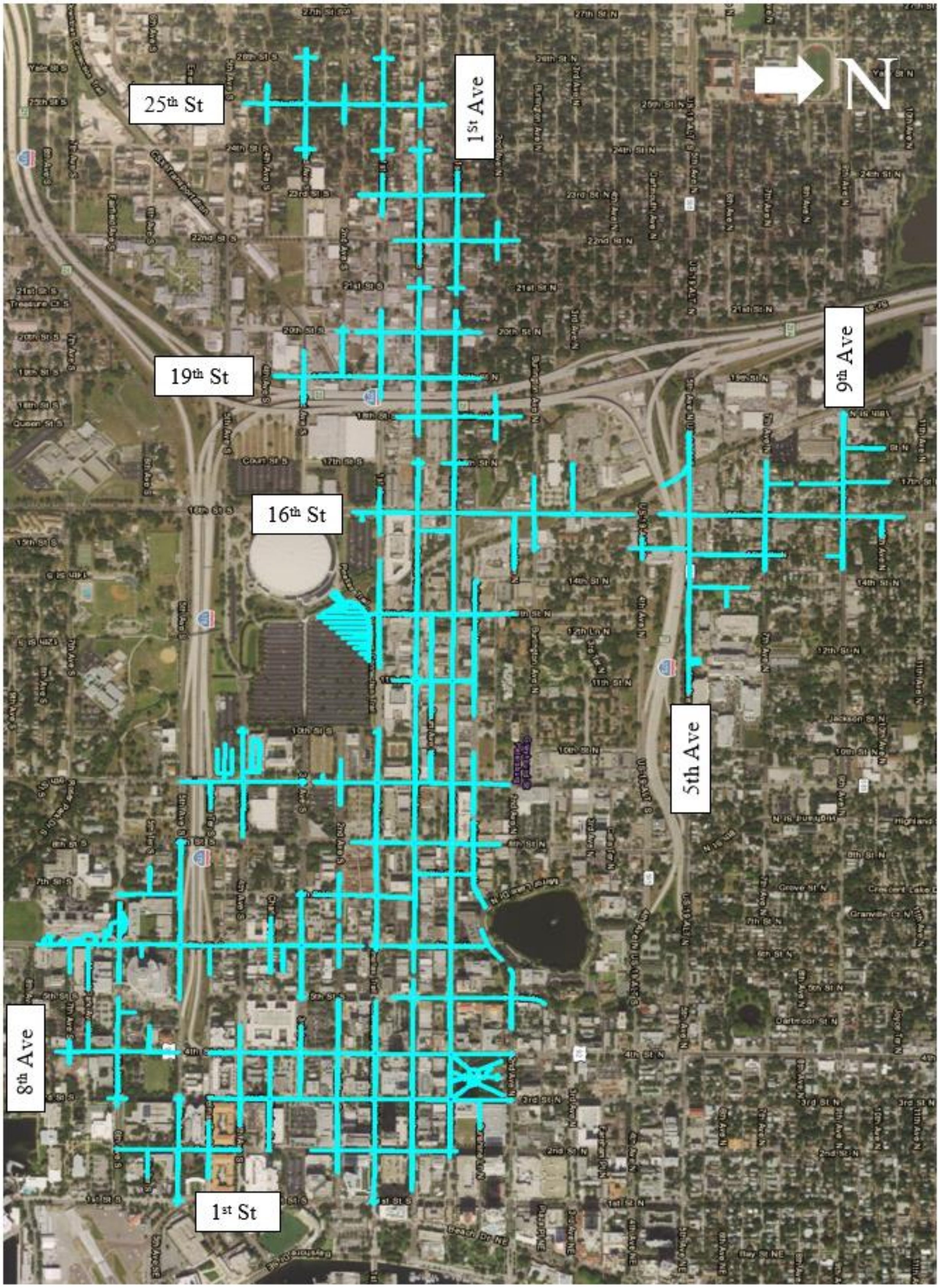

Figure A-33: Hot spot 3 in District 7 (Total Crashes: 70) ([Map](Map))

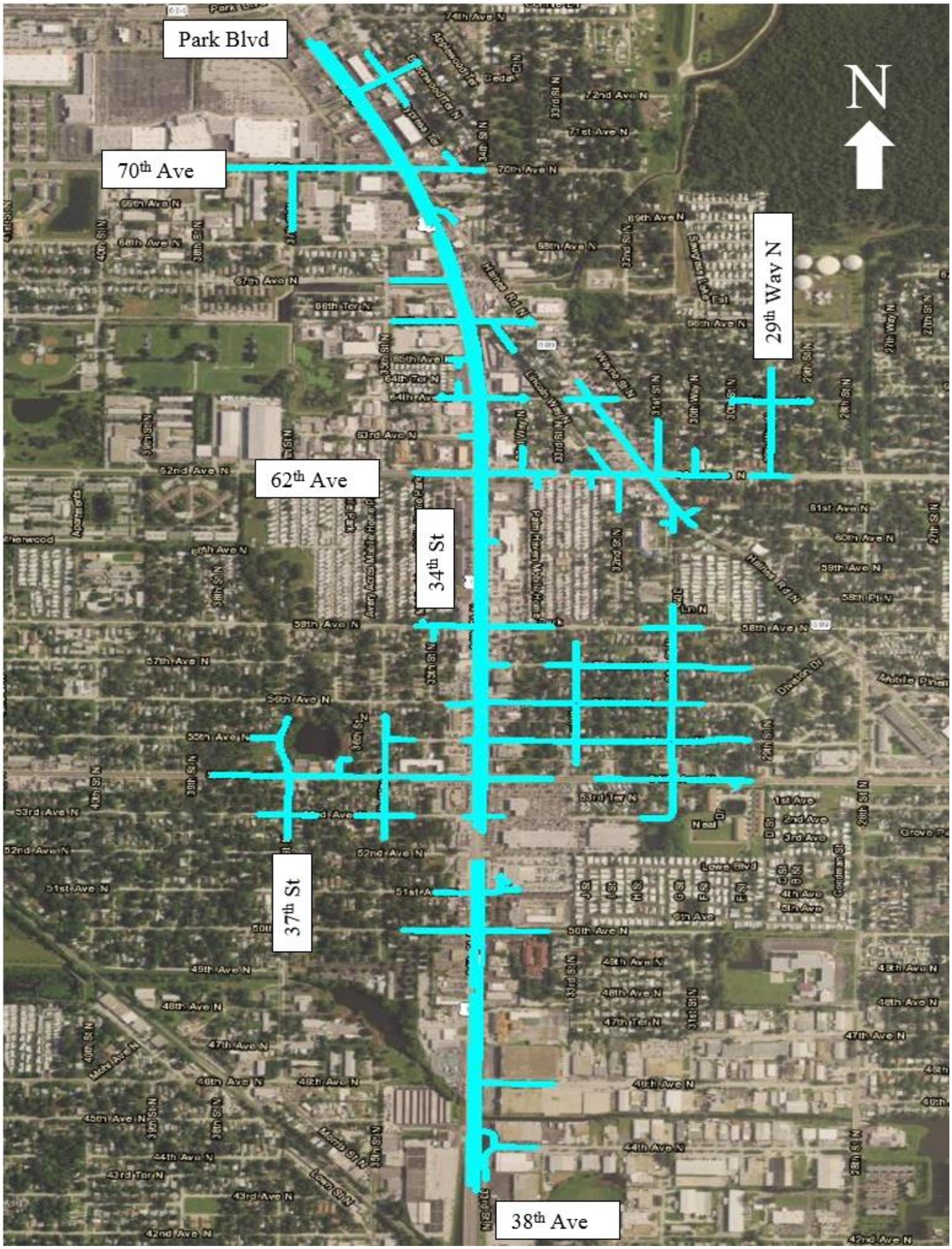

Figure A-34: Hot Spot 4 in District 7 (Total Crashes: 56) ([Map])

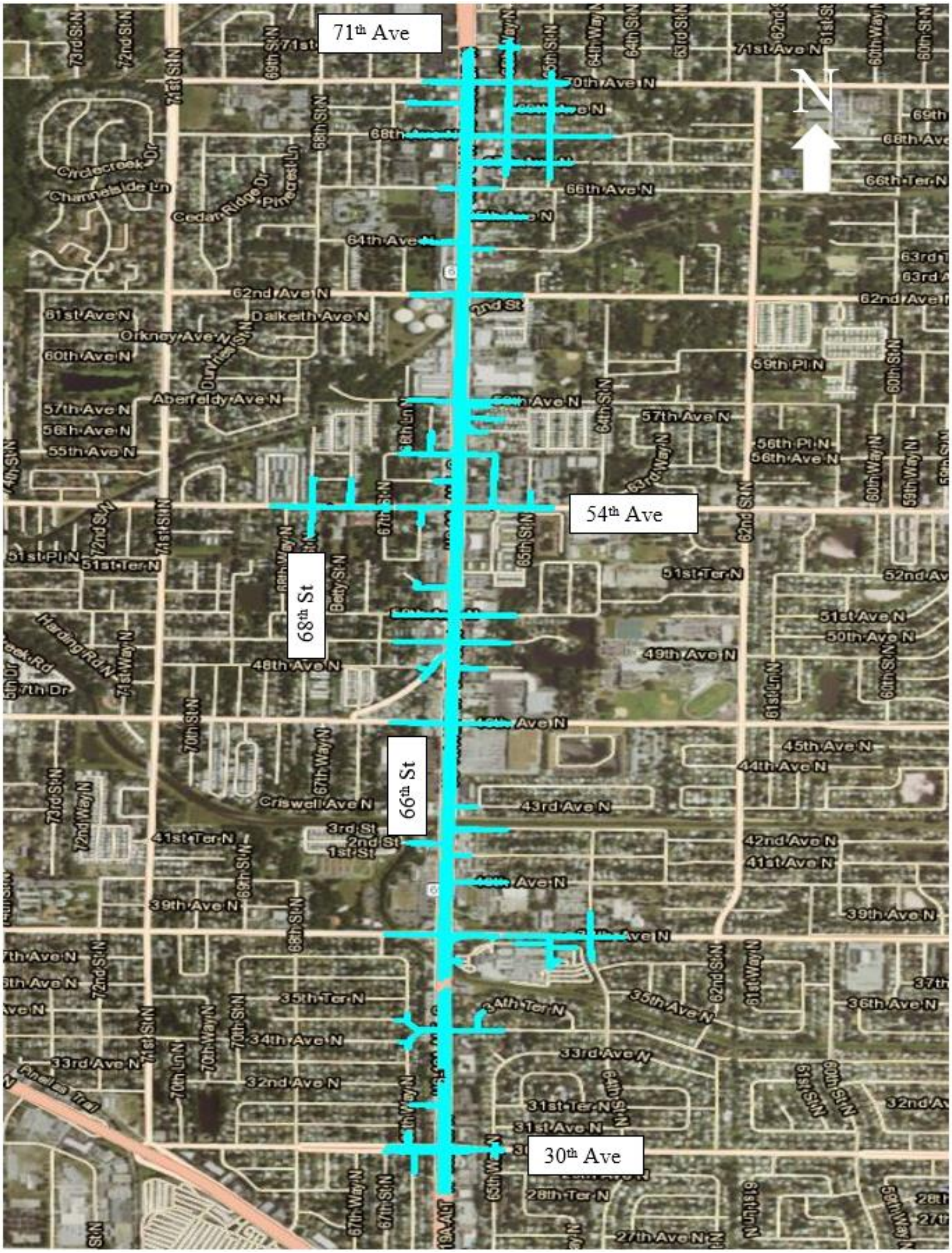

Figure A-35: Hot Spot 5 in District 7 (Total Crashes: 52) ([Map](#))