BICYCLE COUNT DATA: WHAT IS IT GOOD FOR? A STUDY OF BICYCLE TRAVEL ACTIVITY IN CENTRAL LANE METROPOLITAN PLANNING ORGANIZATION

Final Report

PROJECT 304-761

RESEARCH

Oregon Department of Transportation

BICYCLE COUNT DATA: WHAT IS IT GOOD FOR? A STUDY OF BICYCLE TRAVEL ACTIVITY IN CENTRAL LANE METROPOLITAN PLANNING ORGANIZATION

Final Report

PROJECT 304-761

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This report documents the use of bicycle traffic volume data for the purposes of travel monitoring, crash analysis, and health impact assessment in the Central Lane Metropolitan Planning Organization. The report showcase a new method for estimating annual traffic from short term counts using the Seasonal Adjustment Regression Method (SARM) and demonstrates low error provided enough data is available. A direct demand model is created and employed to estimate annual average daily bicycle traffic on each link within the network to show bicycle traffic patterns at the street and system level. These bicycle traffic estimates are used in crash analysis to highlight the injury-crash risk disparity between motorized and bicycle travel. The report demonstrates how safety performance functions can be developed for segments and intersections using these bicycle traffic estimates and then shows how these safety performance functions can be applied for project prioritization. Utilizing the bicycle traffic estimates, an analysis of the health benefits associated with the bicycle activity is conducted in order to highlight the positive health outcomes derived from the physical activity related to bicycling. The positive health outcomes are then quantified using a cost of illness methodology to reveal the health care cost savings associated with the estimated bicycle travel activity in the Central Lane MPO.</td></tr>
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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	millimeters squared	mm^2
ft^2	square feet	0.093	meters squared	m^2
yd^2	square yards	0.836	meters squared	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	kilometers squared	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	ml
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	meters cubed	m^3
yd^3	cubic yards	0.765	meters cubed	m^3
NOTE: Volumes greater than 1000 L shall be shown in m^3.				
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams	Mg
		TEMPERATURE (exact)		
°F	Fahrenheit	(F-32)/1.8	Celsius	°C

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	millimeters squared	0.0016	square inches	in^2
m^2	meters squared	10.764	square feet	ft^2
m^2	meters squared	1.196	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	kilometers squared	0.386	square miles	mi^2
		VOLUME		
ml	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	meters cubed	35.315	cubic feet	ft^3
m^3	meters cubed	1.308	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.205	pounds	lb
Mg	megagrams	1.102	short tons (2000 lb)	T
		TEMPERATURE (exact)		
°C	Celsius	1.8C+32	Fahrenheit	°F

*SI is the symbol for the International System of Measurement

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Frank Proulx	Toole Design	Researcher
Ellen Currier	CLMPO	Transportation Planner

This work also benefited from data processing and data wrangling by the GIS staff at the Lane Council of Governments.

DISCLAIMER

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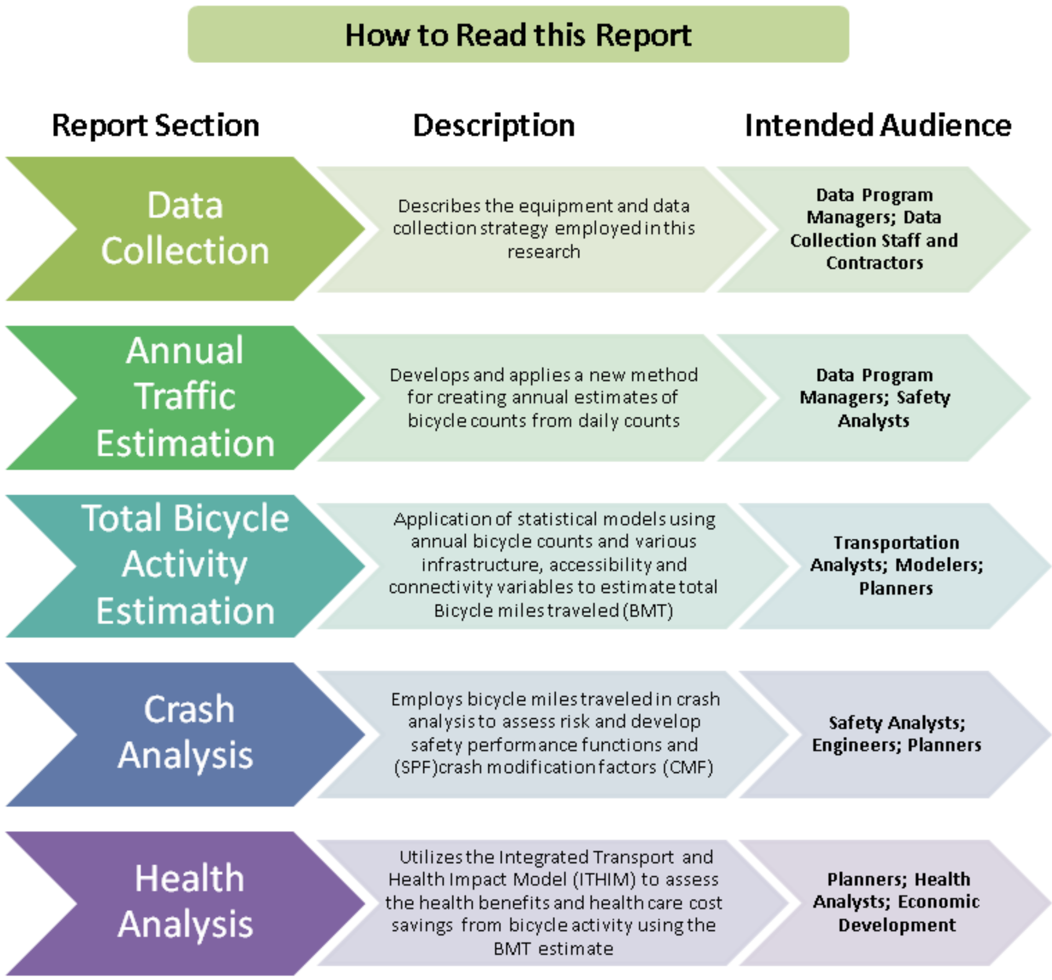
1.0 INTRODUCTION

Throughout the U.S. public agencies of all sizes have been placing greater emphasis on bicycle planning and infrastructure projects. As the importance of bicycle planning has grown questions about how best to monitor bicycle activity has also increased. This report aims to answer multiple questions related to bicycle traffic monitoring and usage analysis with a hope of informing practice. The report should also be a guide to the types of applications traffic counts data can be used for by show casing multiple sets of information attainable with these data. This report is aimed at multiple types of practioners including those traffic data collection managers and staff, traffic and crash analysts, planners, engineers, and even public health officials and policy makers. The report is broken into five sections with the aim to make each portion useful on its own though some reference is made to other sections in the report.

The Data Collection section covers procedures used in this analysis to collect traffic counts and is aimed at practioners out in the field doing this rudimentary but important task. The section covers the count collection devices employed to collect data used in this report and proposes a framework for stratified sampling data collection strategy. The Annual Traffic Estimation section describes a new method for estimating annual average bicycle traffic (AADBT) using a new method recently proposed in Roll and Proulx (2018) which removes the need for traditional traffic factor derived from permanent count sites. The next section on Total Bicycle Activity Estimation develops a series of facility demand model estimates for system wide bicycle miles traveled (BMT) using experience from past research as well as testing some new approaches. The Crash Analysis section utilizes the BMT estimates to better understand crash outcomes in the study region and pushes towards more complete picture of relative risk for motorized and bicycle road users. Finally, the Health Analyses section examines the health benefits of bicycle activity in the Central Lane MPO by combining estimates of bicycle activity with the Integrated Transport and Health Impact Model (ITHIM). The ITHIM tool is able to quantify health outcomes related to bicycle activity and the associated healthcare costs to understand the community wide benefits of bicycle activity. The guide below is meant to help readers of this report target the section that will most apply to their respective field.



With all of these elements in one document this report helps to answer questions related to bicycle traffic data including:

- How to best collect data?
- Why do we collect bicycle traffic count data?
- How can bicycle count data be used?
- What do the uncertainties in modeling bicycle activity mean in application?
- What crash disparities exist between motorized and bicycle crash outcomes?
- What are the health benefits of bicycle activity for the study area?

By answering these questions and showing the value of data, this report will hopefully encourage other agencies to value and invest in data collection not just for bicycle traffic.

The research in this report focuses on the Central Lane Metropolitan Organization (CLMPO) which includes the cities of Eugene, Springfield, and Coburg in the state of Oregon (see Figure 1.1). The CLMPO is a medium sized MPO with a population of about 250,000 people and home to the University of Oregon with about 25,000 students, an important note when evaluating bicycle travel. The CLMPO has a commute to work mode share by bike of about 6.0%[1] and has a network of off-street paths, bike boulevards and bicycle lanes that combine with a bicycle-friendly culture to make getting around the region by bicycle relatively easy. Since 2012, the CLMPO has been monitoring bicycle traffic through the Regional Bicycle Count Program and has been working on expanding the program to pedestrians.

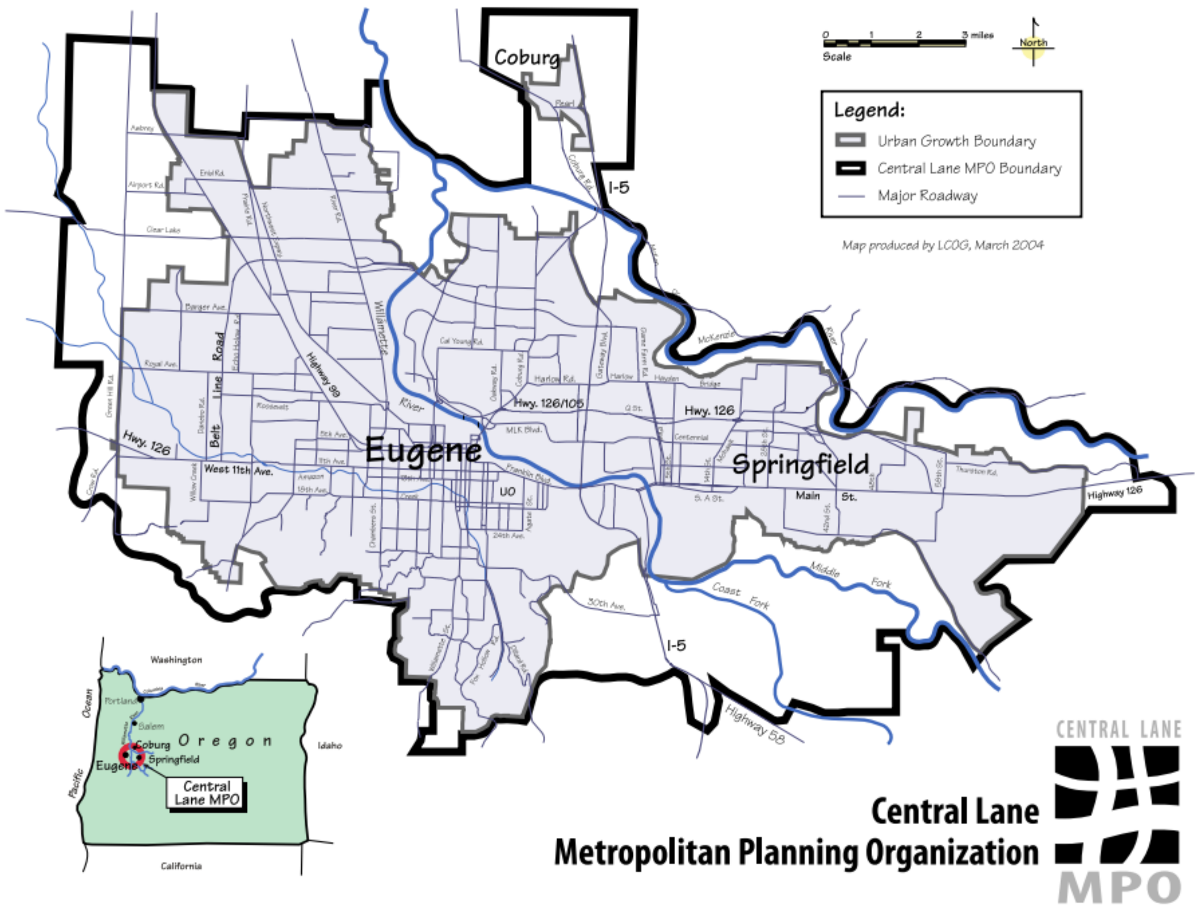


Figure1.1: Central Lane Metropolitan Planning Organization

[1] https://www.thempo.org/905/Commute-Mode-Share

2.0 DATA COLLECTION

Bicycle traffic data collection began in the CLMPO in 2012 through the formation of the Regional Bicycle Count Program. The section below will summarize the types of data collection devices used to collect bicycle traffic counts in the CLMPO as well as the methods and strategies employed over time to meet multiple demands placed on the data. The last portion of this section proposes a method for stratifying the network for system wide data collection.

2.1 BICYCLE COUNT COLLECTION DEVICES AND DEPLOYMENT

Starting in 2012 CLMPO staff began collecting bicycle traffic counts using the Eco-Counter ™ bicycle traffic data collection devices. The data collection effort relies on portable pneumatic tube counters though one permanent count device was installed in 2013 on an off-street path facility. The CLMPO started collecting data using trained interns to deploy the portable devices but has since moved to a paid staff person and spends between $20,000 and $30,000 a year to collect bicycle traffic data. This does not count the initial purchase of equipment which was about $3,000-$4,000 per device.

The Eco-Counter devices are proven reliable and simple to install. If deployed properly these devices produce traffic counts data with low amounts of error. For a more thorough examination of error from different bicycle traffic data collection devices see Munro 2013 and Nordback et al. 2016.

The CLMPO collects data at both on-street and off-street locations. When the devices are installed at on-street locations care must be taken to avoid counting vehicles by deploying away from intersections and driveways. Devices will not capture bicycle traffic if vehicles are stopped or parked on top of the tubes and therefore should be installed in places where vehicle queues and on-street parking is minimized. It was also found that when the device tubes are anchored into blacktop during the summer heat asphalt will often times break apart at the anchor point freeing the tubes and usually getting them caught on a passing vehicle causing damage to the tubes. Therefore it is recommended to install the anchors into concrete curbs at the edges of the street. This reduces the types of locations that can be properly monitored which present challenges for fully implementing any kind of random count location selection methodology. For a complete guide on device deployment please see Minnesota Department of Transportation's report Bicycle and Pedestrian Data Collection Manual (2017). The figures below show examples of portable Eco-Counter devices in the study area.

Figure 2.1: Example of on-street deployment of portable device

Figure 2.2: Example of off-street deployment of portable device

Figure 2.3: Example of permanent counter on off-street path location

2.2 DATA COLLECTION METHODS AND STRATEGIES

When the CLMPO began collecting bicycle traffic data the aim was to supply information to validate a bicycle traffic assignment tool for the regional travel model. Therefore a travel survey of regional households was analyzed to determine major origins and destinations of bicycle trips which were combined with local knowledge of the system to envisage likely paths of these trips. The outcome of early data collection then was that devices were deployed in locations with known bicycle activity.

As the program evolved and additional needs were presented to the program manager by local partners, data collection strategies shifted to include locations with less bicycle traffic. These locations were usually locations that would be getting some kind of bicycle facility treatment, like a bicycle boulevard, sometime in the future. Data from these sites could be used to assess the impact the treatment had on bicycle traffic and use this information to assess bicycle crash outcomes using a robust before and after study design.

It was also recognized that gathering bicycle traffic data from a variety of bike and street types at various levels of population and employment accessibility was important if the data were to be used to estimate total bicycle miles traveled (BMT). BMT estimation methods are still being developed and most rely on facility demand models instead of more traditional counts programs that combine permanent and short term counts. These needs are summarized below:

- Travel model bicycle route choice assignment validation
- Before/after monitoring of bicycle facility treatment for usage and safety
- System wide bicycle activity estimation

Since this report delves into facility demand model methods the remainder of the Data Collection section discusses how data collected by the CLMPO reflects needs for facility demand modeling.

2.3 DATA COLLECTION FOR FACILITY DEMAND MODELS

Facility demand models are an increasingly common method for analyzing non-motorized travel. These models use counts of people walking or people riding bicycles as dependent variables and employ weather, built environment, sociodemographic and network characteristics as independent variables to estimate statistical models. For more information on these models refer to section three below on Total Bicycle Activity Estimation where a more in-depth review of these concepts is presented. The remainder of this section will discuss how the current data collection serves the needs of facility demand models and how data collection may need to shift to better supply data for these modeling needs. The section goes on to describe some of the principles used in motorized count programs including the concept of stratified sampling. It then proposes a method to stratify the bicycle network and shows how the data being using in this method for the Total Bicycle Activity Estimation section conforms to sample distributions through this defined strata.

Guidance on data collection for motorized traffic is well documented in the Highway Performance Monitoring Field Guide (2012). This document guides statewide traffic count program staff on methods and requirements for reporting to FHWA on usage of roads by vehicles. Important terms found in HPMS and utilized below in the discussion of bicycle count data collections strategies include sampling population, sampling frame, and sampling unit. The sampling population refers to the list of possible samples that could be collected, in this case network links in the CLMPO study area. Sampling panel refers to a stratified selection of units grouped by some characteristic like functional classification or bicycle facility type. The sampling unit refers to transportation network sections where counts are collected.

These methods are meant for motorized traffic and similar guidance has yet to be developed for non-motorized traffic. Motorized traffic count program managers are able to categorize the network into categories that roughly approximate the level of traffic volume on that segment making stratification processes simpler. This mostly stems from a legacy of monitoring the motorized system which has not been available to the non-motorized system. Using the existing motorized approach as a guide, a proposed stratification scheme is described below that uses the functional classification, bicycle facility type, and two measures of accessibility to initiate a stratified sampling process.

The stratification framework proposed below relies on relationships described below in the Total Bicycle Activity Estimation section where functional classification is shown to have a negative correlation with bicycle traffic volumes while the presence of bicycle facilities are positively correlated to bicycle traffic. A description of these facility types are found in Table 2.1 and Table 2.2 below. For the stratification process bicycle facility types include no bicycle facility, bicycle boulevards, and bicycle lane. Cycle track is included below since it’s used in a latter part of the research but is not included in the proposed stratification.

Table 2.1 – Definition of Functional Classification System

Functional Classification System	Services Provided
Arterial	Provides the highest level of service at the greatest speed for the longest uninterrupted distance, with some degree of access control.
Collector	Provides a less highly developed level of service at a lower speed for shorter distances by collecting traffic from local roads and connecting them with arterials.
Local	Consists of all roads not defined as arterials or collectors; primarily provides access to land with little or no through movement.

Table 2.2 – Definition of Functional Classification System

Facility Type	Description
Bike Boulevard (Neighborhood Greenways)	A bike boulevard is a street segment, or series of contiguous street segments, that has been modified to accommodate through bicycle traffic and minimize through motor traffic. Oftentimes, but not necessarily, traffic calming features are utilized.
Bike Lane	A bike lane is a portion of roadway that has been designated for preferential or exclusive use by bicyclists by pavement markings and, if used, signs. It is intended for one-way travel, usually in the same direction as the adjacent traffic lane, unless designed as a contra-flow lane.
Cycle Track	A cycle track is a bikeway physically separated from pedestrians and motor vehicle traffic by a barrier. Cycle tracks may only be used by bicyclists and can be designed for one-way or two-way travel. Common barriers include bollards, curbs, or medians include bollards, curbs, or medians.

Population and student population accessibility are also positively correlated with bicycle traffic volumes. Since motorized traffic count stratification schemes also rely on prior knowledge of the network traffic volume *to* group segments this approach seems sensible. To simplify the matter, the population related accessibility measures are grouped into categories. For population there are four categories based on the quartiles of observed population accessibility to links within the study network while student population is broken into two categories where half the observed maximum sets the first break point. **Table 2.3** describes these accessibility categories in more detail. For more information on how these measures were calculated see section 5.1.3.1 below.

Table 2.3 – Accessibility Category Definitions for Stratified Sampling

Population		Student Population	
Category	**Accessible within 1.0 miles**	**Category**	**Accessible within 0.5 miles**
1	0-1,791		
2	1,792 - 3,785	1	0-1,600
3	3,786-5,767		
4	5,768 - 14,538	2	1,601 - 3,569

Using this combination of attributes (functional classification, bicycle facility type, accessibility), the network is stratified below with summary metrics also presented within each stratum. To simplify this description Figure 2.4 shows the stratification for just off-street paths so the accessibility metrics are the primary dimensions. For each stratum there are four metrics reported and include the following:

- Proportion of the stratum network distance with an AADBT estimate
- Number of count locations in the stratum
- Total network miles (within the stratum) that have a count
- Total network miles within that stratum.

Figure 2.4 points each of these metrics out with high visibility descriptions. These labels highlight that for the specific stratum 29.4% of the total network within this stratum has been counted using data from 3 locations which equals 0.25 miles of network of the 0.9 total miles of network within this stratum.

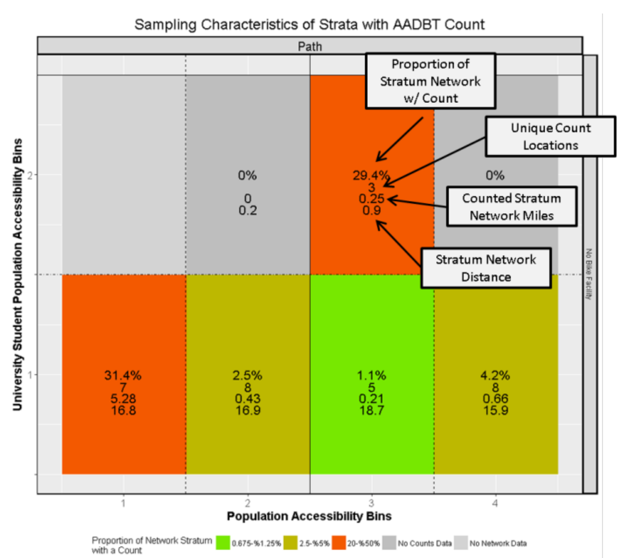


Figure 2.4: Strata network description for off-street paths

There are 52 count locations with an AADBT estimate. These counts are on links that represent 9.15 miles of total network which includes 1,224 total miles of roads and off-street. Overall this represents a sample rate of less than 1%. However, this total network sample rate varies by stratum and is described in detail in Figure 2.5 below. Network sample rate varies from a low of 0% in many strata to a high of 31%, with an average of 1.8%. Not all possible strata have network to sample and is denoted in Figure 2.5 by a light gray. Stratum where no sample was collected is denoted by a darker gray and includes stratum metrics (note these show 0%).

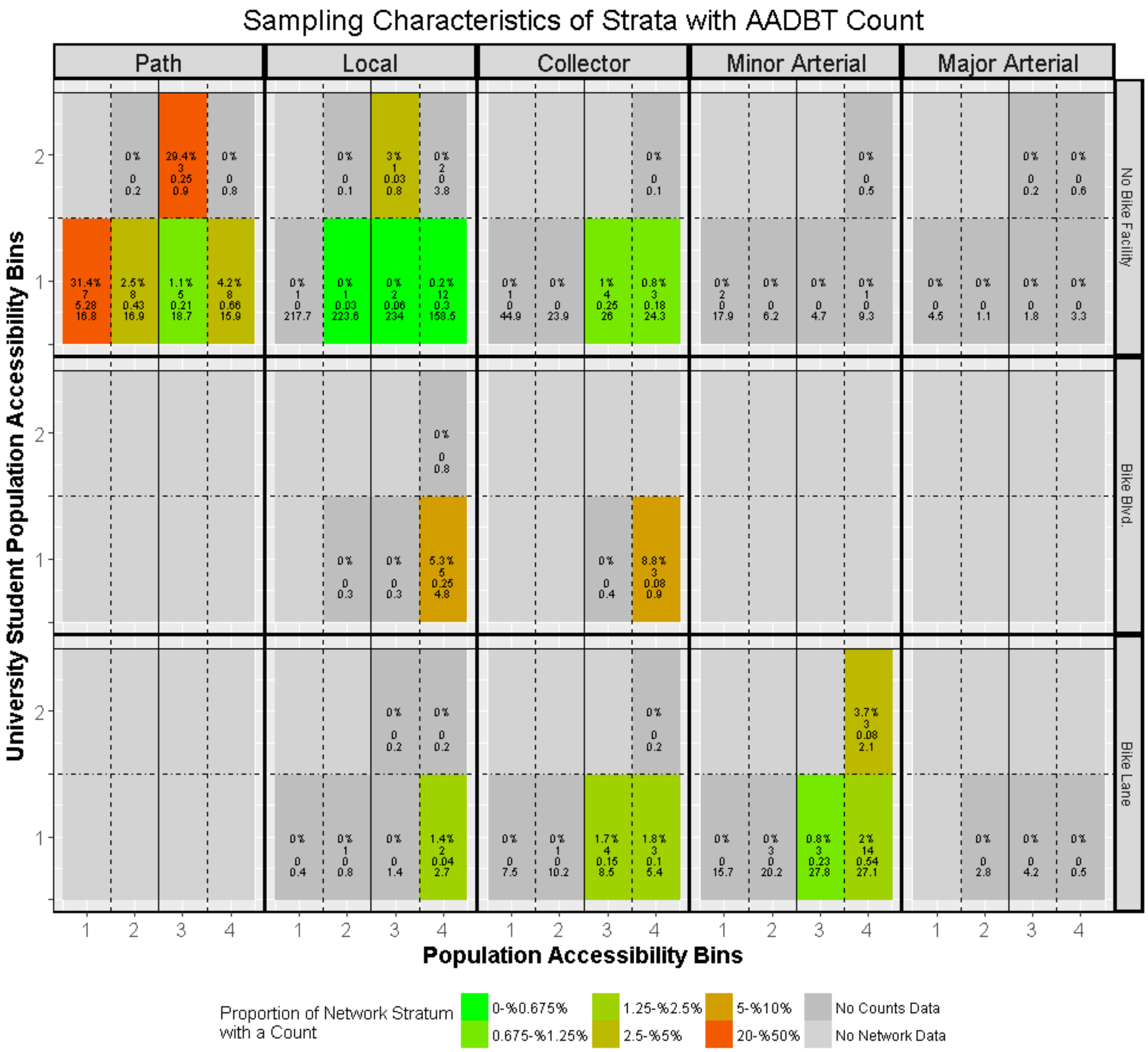


Figure 2.5: Strata network description for entire network

This approach might be useful to classify the network and set up a sampling regiment going forward. Currently the sample rate does not look ideal and future efforts to reach a higher sample rate across more strata should be a goal. An eye towards collecting data on strata where higher proportions of total bicycle activity occur is ideal. If this were the goal then the proposed strata configuration would lead data collection to areas with higher accessibility, assuming those are places with more activity. The CLMPO count program counts at over 110 locations but since only 52 locations had enough data to estimate a reliable AADBT figure, only a subset of locations were used (See the Annual Traffic Estimation section below for more information).

To better understand how many bicycle count sites might be necessary a quick review of the Oregon Department of Transportation (ODOT) counts for motorized vehicles is described. ODOT collects motorized traffic counts at 435 locations at least once every three years, or roughly 145 per year in the study region. Of those locations, six are permanent counters used to derive traffic factors for temporal expansion. For more reliable BMT estimates is likely that AADBT estimates at 110 count locations would improve the accuracy but that 160-190 locations would be ideal. This proposed number of sites would achieve a 5% and 10% sample rate (respectively for 160 and 190) for each stratum. However, this does not include local streets where due to a high number of network miles a much larger number of samples would be needed. A small sample rate on local streets might be acceptable if it's assumed that little to no traffic occurs on these facilities, especially on low access roads. A likely way forward in bicycle traffic data on local streets might be to focus on streets in an around schools and other activity centers like parks and off-street paths.

More research is necessary on how to best collect data on local roads but its worth mentioning that motorized traffic count program have all but disregarded these facilities for the most part.

For motorized traffic counting, the HPMS sample size requirements for principle arterials is much higher and requires a higher degree of precisions due to their national significance. This principle should be replicated by aiming for a high sample rate on off-street path system and other facility types with known bicycle activity. For the study area the sample rate is much better for the path system but still lower than the ideal scenario.

To summarize, the proposed stratification method above is one attempt at developing a framework to guide data collection. This proposes framework could benefit from further analysis including how traditionally produced traffic factors vary by stratum and how different amounts of data within each stratum affect final total bicycle activity estimates.

Public agencies at all levels have been involved in bicycle traffic monitoring programs in order to better understand the impacts bicycle related investments are making. Bicycle traffic data is useful on its own, allowing planners the ability to observe changes over time but increasingly planners and researchers are putting these data to work in order to produce more sophisticated analyses related to health, safety, and greenhouse gas reduction.

Vehicle miles traveled (VMT) is a useful metric for understanding total motorized vehicle travel. VMT estimates based on motorized traffic count data accumulated through the Highway Performance Monitoring System (HPMS) is often cited as an indicator of motorized travel patterns. The HPMS based VMT estimates are also used to validate and calibrate travel models since they offer an independent estimate of vehicular travel.

The research presented below uses bicycle traffic count data collected in the Central Lane Metropolitan Planning Organization (CLMPO) to estimate bicycle miles traveled (BMT) for the entire bicycle network. This process leverages data from the CLMPO Regional Bicycle Count

Program as well as detailed information from a routable bicycle network data set. This research also lays out a new approach to estimating average annual daily bicycle traffic (AADBT) without the need for permanent counters

The approaches described in this research should be applicable to any agency that has collected daily bicycle counts. The methods are relatively simple compared to other procedures like travel model systems that require travel surveys and sophisticated route assignment software. However, the methods described in this report should be considered first-generation and will ideally improve over time as more data is collected and the process is refined. Therefore this research is aimed at informing the analytic area so as to move the field forward but also at practioners that may come to rely on this data for planning and project development.

3.0 ANNUAL TRAFFIC ESTIMATION

Except for roads where permanent counters are collecting data every day of the year, most traffic count based estimates of annual traffic are derived from a short term count of one week or less. For motorized traffic count estimation the short term count is usually collected for 48-hours during the week. Guidance for non-motorized traffic data collection is still developing but it's recognized that a count longer than 48-hours is necessary to reduce annual traffic count estimation error to acceptable levels. This section contains two parts with the first summarizing existing practices and research literature for non-motorized and motorized traffic factoring. The second then describes a new method called Seasonal Adjustment Regression Model (SARM) for estimating annual bicycle traffic that does not rely on traditional methods of traffic factoring.

Procedures for developing and applying expansion factors for non-motorized traffic have been steadily developing and more is being understood every year. Because of the highly seasonal nature of bicycle traffic, the traditional methods from the motorized traffic realm offer clues but have found to be less directly applicable which has encouraged researchers to try new approaches.

State DOTs and many local agencies collect traffic counts data for a variety of program and project needs. The process for expanding short term counts into annual estimates using expansion factors is well established for motorized traffic but still developing for non-motorized traffic. As described in the Traffic Monitoring Guide (TMG) the basic concept of traffic factoring is to use counts taken from permanent count sites using automated technologies to create hourly, daily, and monthly adjustment factors which are then applied to counts taken on a shorter time interval but at geographically dispersed locations (FHWA 2013a). A formula for calculating AADT using a set of expansion factors from the American Association of State Highway and Transportation Officials (AASHTO) is presented below.

$$\boldsymbol{AADT = \frac{1}{7}\Sigma_{i=1}^{7}\left[\left[\Sigma_{j=1}^{12}\left(\frac{1}{n}\Sigma_{k=1}^{n}VOL_{ijk}\right)\right]\right.} \qquad \textbf{(3-1)}$$

Where:

VOL = daily traffic for day k, of day of the week i, and month j

i = day of the week

j = month of the year

k = index to identify the occurrences of a day of week i in month j

n = the number of occurrences of day i of the week during month j.

As mentioned these data have many uses but a primary use is for reporting to the federal government through the Highway Performance Monitoring System (HPMS). This system has an established set of standards and protocols that help make reporting processes uniform across the states. Compared to the HPMS program, no similar program exists for non-motorized traffic counts (FHWA 2011).

3.1 NON-MOTORIZED EXPANSION FACTOR LITERATURE REVIEW

The Traffic Monitoring Guide now offers information about how to collect bicycle and pedestrian count data as does the Transportation Research Board’s guidebook NCHRP Report 797. The Oregon Department of Transportation reported on non-motorized data collection in 2014, reviewing technologies and existing best practices (ODOT 2014). A common practice among many cities is to focus resources on hourly counts collected by volunteers(FHWA 2011, Toole Design Group et al. 2014) Evidence now suggests that for estimating longer term traffic these short term counts will produce estimates with considerable error (Nordback 2013, FHWA 2011, Roll 2013).

In addition to collecting manual counts, some cities are pursuing count programs aiming towards a more complete approach using automated equipment that collects data on a longer term basis (Toole Design Group et al. 2014). These programs have supplied data for research that attempts to replicate methods previously used to estimate average annual daily traffic (AADT) for motorized traffic. Research has also expanded on traditional methods, attempting to consider techniques that handle the unique nature of non-motorized traffic in hopes of reducing estimation error. The primary issue these traditional methods must contend with is the seasonal nature of bicycle traffic and the sensitivity people riding bicycles have to weather conditions the influence this reality has on traffic factors.

A first attempt at using traditional for AADBT estimation was performed by Nordback et al. (2013). The authors use continuous data from 26 permanent count stations in Boulder, Colorado for years 1999 through 2012 to test the application of expansion factors. Based on measured absolute percent error (APE), these researchers demonstrate that at least a full week of counts is best to reduce error associated with estimating annual average daily bicycle traffic. Using one week of counts Nordback et al. showed that error could be as little 17% and as much as 28% for the four sites where factors were applied. Using four weeks of data error was as low as 7% and as high as 24%. However the methods used in this research did not separate the counts data used to create factors from the data where factors were applied, likely biasing measured error downwards.

Miranda-Moreno et al. (2014) test four methods of traffic factoring using counts data from 13 permanent count sites in Montreal. Two of the four methods are relatively traditional with the other two forming experimental approaches. The first of the experimental factoring approaches uses a weather model that attempts to account for the deviation in weather conditions from the average to better predict annual bicycle traffic. The fourth method applies a traditional factor method formulation to each day of the year (DOY), creating 365 discrete factors that theoretically account for daily weather conditions. The authors found that the DOY method performed the best with error as low as 3% for sites where both factor development and application were on the same corridor. The authors also tested duration of short term count on error and found that after 20 days each method performed similarly producing about 9% error. One issue the application of these methods presents is knowing the seasonal pattern of short term sites with only short term counts that may not give you all the information needed to make a pairing.

Esawey et al. (2013) use counts data collected in Vancouver, British Columbia from 74 count stations for years 2009 through 2011 to create daily factors using the harmonic mean as well as creating factor groupings based on weather conditions. The researchers demonstrated error rates as low as 10-16% depending on the days and months used when applying calculated factors. This research did robust validation tests but compared monthly estimates instead of annual, making comparisons with other research difficult.

Figliozzi et al. (2014) use data from a single counter in Portland to test an error correction function on 84 traditionally created day-of-week (DOW), monthly factors. After computing error using the traditionally created factors the author estimate a correction function that uses weather (including lagged versions of variables) and daily condition variables like holidays. Using seven days of counts collected during optimal time of year (April to October) error went from 10.8% using traditional factors to 8.6% using the error correction function. The authors were interested in determining error from one day counts to better align bicycle data collection with motorized count collection and showed that the error correction function could reduce error from 15.4% to 11.9%.

Hankey et al. (2014) use data from six off-street permanent count stations collected in 2011 and employ traditional DOW traffic factoring as well as employ the disaggregate DOY factoring method. The DOY method creates a separate factor for each day of the year performs better than the DOW method, yielding 20%, 15%, 1nd 11% average error using one, three, and seven days of short term counts respectively. In comparison, the DOW method yielded 40%, 27%, and 21% using the same three thresholds of short duration counts. These tests assume the short term counts were collected between April and October.

Building on their previous research, El Esawey (2016) tested day-of-year factors, weather specific factors for day and month, and factors from the *AASHTO Guidelines for Traffic Data Programs.* The resulting error from employing these methods was 17.5%, 24.5% and 30% respectively. The daily factor was again computed using the harmonic mean, as opposed to the straight mean. Additionally this research attempted to develop more generic daily factors by modeling day of year factors using the month, day of week and weather variables finding the average absolute percent error off 26.4%.

A key feature in some of the past research has been to create factor groups based on hourly patterns and a ratio of weekend to weekday bicycle volumes. Miranda-Moreno (2013) use data from five North American cities to establish likely user types by establishing utilitarian and recreational patterns. The authors do not use these patterns to test traffic factoring but this work was the first to establish a quantitative method of classifying bicycle traffic count sites. This classification scheme is used to help understand the differences in the effects of weather on bicycle traffic volume in Nosal and Miranda-Moreno (2014) but the explored methods do not attempt to estimate annual traffic volumes. The research did find that sites classified as utilitarian were less affected by weather compared to the sites classified as recreational.

Miranda-Moreno (2017) attempt to use these grouping methods as inputs to a clustering method that tests a five factor quality measure of short-term bicycle counts. Using a DOY method the authors' show that factors such as time-of-year and duration of short term count can be used to understand the resulting error from an AADBT estimate.

At this time the best factoring methods appears to use the DOY factors and can result in error as little as 10% but lower if the short term site and long term site are on the same corridor. More research should be done to test the use of grouping methods proposed by Nosal and Miranda-Moreno (2014) since researchers have found that misclassification of short term sites can increase average error from 11.65% to 19.35% for motorized (Gadda et al. (2007).

3.2 MOTORIZED EXPANSION FACTOR LITERATURE REVIEW

To better understand the range of results presented above for non-motorized traffic factoring results from past research on motorized traffic factoring is summarized below. Gadda et al. (2007) examined average error using data from Minnesota and Florida finding that average absolute error in urban areas was 11.47% and 14.28% respectively. For rural sites error was slightly higher with 12.8% and 13.3% percent error. The number of days used in the short duration count for these results is not clear but may include tests using 24, 48 and 72-hour short duration counts.

Sharma (1996) tested factoring methods for passenger vehicle traffic counts and found that 95% of the 1,890 simulated 48-hour short term counts were within 15% of the actual values. Sites classified as recreational performed much worse with 95% of the results resulting in nearly 24% error while sites classified as commuter had error of around 11% error. Using 24-hour short term counts resulted in more error with 95% of all the results falling under 16.5% error with recreational sites producing 27% error and commuter sites just 12.9% error.

Tspapakis et al. (2011) test the use of linear discriminant analysis for assigning short term counts to groups using vehicle count data from Ohio. Using traffic factoring guidelines from AASHTO the authors estimate AADT from 24-hour counts revealing improvement over traditional assignment methods using functional classification with average error dropping from 12.1% to 8.3%. The authors also try developing and applying factors based on directional flows instead of total volume which revealed significant drop in error with just 4.3% error.

Gecchele et al. (2012) propose using artificial neural network to assign short term counts to factor groups and compare their findings with methods from Sharma (1996). Using 48-hour counts the authors are able to reduce error for commute sites to a range of 5.15 to 6% and 8.4% to 15.5% for recreational sites. Gastaldi et al. (2013) implemented build on Gecchele (2012) also using artificial neural networks to assign short term counts to groups but create those groups using fuzzy set. Using 24-hour counts to estimate AADT, researchers found average error ranged from around 5% for commuter sites to approximately 24%, for sites classified as recreational.

The *ASSHTO Guideline for Traffic Data Programs* (2009) does not specify an acceptable error rate when factoring short-term counts to AADT but simply states that "AADT estimates developed from a complete set of 84 MADW values are considered to be highly precise estimates for which error statistics are not worth calculating". Estimation results featured below in sections on Annual Traffic Estimation and Total Bicycle Activity Estimation should be considered in light of the literature review above. Less error is always ideal but decision making must always consider uncertainty with the information employed to inform the decision.

3.3 SEASONAL ADJUSTMENT REGRESSION MODEL (SARM)

The review featured in section 3.2 above documents the current state of the practice for expanding short term counts to annual average daily traffic count (AADT). The current section will describe an alternative approach that uses a regression analysis to relate daily bicycle traffic counts to daily conditions such as temperature and precipitation, minutes of light during the day, day of the week and whether or not the large university was in session. Regression model results are then applied to estimate an entire year of bicycle traffic counts at a given location to calculate Annual Average Daily Bicycle Traffic (AADBT). In order to demonstrate the accuracy of this new approach two elements are presented. The first simulates the use of the SARM approach by employing permanent bicycle count data from various counters in Oregon and Washington. Permanent counter data is useful for this step because it allows for comparing estimated AADBT to actual AADBT. The second element compares results of the SARM approach with a traditional expansion factor method in the study area. This process innovates upon previous methods because it does not require permanent count stations to develop factors but is more data intensive requiring longer duration short term counts. Because AADBT is necessary for input into the facility demand models presented in the Total Bicycle Activity Estimation section, the SARM approach was needed since no network of permanent counters exists in the study area.

3.3.1 Methodology Description

It has been established that the weather and day of the week affects bicycle travel (Miranda-Moreno & Nosal 2011; Tin et al. 2012; Thomas et al 2012; Rose et al. 2011; Lewin 2011; Nosal and Miranda-Moreno 2012). Previous research was mostly bound to standard traffic factoring methods with varying levels of complexity. This work attempts to use these daily conditions as independent variables to estimate a statistical model and then apply that model to estimate annual volume. This approach would be applied by estimating seasonal adjustment regression models separately for each location to control for variation in the impact these factors have at each location. Using this approach removes the need for permanent counters to develop and deploy traditional expansion factors. This method also avoids the need to select an appropriate factor group to apply to a given short term count, a recognized source of considerable error (Tsapakis et al. 2011), since it only uses data from the site if interest.

3.3.2 Model Description

To predict AADBT for each site separate regression models using regression models with both Poisson and Negative Binomial error distributions. The model form for the SARM approach is described in the equation below. It was found that if over dispersion exists in the training data then the negative binomial specification is best at reducing error for some locations, however marginal the decrease. In either case, the model is specified as linear-in-parameters with a log-link function:

$$\boldsymbol{Y_{id} \sim Poisson(\mu_{id})} \textbf{ or } \boldsymbol{Y_{id} \sim NegBinom(\mu_{id})}$$
$$\mathbf{log(\mu_{id}) = \beta_i X_{id}} \qquad \textbf{(3-2)}$$

Where:

Y_{id} = 24-hour bicycle traffic volume on day *d* at site *i*

$\boldsymbol{\beta_i}$ = Vector of parameters for count site *i*

$\boldsymbol{X_{id}}$ = Vector of observed covariates for count site *i* on day *d*.

Once parameters are estimated for a given location, those parameters are applied to a year of daily observations that include the independent variables used in the model.

3.3.3 Testing the SARM Approach

The SARM approach is new and its accuracy unknown so will be tested below. In order to test the accuracy of the SARM approach, a series of validation tests have been devised using permanent count data from available count locations in Oregon and Washington. Permanent bicycle counter record data for 365 days and therefore can be used to compare an estimate of comparable annual estimate. This validation approach simulates the use of short term counts by randomly selecting periods of counts from the permanent counter, estimating a SARM, and applying the parameters to independent variables representing an entire year and then comparing the estimated annual traffic volume with observed AADBT. This process will test different durations of short term counts to determine how accuracy is impacted.

3.3.4 Data Description

Data from multiple permanent counters were used to validate the seasonal adjustment methodology. Permanent counter data was available from six locations total, with one location in the study area (Fern Ridge) and three others from Seattle, Washington and one from Portland, Oregon and the sixth from a location in Ashland Oregon. These locations were used because the data was easily available to this research. With equipment issues and path closures the data from these locations was imperfect though mostly usable. 3.1 gives a summary of the average annual daily bicycle traffic (AADBT) and the number of daily observations by year and by location.

Table 3.1 – Average Annual Daily Bicycle Traffic and Sample Sizes

Location	Year							
	2013		2014		2015		2016	
	AADBT	N	AADBT	N	AADBT	N	AADBT	N
Fern Ridge West Chambers (Eugene, OR)	605	308	426	201	557	354	539	324
Fremont Bridge West Sidewalk (Seattle, WA)	1,311	364	1,414	364	1,372	363	1,283	365
Fremont Bridge East Sidewalk (Seattle, WA)	1,230	364	1,347	364	1,331	363	1,408	365
Spokane Street Bridge (Seattle, WA)	NA	NA	777	363	821	364	815	365
Hawthorne Bridge (Portland, OR)	4,670	365	4,706	364	4,620	363	3,321	346
Ashland Dog Park (Ashland, OR)	142	361	192	365	148	365	140	366

3.3.5 Applying the Validation Procedures

Figure 3.1 below describes the tests were performed to gauge the accuracy of the SARM approach.

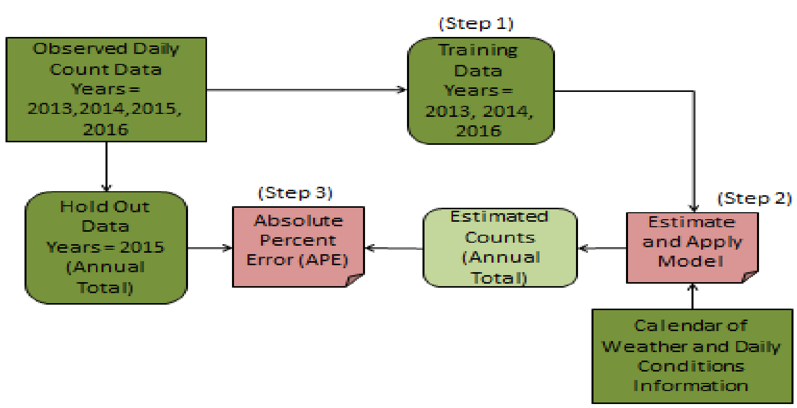


Figure 3.1: Steps in validation tests

In Step 1, short term count data (between 2 and 6 weeks) is randomly selected from the full data set. In Step 2 a regression model is estimated and the parameters applied to a calendar of 365 days of weather and other daily conditions. Finally in Step 3 the absolute percent error (APE) is calculated by comparing the estimated annual bicycle volume with the observed (from the full data set). The equation below details the APE calculation. The above process is repeated 500 times for a given count location to assess the variability in the APE.

$$\boldsymbol{APE = \left|\frac{AADBT_{obs} - AADBT_{est}}{AADBT_{obs}}\right|} \qquad \textbf{(3-3)}$$

Where:

$AADBT_{obs}$ = Observed AADBT for the count location

$AADBT_{est}$ = Model-predicted AADBT for the count location

Figure 3.3 below shows the median APE for 500 iterations of tests using different scenarios to test the seasonal adjustment methodology. Scenario differences include varying the number of weeks and years used in the training data which varies the number of days used in the regression model. For example, in the scenario with three years and two weeks, 42 days of data would be used, or 14 days from three different years. Figure 3.3 demonstrates that median APE for all the tests done in each scenario improves significantly with three years of data compared to two years of data. Only for some locations does the median APE improve when additional weeks of data are added to the training data set. The Hawthorne location presents a case where by adding more days to the training data the error increases. This is likely due to the substantial drop in traffic in late 2015 with the opening of the Tilikum Bridge in Portland. As can be observed in Table 3.1 above, the AADBT drops significantly in 2016 compared to previous years. Since the validation process uses data from 2013, 2014 and 2016 its likely that has more weeks of data were used in the training data more of the days come from 2016 skewing the ability to estimate the 2015 year. This is perhaps a cautionary note on applying these techniques when traffic patterns are known to have changed substantially at a given location.

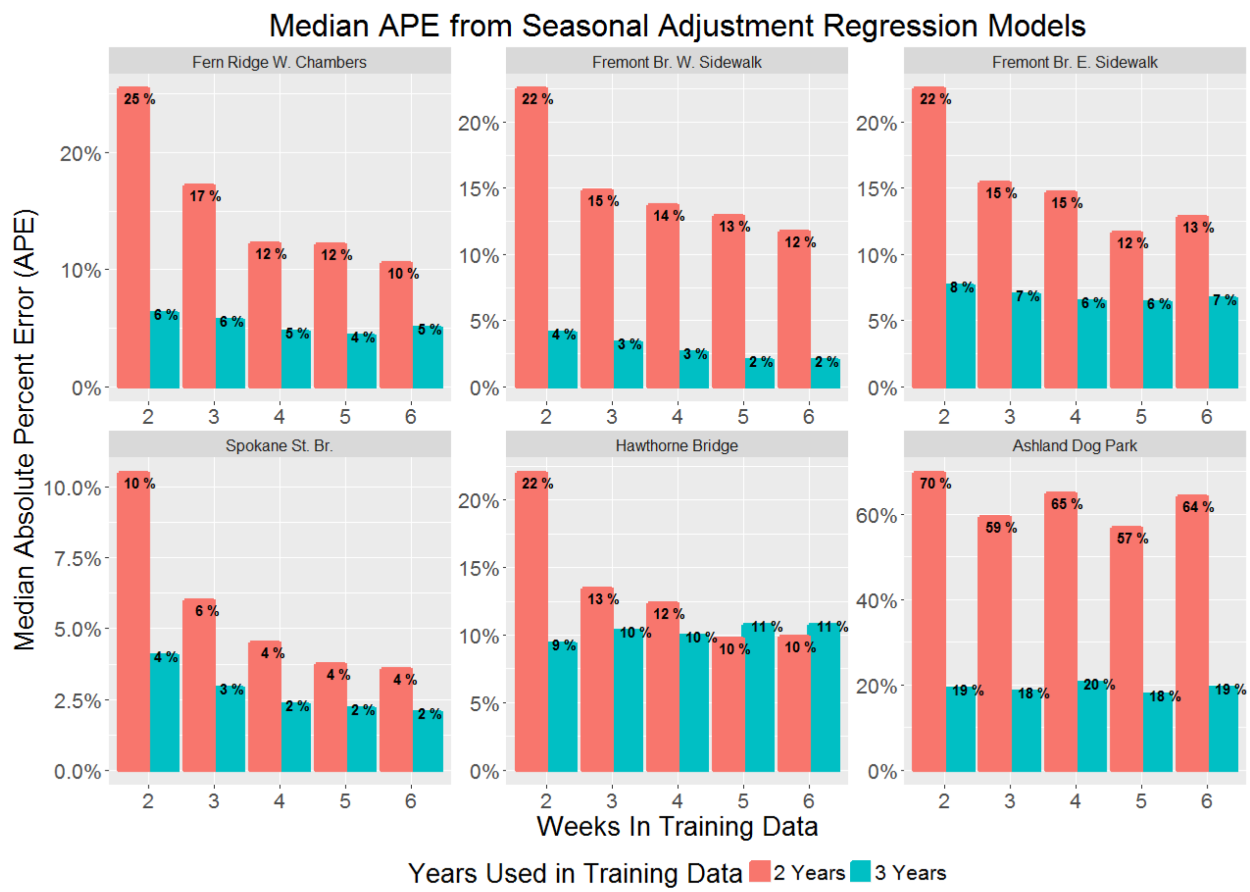


Figure 3.2: Median APE from 500 seasonal adjustment regression models (negative binomial)

Since it was established that using two weeks of daily counts from three years of data represents an optimal balance of reduced error and low data requirements the remainder of results will cover only this scenario.

In the regression models both Poisson and Negative Binomial model specifications were tried. The above results show outcomes using the negative binomial specification. Table 1.3 below shows the median APE for each location comparing results from both model forms. Differences in median APE between model types should result from a misspecification of model form based on the presence of over dispersion of the counts data used in the model estimation. However, the results in the table below seem to indicate the opposite where if over dispersion exists, the Poisson model performs better. These results do show that the difference in median APE is minimal between forms.

Table 3.2 – Comparison of Median APE between Model Forms

Location	Median APE		Tests Detecting Over Dispersion
	Poisson	Negative Binomial	
Fern Ridge West Chambers	6.3%	6.2%	500
Fremont Bridge West Sidewalk	4.1%	4.2%	500
Fremont Bridge East Sidewalk	7.6%	7.2%	500
Spokane Street Bridge	4.0%	4.4%	500
Hawthorne Bridge	9.3%	10.0%	1
Ashland Dog Park	16.8%	19.1%	35

Figure 3.4 below shows error by decile for all the count sites in order to demonstrate the range of error from the multiple (500) iterations of holdout validation tests. Each decile represents the amount of APE associated with that proportion of tests. For example for the Fern Ridge West Chambers location, 50% of the tests results had 6.3% APE or less. These results are also cumulative so each subsequent decile includes the one behind it. Looking at the validation tests this way, readers can see that for some locations 90% of the tests result in error of 12% or less as is the case for the Fremont Bridge West Sidewalk location but as much as 57.4% or less in 90% of the tests as is the case for the Broadway Northeast Union Street location.

Table 3.3 – Deciles of Error in Seasonal Adjustment Regression Models

Location	1-10%	1-20%	1-30%	1-40%	1-50%	1-60%	1-70%	1-80%	1-90%
Fern Ridge West Chambers	1.25%	2.5%	3.7%	4.9%	6.2%	7.9%	9.8%	12.4%	16.6%
Fremont Bridge West Sidewalk	0.73%	1.6%	2.6%	3.6%	4.5%	5.6%	7.1%	8.4%	11.8%
Fremont Bridge East Sidewalk	1.27%	2.8%	4.2%	5.7%	7.0%	8.7%	10.6%	12.6%	15.5%
Spokane Street Bridge	0.79%	1.5%	2.4%	3.4%	4.5%	5.6%	6.9%	8.5%	12.0%
Hawthorne Bridge	3.37%	5.3%	6.7%	8.1%	9.3%	10.5%	12.3%	15.4%	20.8%
Ashland Dog Park	2.55%	5.5%	8.9%	12.4%	16.5%	21.7%	27.2%	36.3%	57.4%

Table 3.5 below summarizes another set of validation tests where different combinations of months are used to estimate the SARM with associated APE presented. The table compares results using months that previous guidance has recommended with two other sets of months including a non-restrictive scenario where all months are available and one which results in some of the lowest error results. Previous guidance from the National Bicycle and Pedestrian Documentation Project suggests bicycle counts be collected in May, October, and September so the application of SARM using these months is presented. Additionally, Nordback et al. (*9*) concluded that using the months of July, August, September, and October are best to reduce error when using traditional traffic factoring methods. Presenting results from SARM validation tests in this way should be helpful to understand the expected accuracy of SARM results based on when short term data collection would take place.

In addition to testing different months the table breaks out the results based on proximity of the months to one another, or what is described as spread. This attribute is a computed quantity where the time (distance) between months is measured and averaged resulting in a value between one (lowest spread) and four (highest spread). For instance, if data was collected from January, May, August, the spread value would be greater than the if the months May, June and April were used to calculate the spread value since the latter months are all consecutive months.

The results presented in Table 4 demonstrate which months used in the SARM would produce the lowest error. It should be noted here that the results presented here simulate using two weeks of data collected in three different years to predict the AADBT. Therefore it could be expected that if six weeks of data were collected across three years with little variation in the months uses (e.g. June, July, August) the SARM approach could predict AADBT for the Fremont Bridge West Sidewalk location within 29% APE and if short term counts were gathered aiming to spread out the collection (e.g., January, May, August) expected AADBT error from a SARM estimate would be reduced to 18%. In nearly every case error is reduced by using a higher spread of data in the SARM model. In most cases the SARM approach using TMG months does not produce better results compared to those tests using all the months. This is not true for the Hawthorne Bridge location where the TMG months produce the best results.

For most locations, using the months March, April, May, October, and September produce the least amount of error and in most cases those tests using these months but spread out data collection achieve even lower amounts of error. The Ashland location is one exception to these results, where the tests that use all the months of the year produce the least amount of error. Another exception to these months being best for reducing error is the Hawthorne Bridge location where the NBPD months are best at reducing error.

Table 3.4 - SARM Results for Selected Months

Months Used in SARM	Spread of data collection	Fremont Bridge West Sidewalk	Fremont Bridge East Sidewalk	Spokane Street Bridge	Hawthorne Bridge	Ashland Dog Park
All Months (Jan-Dec)	Low Spread	29%	29%	31%	20%	56%
	High Spread	18%	19%	17%	16%	55%
	Median	20%	21%	20%	17%	56%
NBPD Months (May, October, September)	Low Spread	-	-	-	-	-
	High Spread	22%	27%	22%	6%	79%
	Median	22%	27%	22%	6%	79%
Nordback et al. 2013 (July, August, September, October)	Low Spread	24%	34%	23%	14%	49%
	High Spread	-	-	-	-	-
	Median	24%	34%	23%	14%	49%
March, April, May, October, September	Low Spread	15%	16%	19%	8%	92%
	High Spread	14%	17%	14%	8%	68%
	Median	15%	16%	17%	8%	70%

3.4 APPLICATION OF SEASONAL ADJUSTMENT REGRESSION MODEL APPROACH

The SARM approach described and tested above will now be applied to short term counts collected in the study region. Data includes short term bicycle counts collected through the Central Lane Metropolitan Planning Organization's (CLMPO) Regional Bicycle Count Program. These counts need to be expanded to represent and annual average daily bicycle traffic (AADBT) value and so the SARM approach will be applied.

3.4.1 Model Description

To estimate annual bicycle volume for locations where only short term daily counts are available separate seasonal adjustment models were estimated for each location. To ensure that the necessary data exists to estimate reliable models a few constraints are placed on the model estimation and application process. The first check ensures sufficient number of observations on weekdays and weekends and also when the university is in session and not in session. A second and third check follows the model estimation and looks to ensure that the temperature and precipitation coefficients are in the expected direction, positive and negative values respectively for each of these variables. A last check removes data from December, January, and November since those months were found in the validation section above, to produce higher amounts of error. Lastly, counts data are assessed to determine if over dispersion is present and if so uses a negative binomial form and otherwise implements a Poisson model form in the SARM. This process starts with 88 count locations but after the constraints are applied and a separate model estimated for each count station, only 52 locations remain.

3.4.2 Data Description

The SARM approach described above will be used to create AADBT estimates for 52 locations where short term daily counts were collected using portable counters. The number of daily counts at these sites varies with a minimum of 14 days of daily counts to a maximum of 58 daily observations. Additional summaries of the number of counts used in the seasonal adjustment models are described in Table 3.6 below.

Table 3.5 – Summary Statistics for Daily Count Observations

Measure	Observations
Minimum	14
1st quartile	20
Median	28
Mean	27.8
3rd Quartile	34
Maximum	58

It should be noted that in some cases less than the optimal number of daily counts are used in the SARM procedure. In order to maintain adequate number of count locations for the next stage of research it was decided to use 14 days of daily counts as the cutoff in order to maintain at least 50 locations to use in the demand modeling below.

3.4.3 Model Results

Separate models are estimated for each location with checks to make sure sufficient data exists and that model results for certain independent variables produce the expected sign. The results of the final 52 locations (estimated for each location) are described in Figure 3.2 below. These graphics show the estimated coefficient and confidence intervals and the shape and color of the point describes if the model produced a significant result with a p-value of 0.10 or less. It was decided that though some of the resulting coefficients were not significant at this level, it was likely due to small sample size and model results were retained. These results exhibit some difference in parameter estimates with some locations showing significantly large standard errors.

Figure 3.3: Coefficient (with confidence intervals) and p-value results for estimated models

3.4.4 Comparing the SARM with Traditional Factoring Method

Application of the SARM procedure above results in AADBT for 52 locations. It's not possible to do a robust validation test for these results and instead the SARM results will be compared to results using the traditional expansion factor method described in the TMG. The traditional factor approach is described in the equation below

$$\boldsymbol{AADBT_e = ckh * Dyf * Myf} \qquad \textbf{(3-4)}$$

Where;

AADBT *e* = estimated annual average daily bicyclists;

ckh = known count for 1 h;

Dyf = daily factor for given day of week in given year *y* for factor group *f* : (actual AADB for that year)/(average daily bicyclists for that day of the week in that year);

and

Myf = monthly factor for given month in given year *y* for factor group *f*: (actual AADB for that year)/(average daily bicyclists for that month of that year)

It should be reiterated here that the traditional expansion factor method is not employed to estimate AADBT for all of the available short term data because insufficient permanent counters exist for factor development. However, the permanent counter location at Fern Ridge West Chambers is available for this purpose and will be used to extrapolate short term counts at six locations. In theory the SARM method can be applied to any location provided sufficient numbers of days of data are available. However, guidance on application of traditional factors suggests matching hourly patterns and weekend to weekday indices (Miranda-Moreno et al. 2013), therefore these measures were used to decide which sites to use in this comparison. Table 3.7 below describes the average weekend and weekday volumes and the calculated WWI. The WWI is calculated as:

$$\boldsymbol{WWI = \frac{\bar{v}_{we}}{\bar{v}_{wd}}} \tag{3-5}$$

Where:

$\bar{v}_{we}$ =Average daily volume on weekends

$\bar{v}_{wd}$ =Average daily volume on weekdays

Table 3.6 – Short-duration Site Summary Information

Location	Average Daily Bicycle Volume		Hourly R^2	WWI	Daily Observations		Distance from Reference
	Weekend	Weekday			Weekend	Weekday	
Fern Ridge West Chambers*	406	492	-	0.825	297	715	-
Heron Bridge South Fern Ridge	405	467	0.973	0.87	12	27	0.184
DeFazio Br. South River	391	546	0.959	0.71	8	18	1.95
DeFazio Br. North River	462	544	0.952	0.85	8	18	2.09
15th Ave. West Jefferson St.	453	621	0.946	0.73	10	24	0.857
Frohnmayer South River	714	982	0.923	0.73	10	27	2.43
Northbank South Greenway Br.	392	544	0.973	0.72	10	18	1.81

*Reference Site

Figure 3.4 below to give readers a sense of how the hourly patterns align with the reference site represented by the dashed line.

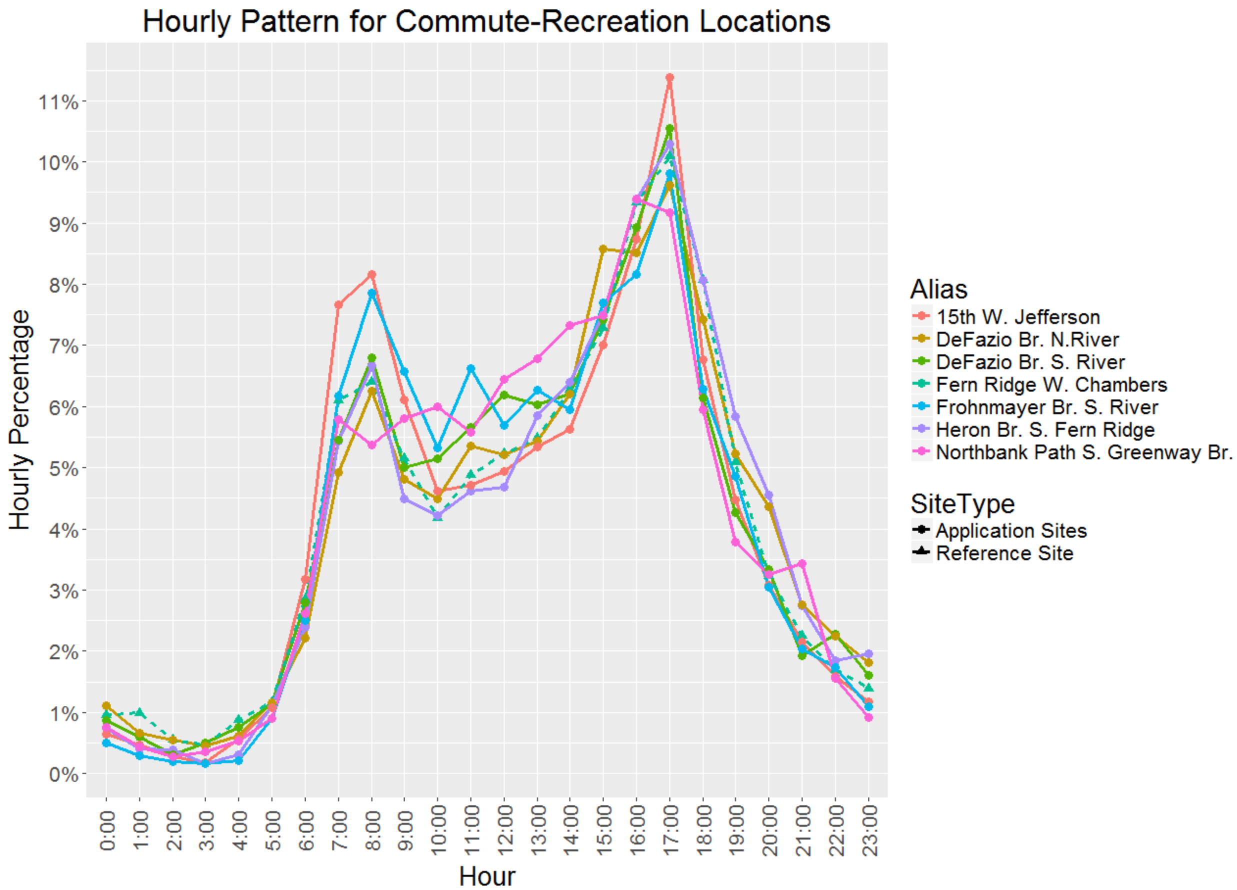


Figure 3.4: Hourly pattern for fern ridge west chambers and traffic factor application sites

Since the hourly distribution pattern and the WWI are similar its reasonable to apply a monthly expansion factor created using the Fern Ridge West Chambers site to these application sites to compare with AADBT estimates from the SARM approach. Table 3.8 shows the results of this comparison along with the APE between the two estimates and other summary information including the number of daily observations used in both methods and the monthly expansion factor used in the traditional factoring process.

Table 3.7 – Comparison of Traditional Expansion Factor and SARM Estimates of AADBT

Location	AADBT Estimate		APE	Days Used in Estimate		Monthly Factor Info	
	Traditional	SARM		Traditional	SARM	Factor	Month
Heron Bridge South Fern Ridge	398	415	4.3%	7	45	0.984	April
DeFazio Br. South River	484	457	5.6%	7	33	0.83	September
DeFazio Br. North River	445	453	1.9%	7	25	0.83	September
15th Ave. West Jefferson St.	556	513	7.8%	7	34	1.29	February
Frohnmayer South River	749	741	1.1%	7	47	0.835	May
North bank South Greenway Br.	464	471	1.6%	8	43	1.479	November

3.4.5 Conclusion

According to the results presented in the Table 3.8 the two AADBT procedures produce similar results with differences as small as 1.1% and as great as 7.8%. The two approaches have different data requirements with the traditional approach only using seven daily observations while the SARM process uses up to 47 days of data. This should lend confidence to the AADBT estimates created for the other locations using the SARM approach. Though it would be desirable to have a network of permanent count stations to develop and apply traditional traffic factors this is not possible.

For public agencies collecting bicycle traffic counts, permanent count stations should be installed but for those without permanent count stations or those without permanent count stations that have hourly and WWI patterns matching their short term counts the SARM approach may be an interim solution. This research will utilize the SARM method and its resulting AADBT for the duration of this research.

4.0 TOTAL BICYCLE ACTIVITY ESTIMATION

The above sections focus on interim processes of bicycle data collection and annual estimation techniques employed to generate usable inputs for system wide demand estimates of bicycling in the study region. This section is divided into three sections with the first section offers a brief review of the traditional methods used to estimate vehicle miles traveled (VMT). The next sub-section reviews past research on methods for estimating bicycle travel activity. The third part of this section will describe a modeling approach which uses AADBT estimates using the SARM approach to estimate bicycle miles traveled for an entire bicycle network in the study region using a direct demand approach.

4.1 METHODS FOR ESTIMATING MOTORIZED TRAVEL

Measures of vehicle miles traveled (VMT) are a basic and yet instrumental metric for understanding motorized vehicle travel. These estimates are used for infrastructure planning, funding-allocation decision making, crash exposure, access and economic activity as well as greenhouse gas and air quality analyses. Processes for estimating VMT have been established for many years and use one of three approaches. The first approach is a more direct observation of vehicle activity where traffic counts are collected throughout the road system. The second approach to estimating travel activity rely on complex travel demand models that utilize travel surveys, population and employment data, and detailed transportation network information. This method employs a common framework including: *trip generation, trip distribution, mode choice,* and *route choice*. The third approach, often called the direct demand or facility demand approach uses statistical models that employ socio-demographic data to estimate vehicle travel.

The travel demand modeling approach is well suited for infrastructure projects focused on automobile and transit modes but have been lees capable of properly estimating non-motorized demand at the network level (PBIC 2015; NCHRP 08-78). The traditional four-step model framework has been replaced in many places with activity-based approaches that allow for more detailed dissection of travel behavior but ultimately offer little change in macro estimates of VMT.

Each state collects and reports on vehicle traffic volume through the Highway Performance Monitoring System discussed above in the Data Collection section. These reports are required for funding disbursement and are available across all 50 states. VMT estimates are available at different levels of road type and geographic scale.

4.2 METHODS FOR ESTIMATING BICYCLE TRAVEL

4.2.1 Travel Demand Forecasting for Bicycle Traffic Review

Though efforts have been made in recent years, travel models generally do not account for bicycle traffic in a meaningful way useful for estimating all bicycle miles traveled for a study region. NCHRP Report 770 summarized efforts to include non-motorized traffic in travel models and found the Atlanta Regional Commission (Georgia), Capital Area Metropolitan Planning Organization (Texas), Portland Metro (Oregon), Durham, North Carolina, and Buffalo New York, San Francisco, California. These efforts include non-motorized travel at various stages of trip and activity based models.

4.2.2 Facility Demand Modeling Research Review

Facility demand models are an increasingly common method for analyzing non-motorized travel but were tried as early as 1977 with Benham and Patel (1977). These models use counts of people walking or people riding bicycles as dependent variables and employ weather, built environment, sociodemographic and network characteristics as independent variables to estimate statistical models. These models are simpler than travel demand models and do not include a behavior components or data from travel surveys. Some of the research below, especially the more recent research, attempts to estimate network wide demand while other research only estimates models to determine how each dependent variable relates to the counts without ever applying the model to the rest of the study area.

Lindsey et al. (2007) uses mixed-mode (bicycle and pedestrian) counts collected by infrared devices in Indianapolis, Indiana to correlate weather, temporal, sociodemographic and urban form variables with non-motorized travel activity. The authors use a log-linear model specification to determine the effect that these variables have on observed daily traffic volumes. Findings suggest reasonable relationships between dependent and independent variables across four model specifications with high explanatory power, with adjusted R^2 of 0.7966. This research uses gross measures of sociodemographics and urban form, assigning Census tract information where counts are collected to the count location. Counts for this research were collected on off-street paths and were not applicable to on-street locations.

Hankey et al. (2012) use two-hour evening peak period (4:00 - 6:00 pm) counts of bicyclists and pedestrians from 259 locations in Minneapolis, Minnesota to estimate models relating counts to weather, built environment, sociodemographics, and infrastructure variables. Measures of sociodemographics and some of the built environment variables' areal unit is at the Census block group level. The authors tried two model specifications, ordinary least squares (OLS) and negative binomial regression to understand the relationship between the dependent and independent variables concluding that due to the over dispersion of the count data the negative binomial distribution is best. For the bicycle count models, Hankey et al. produce results using the negative binomial regression technique with pseudo R^2 value of 0.476 with eight of the independent variables not significant at the 0.05 level. The authors attempt some validation, comparing estimated counts with observed counts though with no hold out and no discussion of absolute error just a visual inspection. Additionally, the authors expand the two-hour counts up to 12-hour counts using some locally derived factors which however substantiated, would likely introduce some error into any application of these models to the entire network. This application of the model to the entire network results in citywide estimates of 12-hour non-motorized traffic for each link of the network.

Wang et al. (2014) estimate models relating weather and sociodemographic variables to mixed-mode counts from six off-street counters. The authors compare the use of OLS and negative binomial regression techniques, concluding that the latter is a better specification based on the distribution of the counts data and resulting error from validation tests which was as low as 16.6% for the general model (pooled data from all six locations). The authors suggest that the models could be used to estimate non-motorized volumes at locations where trails construction is proposed.

Hankey and Lindsey (2016) build on past research using additional mixed-mode count data from the Minneapolis, Minnesota which include afternoon peak period (4:00 pm – 6:00 pm) counts from 954 locations for years 2007 through 2014. The authors use linear regression models to relate weather, sociodemographic, and infrastructure to collected counts data experimenting with models using varying numbers of independent variables hoping to find a reduced form specification usable in areas with less available data. This research is the first to try network density variables where the total length of certain network characteristics (e.g. on-street bicycle facilities) are employed as independent variables with results yielding intuitive results in some but not all cases. For example in the statistically optimal model off-street trail network meters within the vicinity of the bicycle count location are positively correlated with more bicycle volume but local roads are negatively correlated. The authors perform robust validation steps for their core and time-averaged models where they hold out (10%) a random sample of their data, estimate and apply their model, and compare with the held out data and do this process 100 times to assess predictive capability. Using R^2 as a performance metric the authors report measures no higher than 0.55 suggesting the models work moderately well as predictive models.

Wang et al. (2016) use mixed-mode counts from multiple places in the U.S. including Minneapolis, Columbus, and the Central Ohio to test the transferability of the facility demand approach across these areas. The authors estimate separate models for each city using AADT as the dependent variable which was possible because counts data were collected from 17 (from all areas) permanent counters collecting year round. Independent variables included sociodemographic and built environment variables from U.S. Environmental Protection Agency (EPA) 2010 Smart Location Database (SLD) in addition to accessibility measures from the National Accessibility Observatory based at the University of Minnesota. The models used a negative binomial specification but did not include any infrastructure variables. The resulting models for each city had pseudo R^2 values of 0.64, 0.576, and 0.318 for Minneapolis, Columbus, and Central Ohio region respectively. Validation tests were performed similar to Hankey and Lindsey (2016) where some data is held out and later compared to estimated counts. Different tests applying the models within each of the cities and also across cities were performed with error of 27% 22% for Minneapolis and Columbus respectively. The cross city validation resulted in considerably higher reported error suggesting transferability of models across cities results in less much less reliable estimates. Since most studies are done using slightly different methods and data it’s hard to directly compare the outcomes.

NCHRP 770 describes the use of direct demand models as an accepted practice and notes their simplicity as a primary driver for their use but cautions that since they fail to account for behavior directly are more limited in practice that a fully specific travel demand model. Other limitations noted in the report include the non-transferability of a specified model from one area to another and the inability for a direct demand model to accurately forecast new facilities since the approach does not account for diversion from existing facilities. The report also mentions the need to be weary of uncertainty in the counts data. This is a reference to the fact that much of the above literature is limited in its application because it relies on hourly counts which fail to represent AADBT making a system wide application representative of peak hour demand only.

It should be noted that facility demand approaches have been employed to estimate motorized traffic for many years and continue to be used in the research literature and as the main travel forecasting tool for some small communities. Using a variety of specifications including linear, non-linear and spatial regression, researchers and practioners have used vehicle traffic counts and their relationship with population, sociodemographics, employment and infrastructure variables like functional classification to estimate traffic in locations without counts.

Dadang et al. (1998) used multiple linear regression to predict AADT on county roads using population, households, vehicle registrations, employment, and income per capita and facility variables with error in predictions averaging 16.78%. Xia et al. (1999) also used multiple linear regression to estimate AADT on non-state roads with validation tests resulting in an average error of 22.7%. Barnet et al. (2015) applied multiple linear regression techniques using counts data in Ohio, Washington, and North Carolina found it possible to estimate AADT with an average error of 59%. Staats (2016) and Souleyrette et al. (2016) tried applying non-linear regression with validation tests resulting in error of between 61% and 97% for rural areas and 354% and 1956% for urban areas. Other research exists using various techniques to relate counts to various contextual variables with a range of outcomes. Input data and independent variables as well as validation techniques play a role in the validation tests making direct comparison among the research difficult.

4.3 DEVELOPMENT OF A DIRECT DEMAND MODEL FOR THE CLMPO REGION

The Annual Traffic Estimation section above described the analysis techniques used to develop the AADBT data used in this section of the report. The below section will utilize these AADBT estimates along with network, population, and employment data to estimate facility demand models. These model parameters will then be applied to the entire network to produce an estimate of bicycle miles traveled (BMT).

4.3.1 Data Description

The following section will describe the data used in the facility demand modeling analyses below. AADBT is derived from application of the SARM procedure described above and is based on data form the Central Lane Metropolitan Planning Organization’s (CLMPO) Regional Bicycle Count Program. The study region for this research includes the cities of Eugene, Springfield, and Coburg in the state of Oregon with a collective population during the study period of just over 250,000 people. The CLMPO is home to the University of Oregon (UO) which offers higher education services to nearly 25,000 students. In addition to collecting bicycle counts, the CLMPO manages the street network data which includes a detailed routable network with information on both on-street and off-street segments. Network data is used to calculate accessibility and network density variables described in more detail below.

A summary of the AADBT data is featured in Tables 4.1 and 4.2 below. Table 4.1 describes the number of count sites for each of the functional classifications and bicycle facility classifications.

A total of 52 sites are used in the demand modeling with the most data being collection on off-street paths followed by local streets, minor arterials and finally collectors. Bike lanes have the second highest number of count locations followed by streets with no bicycle facility, then bike boulevards and a single observation on a cycle track facility.

4.3.2 AADBT Summary

Table 4.1 – Count Locations by Functional Classification and Bicycle Facility Type

Functional Classification	Bicycle Facility Type: No Bike Facility	Bike Lane	Bike Blvd.	Cycle Track	Off-Street Path	Total
Path	0	0	0	0	19	19
Local	9	0	2	1	0	12
Collector	4	4	2	0	0	10
Minor Arterial	0	11	0	0	0	11
Major Arterial	0	0	0	0	0	0
Total	13	15	4	1	19	52

Table 4.2 summarizes the mean AADBT for each of these cross classifications of functional and bicycle facility classifications. Local streets exhibit the highest average AADBT followed by off-street paths then collectors and minor arterials. The cycle track facility has the highest average AADBT of all of the bicycle facility classifications followed by bike boulevards, off-street paths, bike lanes and lastly streets with no bicycle facility. No data was collected on major arterials facilities.

Table 4.2 - Mean Average Annual Daily Bicycle Traffic (AADBT) by Functional and Bicycle Facility Classification

Functional Classification	Bicycle Facility Type: No Bike Facility	Bike Lane	Bike Blvd.	Cycle Track	Off-Street Path	Total
Path	-	-	-	-	317	317
Local	191	-	395	878	-	488
Collector	63	323	281	-	-	222
Minor Arterial	-	208	-	-	-	208
Major Arterial	-	-	-	-	-	-
Total	127	265	338	878	317	385

4.3.3 Network Characteristics Description

In order to ensure a consistent understanding of street and bicycle infrastructure classifications descriptions are provided above in Tables 2.1 and 2.2. These classifications of roadways are important since this study employed these functional classifications for street infrastructure used as proxies for motor vehicle volumes and speed since comprehensive motorized vehicle counts are not available in the study region. A summary of the estimated auto volumes for street classifications described above for the study region can be found in Table 4.3. These values are provided to give the reader a sense of the relative levels of motorized vehicle volume expected within each street functional classification. It should be noted that for this analysis arterial classifications are split into major and minor arterials to better account for motorized traffic exposure that bicyclist may experience.

Table 4.3 - Average and Median Motorized Traffic Volumes by Functional Classification

Street Classification	Average Daily	Median Daily
Path	-	-
Local	1,340	1,103
Collector	3,615	2,980
Minor Arterial	12,420	9,218
Major Arterial	24,160	19,420

The study region includes four separate bicycle infrastructure classifications including shared lane marking, bike boulevard, bike lane, and off-street bicycle and pedestrian paths. For more complete descriptions please see Table 2.2 above.

4.3.4 Independent Variables Description

As demonstrated in literature review, factors that help explain the variation in non-motorized count volumes and can be categorized into three groups including:

- Infrastructure (street and bicycle facility classification)
- Accessibility to amenities like population and employment
- Network density

Variables within each of these categories come from different sources with some being developed for this analysis. The following sections will describe the origin and calculation methods used to derive these variables.

4.3.4.1 Accessibility Measures

Accessibility is generally defined as some measure of the size and closeness of activity opportunities of a given amenity at a given location whether it is population or employment. This research employs the isochronic or cumulative opportunity measure in its approach to measuring accessibility. Cumulative opportunity is one of the basic and early measures of accessibility (Vickerman, 1974; Wachs & Kumagai, 1973) and counts the number of potential opportunities that can be reached within a predetermined travel time (or distance). This measure is expressed below.

$$\boldsymbol{A_i \sum_{i=0}^{n} B_j\ a_j}$$

(4-1)

Where:

$A_{i\ =}$ Accessibility measured at point i to potential activity in zone j

a_j = Opportunity in zone j

B_j = A binary value equal to 1 if zone j is within the predetermined threshold and 0 otherwise

This method of calculating accessibility uses the opportunities within differing threshold measures from the count location to surrounding TAZ centroids. Figure 4.1 demonstrates an example of the TAZs that were calculated as being within the particular distance threshold, 1.5 miles in the figure, of a count location.

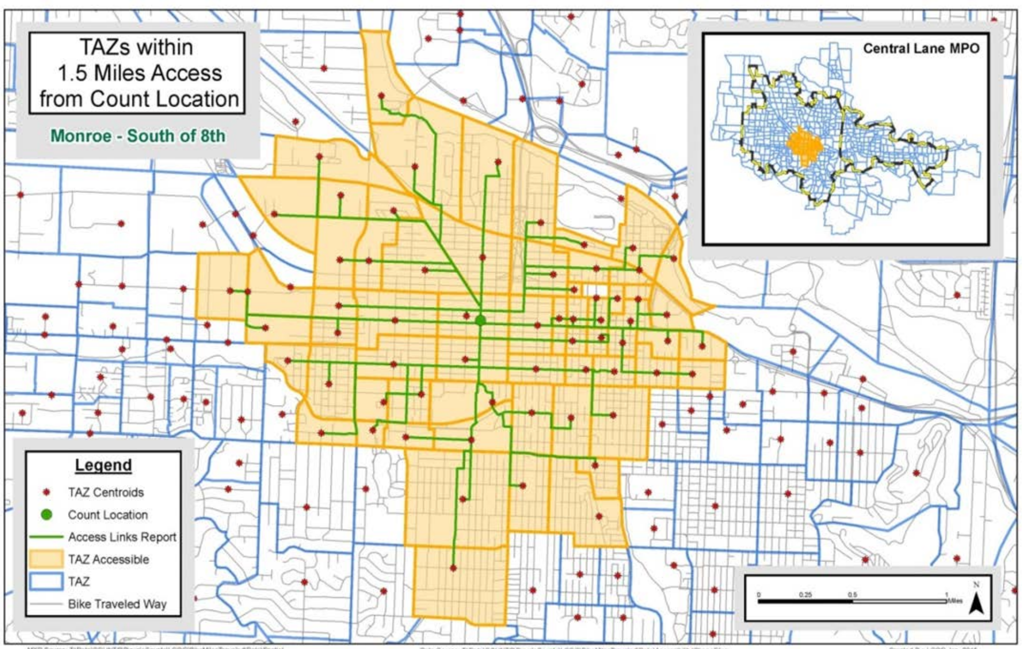


Figure 4.1: Example of cumulative accessibility measure for count location at Monroe South of 8th Avenue in study region

Opportunity information is derived from TAZ level household, population, and employment information from the CLMPO four-step travel model system for input year 2011. Using information at the TAZ level limits the geographic resolution of the analysis in two ways. The first limitation concerns origin link that access information has assigned. Since skim information is calculated on a zone to zone basis all links within a given zone have the same value. In some cases zones are only a few blocks in size but in others zones can be very large and so assigned values are very course. The second limitation is related and concerns access destination. Again since zone to zone skims are used in the calculation, access to a given zone *centroid* means access to *all* amenities in the zone. The most detailed approach would be to calculate access for each link separately in the network to measure access to each household and employment establishment in the study region though this would require significant computational power.

Figure 4.2 demonstrates the coarseness of this measure by showing the calculated accessibility to University of Oregon students for each link in the study region's network. Hotter colors indicate greater access to student population at a given link. This map shows how network links near campus where concentrations of student population are greatest also have greater access to students within a half-mile bike trip though because students live throughout the study area there is some access even in the outer areas near the edge of the urban growth boundaries. This accessibility measure was chosen because of its ease of interpretation. Using other forms of accessibility such as composite measures or those that apply a distance decay function were not tried the difficulty in explaining the model results when using it as an independent variable in a regression model.

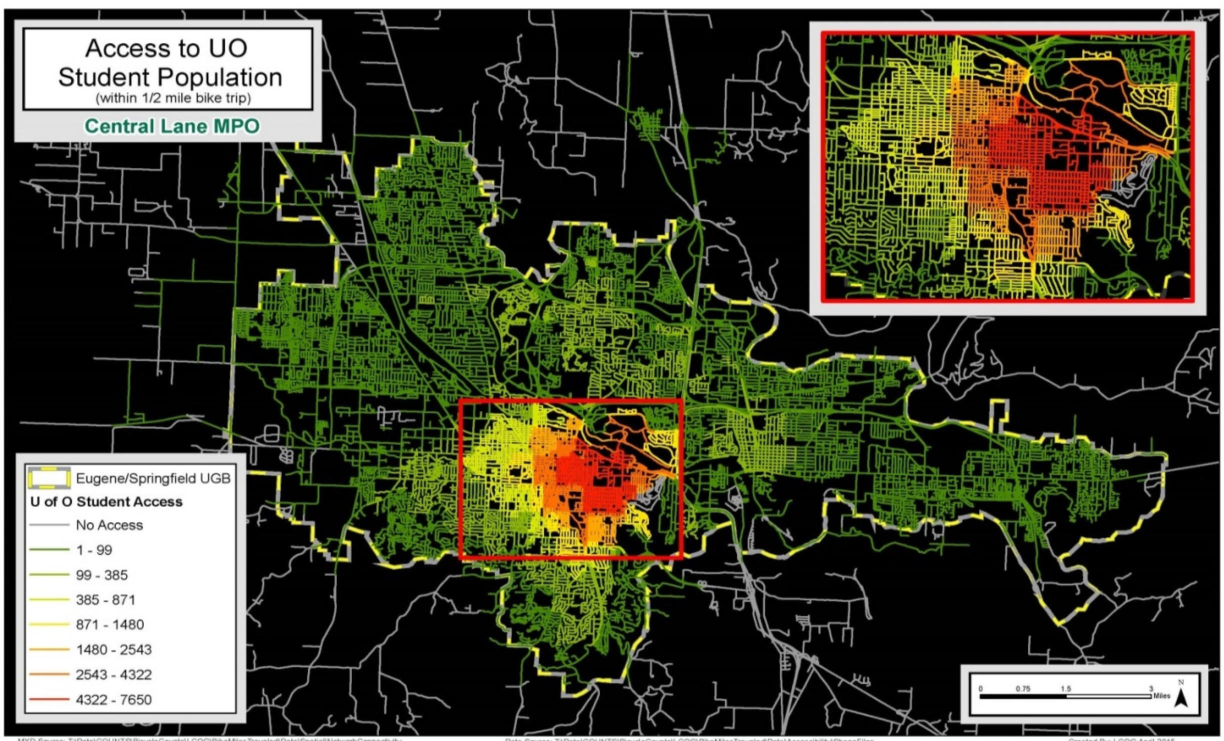


Figure 4.2: Example of cumulative accessibility measure for count location at Monroe South of 8th Avenue in study region

4.3.4.2 Network Density

Network density variables attempt to capture the amount of a given network attribute in proximity to a given link in order to capture the effects of well-connected segments compared to those with less connections or connected to link types that may make bicycling on the link unattractive. The two variables used in this research include local street connectivity and intersection density. Other network attributes were tried including bicycle facility types and arterial road density but none proved to be consistently significant in the models testes below.

- Number of feet of local street within 0.125 and 1.5 miles of count site
- Number of intersections within 0.125 and 1.5 miles of count site

The network density measures were calculated by first selecting all of the links within the given threshold around a link using network analyst tools found in ArcGIS® software. The attributes described above are then aggregated using the network links within this buffer to arrive at the network density measure for that link.

The figure below demonstrates the network density of on-street bicycle facilities across the entire network. Figure 4.4 shows how on-street bicycle facility density varies across the network, with much higher density of these kinds of facilities in downtown Eugene and near the university campus. With this figure it's also possible to see how a corridor with an on-street bicycle facility offers some residual value (presumably positive) to nearby segments.

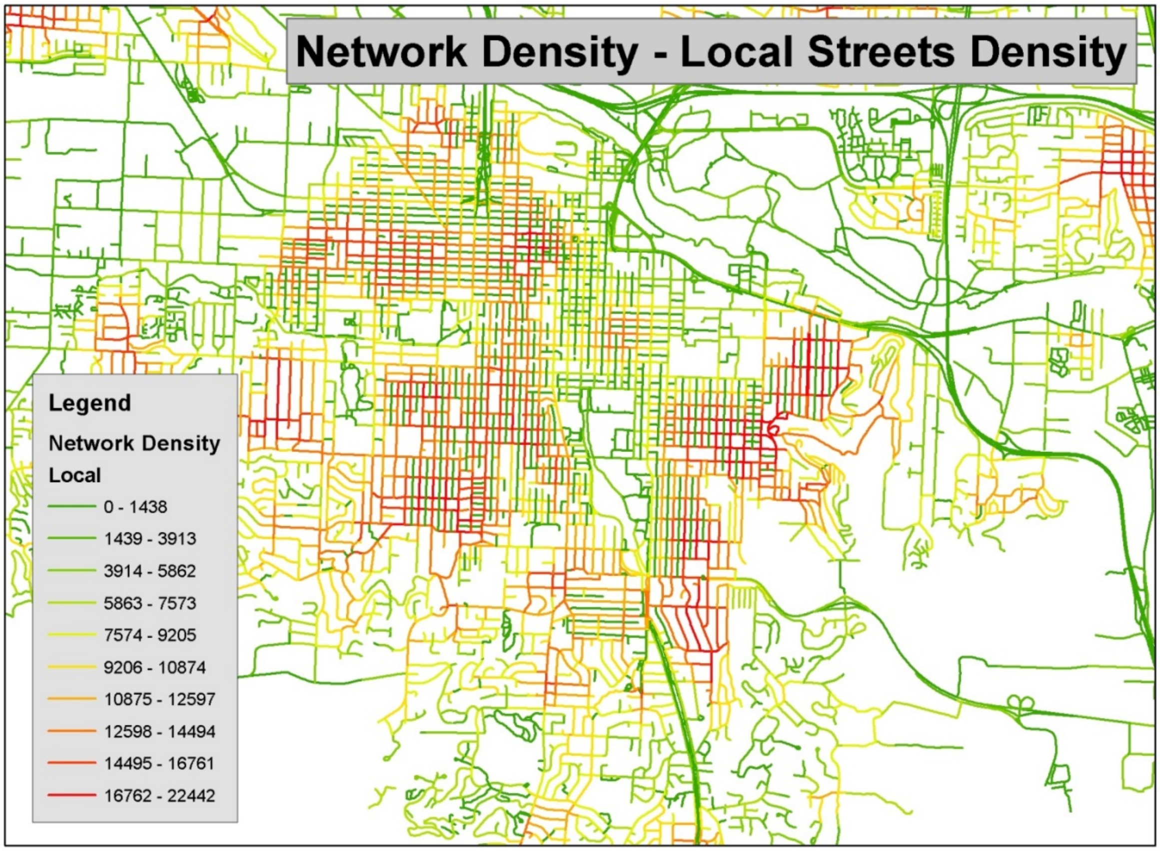


Figure 4.3: Example of network density measure – sum of feet of local streets within 0.25 miles

4.3.4.3 Network Centrality

Network centrality measures are used in the demand models to try and account for the importance of network links within the entire network system. In network analysis centrality measures quantify the key links and nodes that are traversed most often given a certain set of constraints. For this research centrality measures for the bicycle only transportation network were created by using a network assignment tool developed by Broach et al. (2009) to predict bicycle and shortest path routes between TAZ centroids. Based on information gathered via GPS device, Broach et al. (2009) created a weighting algorithm that predicts the bicycle path using network characteristics such as bike path and vehicle volume to place values of attractiveness or comfort. Shortest path routes are calculated using the shortest network distance (bicycle restricted facilities like interstates not included) between origin and destination pairs. Origin and destination pairs include all of the TAZ centroids. Figures 4.4 and 4.5 show how these measures describe a portion of the study region network. Comparisons between the two figures reveal how the bike path assignment and the shortest path assignment differ. For instance the bike path gives greater preference to the off-street path systems along the river while the shortest path assignment directs paths to higher class streets like Franklin Blvd. and Coburg Road, both arterials with high volumes and high speed vehicle traffic.

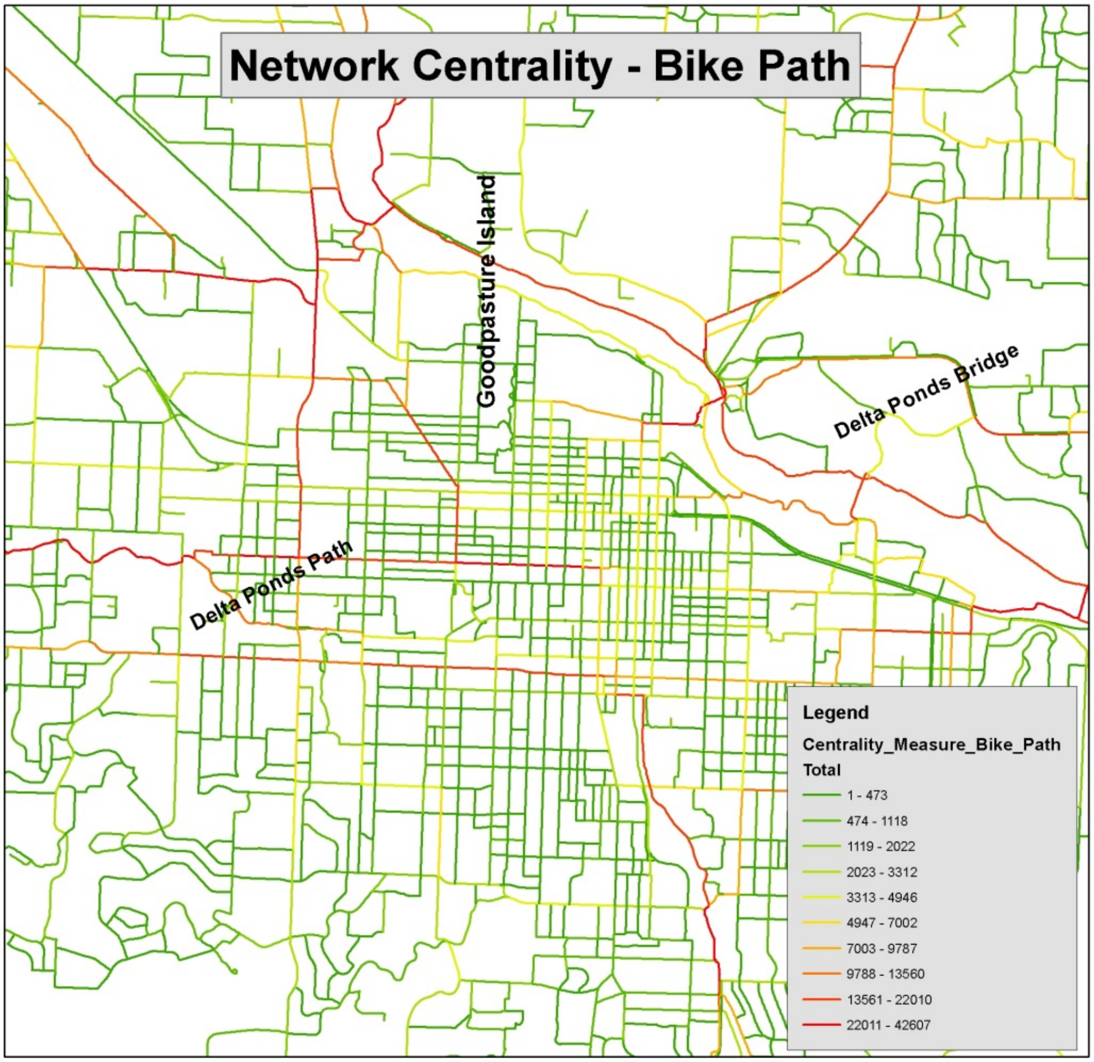


Figure 4.4: Network centrality – bike path

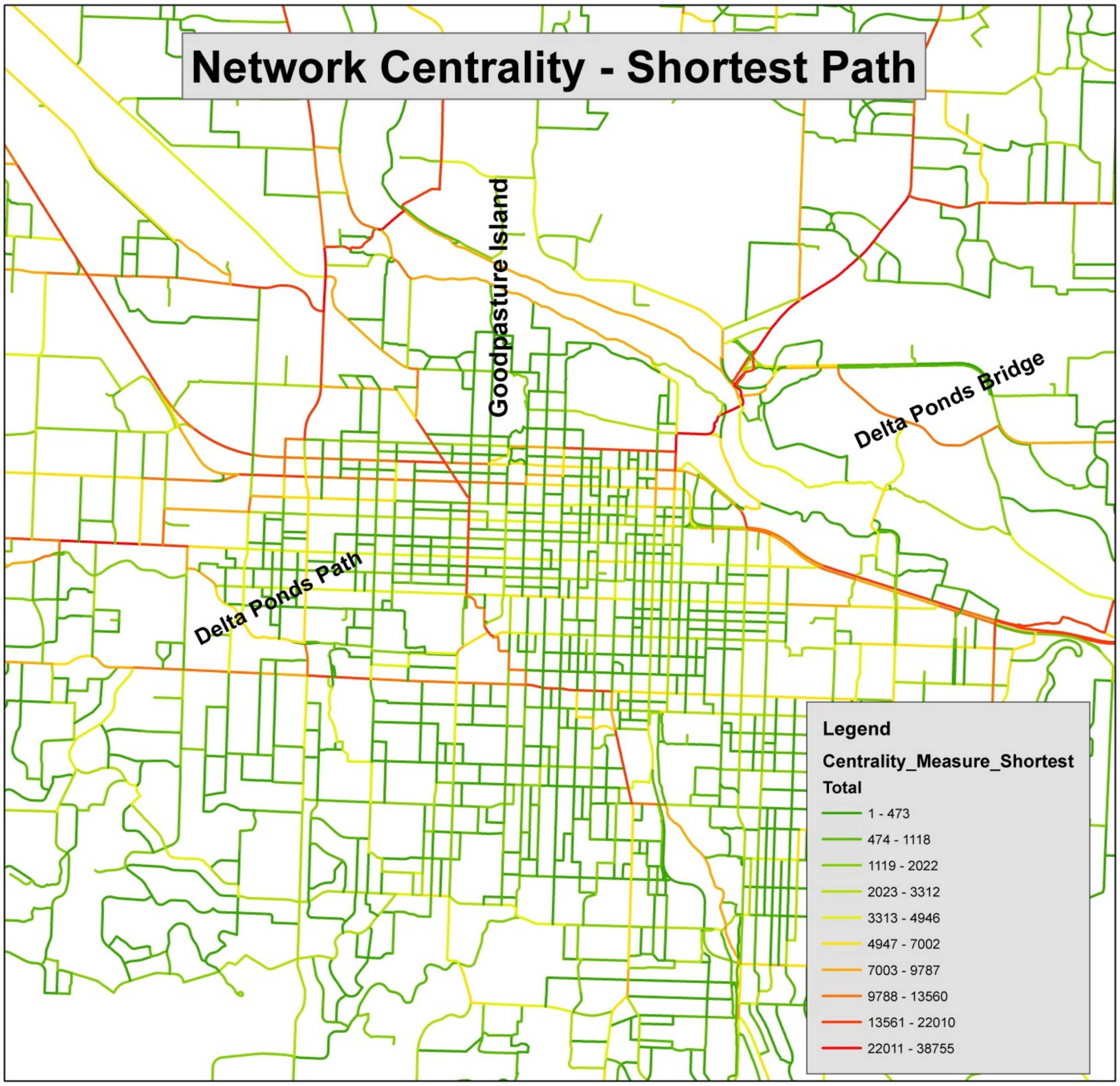


Figure 4.5: Network centrality – shortest path

4.3.4.4 Strava® Smartphone Application Data

Strava ® is a smartphone application that users voluntarily download in order to track their running and bicycle activity. The company now offers these data for sale to organizations interested in using the data for understanding non-motorized travel. As of the publication of this report, no comprehensive study of the Strava has been completed where its representativeness of all bicycle activity has been established. It is widely accepted that Strava represents mostly recreational bicycle travel from high level bicyclists. Some cursory reviews of Strava have demonstrated that Strava represents 1%

of total users in a given path[2]. In 2014, the department of Oregon Department of Transportation purchased data from Strava which included the total number Strava trips assigned to a network. The network chosen for assigning the trips was derived from Open Streets Map. For this research these Strava Trips were further assigned to the local bicycle network data set to use as an input for facility demand modeling.

4.4 MODEL FORM

Past studies have used ordinary least squares (OLS) regression models though it is generally known that OLS is not the best approach for traffic counts because count data is not necessarily normally distributed and values can only be non-negative (Hankey et al. 2012, Wang 2016). Both A Poisson and Negative Binomial model form was testes but due to the presence of overdispersion in the dependent data (AAADBT) the Negative Binomial specification was determined to be the appropriate model form. An approach was taken to determine which independent variables to use which tested various combinations based on theoretical relationships and empirical examinations. Variables like accessibility and network density were constructed at different scales and were tested and either retained or discarded based on the stability of the model and whether the resulting coefficients had intuitive signs. The final model description is below:

$$\begin{gathered}\boldsymbol{Y_i \sim NegBinom(\mu_i)} \\ \boldsymbol{log(\mu_i) = \beta_i X_i}\end{gathered} \tag{4-2}$$

Where:

$Y_i =$ AADBT bicycle traffic volume at site *i*

$\boldsymbol{\beta_i}$ = Vector of parameters for count site *i* including *street* and *bicycle facility, accessibility, network density,* and *network centrality*

$\boldsymbol{X_i}$ = Vector of observed covariates for count site *i*

4.5 MODEL ESTIMATION RESULTS

Multiple models were testing using a combination of the independent variables described in 4.1.3 above. Variables for the street network and bicycle facility were operationalized differently in the models to test different types of facilities and methods quantifying their effects. Figure 4.4 below summarizes model coefficients and confidence intervals are described with the coefficient information summarize in Table 4.6. Model variables were tested to ensure that collinearity in variables was not present, these results are shown in for each model in Appendix A.

4.5.1 Infrastructure Effects on Bicycle Counts

The models show considerable consistency even though variables are operationalized differently. In all model results, there is a consistent negative effect from higher level functional

[2] https://blogs.uoregon.edu/sensorscourse/files/2015/05/Lecture14-q8fthv.pdf

classifications. Model 1 uses an off-street path designation as the reference level and compares the impact of local, collector, and minor arterials facility designations on bicycle counts showing that as compared to off-street paths, minor arterials have the strongest negative effect on bicycle volumes, followed by collectors, and local streets. Models 2 through 5 use dummy variables for collector and minor arterial facilities with results indicating a consistent impact from each functional classification. These results show that minor arterials are more strongly correlated with lower bicycle volumes with collectors having a less powerful negative impact. The results all make sense considering higher functional classifications are related to higher speeds and traffic volume which make people riding bicycles feel less comfortable and would likely reduce bicycle counts.

Bicycle facility type is tested in model 1 by using a categorical variable with no bike facility as the reference level. Results show that cycle tracks have the strongest positive correlation with bicycle traffic, followed by bike boulevards, and bike lanes. Models 2 through 5 do not include a variable for cycle tracks due to the large confidence intervals in model 1 (shown below in Figure 4.7). The positive effect that bike lanes and bike boulevards is very small and inconsistent between models. In models 1, 3, and 5 bike boulevards have a stronger effect on bicycle traffic volumes whereas in Model 2 bike lanes are stronger and in model 4 the effect is nearly equal. If the confidence intervals are considered the difference disappears completely. One reason these results may be imprecise is because of the gross nature of the variables that do not account for specific design features either facility type. For instance measures of bicycle boulevard characteristics like traffic calming features might be stronger on certain segments of the boulevard making a difference in the level of comfort and the subsequent bike volumes.

Another way to view the estimated coefficients is to apply them in sensitivity tests holding some parameters constant as controls as varying those parameters of interest. The Figure below shows sensitivity tests for the infrastructure variables for all of the models holding the accessibility, connectivity and network centrality measures constant. Viewing the estimation results in this way you can see more clearly how much difference in the parameters may affect the application in an area wide bike miles traveled estimation.

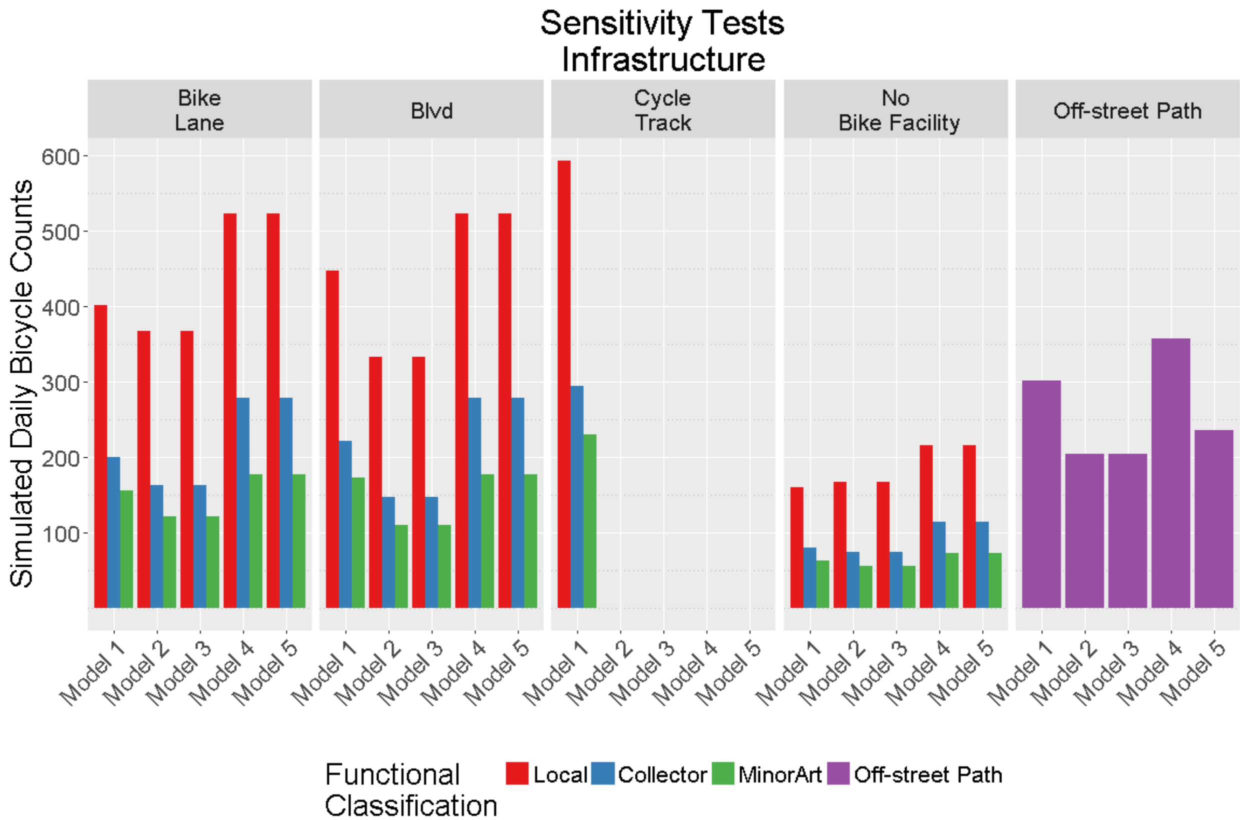


Figure 4.6: Sensitivity tests - infrastructure

4.5.2 Accessibility Effects on Bicycle Counts

Accessibility to population, University of Oregon students, and retail employment are used in each model though with slightly different thresholds used in Model 1 compared to models 2 through 5. The results across models are generally consistent with the student population access variable exhibiting stronger positive correlation to bike counts compared to the general population. The results for the retail employment accessibility variable are less consistent however, with the positive effect of that variable displaying a stronger effect in Model 1 through 3 but weaker in 4 and five. The accessibility measures were used because of the various models tested these variables were consistently significant and in the expected direction and due to their theoretical connection with bicycle traffic. The student population accessibility variable being consistently stronger than population variable makes sense since students likely take more trips by bicycle than the general population.

4.5.3 Network Density Effects on Bicycle Counts

Network density variables include the density of local streets and intersections within 1/8 mile of network distance of each network link. The results for these variables are relatively consistent across models with the local streets density variable exhibiting a consistently negative impact on bicycle volumes and the intersection density variable showing a stronger positive association with bicycle volumes. It has been established (Schoner 2014) that a well-connected street grid has a significant and positive relationship with bicycle activity so the results of intersection variable results are not unexpected. The negative sign of the local streets variable is possibly picking up on some condition present in the residential neighborhoods where this measure is high. In application of these model results in a full network demand model discussed below, this variable helps to maintain lower volumes on local streets in the hinterlands of the study region and has been kept in these models for this reason.

4.5.4 Network Centrality Effects on Bicycle Counts

Multiple measures of network centrality were tried in the different models presented and signify the major distinction between the model specifications. Model 1 does not include any measure of network centrality while model two uses the bike path measure, with model 3 employing the shortest path measure. Model 4 uses the bike path measure coupled with the Strava® rider count and model 5 uses only the Strava® rider count. These measures are exhibited a positive effect on bicycle volumes. The difference in the model coefficients for the bike and shortest path variables are small but measurable with the Strava® rider count variable differing slightly when used in conjunction with the bike path centrality measure. It would be expected that these variables exhibit a positive effect on bicycle volumes since the network centrality measures capture the effect of important network connections between various origin-destination pairs. The Strava® data exhibits a positive impact on the counts because the activity Strava ® measures is very much related to the activity the count devices are detecting.

Table 4.4 – Beta Coefficients for Facility Demand Models

Variable	Estimate		Estimate			
Model 1		Variable	Model 2	Model 3	Model 4	Model 5
(Intercept)	5.0676	(Intercept)	4.3515	4.8135	4.2357	4.2814
Local Street (Reference is Path)	-0.6281					
Collector Street	-1.3301	Is Collector	-0.8124	-1.0068	-0.6294	-0.6823
Minor Arterial Street	-1.5791	Is Minor Arterial	-1.1030	-1.3069	-1.0828	-1.1586
Bike Lane (Reference is No Bike Facility	0.9182	Is Bike Lane	0.788	0.827	0.886	0.907
Bike Blvd	1.0255	Is Bike Blvd.	0.692	0.892	0.887	0.954
Cycle Track	1.3081					
Population Access (1/2 mi.)	0.0001	Population Access (1.5 mi.)	0.00003	0.00001	0.00009	0.00009
Student Access (1/2 mi.)	0.0003	Student Access (1/2 mi.)	0.0003	0.0003	0.0003	0.0002
Retail Access (1.5 mi.)	0.0007	Retail Access (1.5 mi.)	0.0004	0.0004	0.0004	0.0005
Local Street Miles within (1/8 mi.)	-0.0003	Local Street Miles within (1/8 mi.)	-0.0003	-0.0003	-0.0003	-0.0003
Intersections within (1/8 mi.)	0.036	Intersections within (1/8 mi.)	0.0445	0.0465	0.0516	0.0524
		Network Centrality (Bike Path)	0.00005		0.00002	
		Network Centrality (Shortest Path)		0.00003		
		Strava Rider Count			0.00047	0.00057

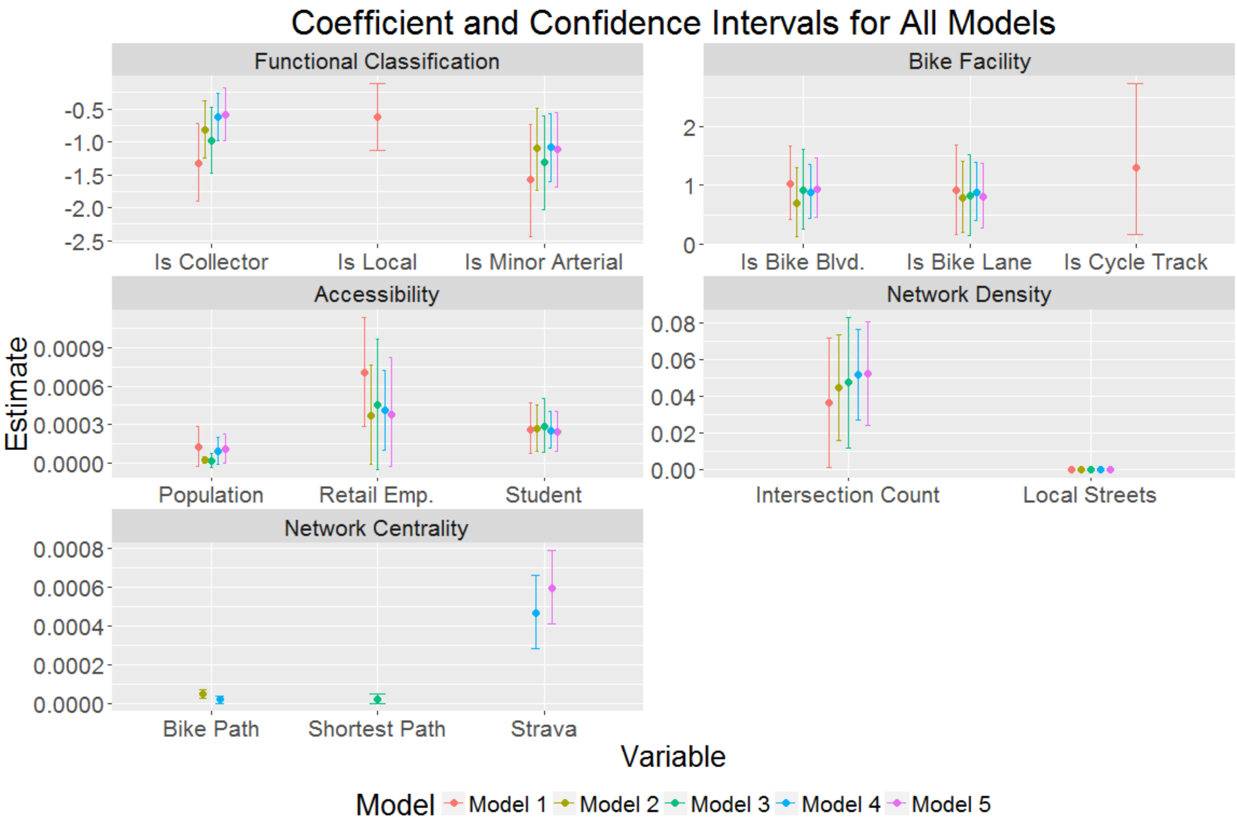


Figure 4.7: Model summaries of estimated coefficients and confidence intervals

4.6 MODEL ESTIMATION DIAGNOSTICS

Model coefficients presented above show mostly consistent results with main difference coming from infrastructure variable specification (comparing model 1 to 2-5) and network centrality measures (including the use of Strava® rider counts). Additional information presented Table 4.5 below which presents the measures pseudo r-squared, Akaike information criterion (AIC), standard error, validation test results summary, and the measure for network centrality used in the model for reference. The summary of validation tests were developed by employing a Monte-Carlo cross-validation process that held out 10% of the original 52 locations in order to test the predictive power of each of the models.

The diagnostic summary presented in the table shows that the pseudo r-squared improved when the bike path measure of network centrality was included (model 2) but then was reduced when the shortest path measure was used (model 3). Including the bike path centrality measure and the Strava® rider count measure significantly improved the pseudo r-squared measure(model 4) though most of this improvement came from the inclusion if the Strava information as seen by the still large pseudo r-squared measure in model 5 which only used Strava rider counts..

Table 4.5 – Model Diagnostic Summary

Model	Pseudo R2	AIC	Standard Error	Validation Tests			Measure of Centrality
				Median	Mean	99th pct.	
Model 1	0.60	656.4	0.65	49%	99%	193%	No Centrality Measure
Model 2	0.68	641.9	0.83	44%	98%	271%	Bike Path
Model 3	0.59	655.7	0.63	58%	115%	246%	Shortest Path
Model 4	0.77	625.4	1.22	37%	89%	179%	Bike Path + Strava
Model 5	0.75	627.9	1.11	35%	88%	180%	Strava

An arguably more important measure of model performance is the outcomes presented in the validation tests. Because of the large number of iterations performed for the validation tests, summary statistics are presented showing the median, mean and 99th percentile results of the APE calculated for the 5000 hold out tests completed for each model. The median APE results are a helpful metric of performance because they describe the resulting APE for half of the validation tests. The results show that model 5 which uses the Strava® rider counts produces the least amount of error with models 4 and 2 performing marginally worse followed by model 1 and model 3.

4.7 MODEL APPLICATION

The below sections will discuss how the models estimated above are applied to the entire bicycle network in the study area in order to estimate bicycle miles traveled. The network will be described to give readers a sense of the characteristics of the network including the features like bicycle facilities and functional classification.

4.7.1 Network Description

The street network and underlying bicycle network will be used to apply the models estimated and discussed in previous sections. Figure 4.8 shows a map of the network within the study area including where the various types of bicycle facilities are located. This map also shows the location of the 48 count stations used in the model estimation. The network includes 17,377separate links that are broken at each intersection of three or more links. The network was originally constructed for the application of a travel demand model assignment model and so is full connected and routable.

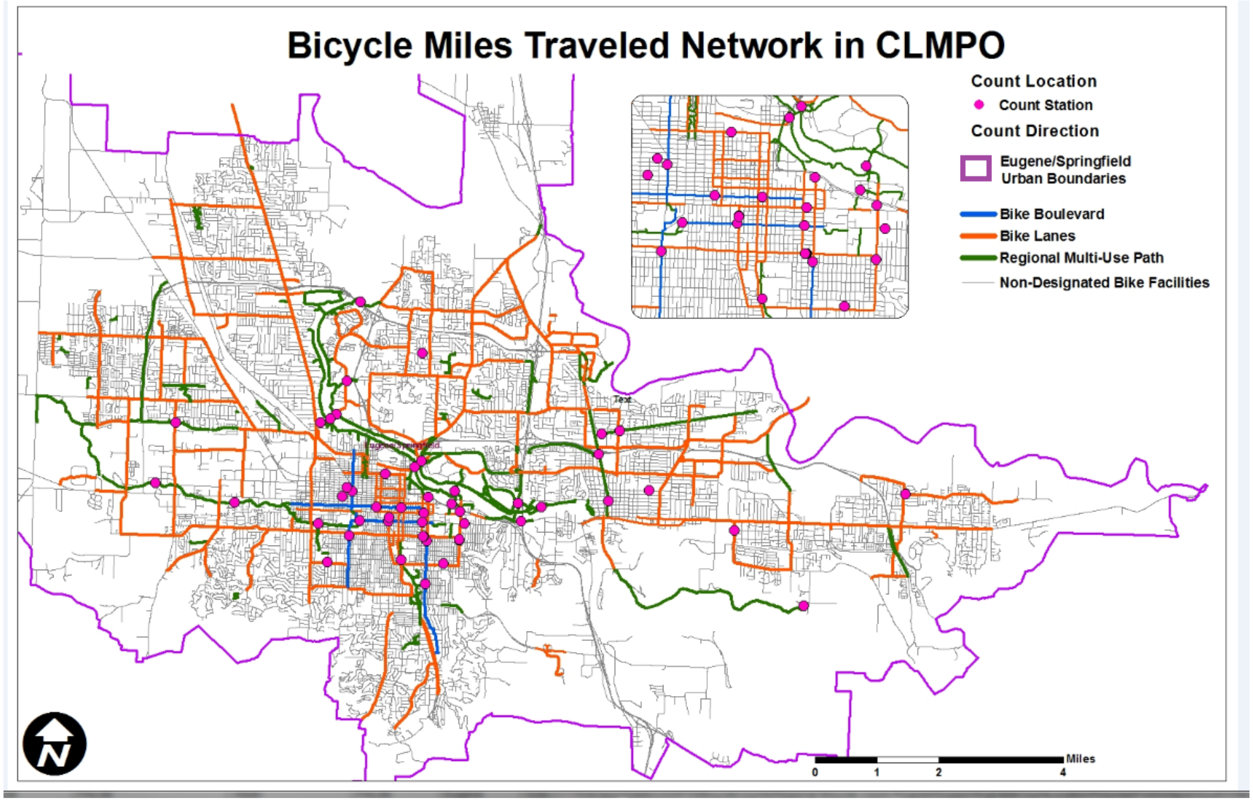


Figure 4.8: Map of application network

Table 4.6 below summarizes the number of miles of infrastructure for a cross classification of bicycle facility and functional classifications. Both of these facility types are important inputs into the models. These network miles do not account for the number of lanes for either the bicycle facilities or the functional classification so a street one mile long with bike lanes on either side would only account for 1 mile of bike lanes. Similarly, the functional classification summaries do not account for multiple lanes on a given street segment, commonly referred to as lane miles.

Table 4.6 - Street Network Miles by Bicycle Facility and Functional Classification

Street Network Miles by Bicycle Facility and Functional Classification						
Bicycle Facility	**Functional Classification**					**Total**
	Off-street Path	**Local**	**Collector**	**Minor Arterial**	**Major Arterial**	
No Bike Facility	0 (0 %)	837.2 (68.4 %)	115.9 (9.5 %)	40.1 (3.3 %)	11.4 (0.9 %)	1004.6 (82 %)
Bike Route	0 (0 %)	7.5 (0.6 %)	4.8 (0.4 %)	0.2 (0 %)	0 (0 %)	12.5 (1 %)
Bike Lanes	0 (0 %)	6 (0.5 %)	32.3 (2.6 %)	91.1 (7.4 %)	7.6 (0.6 %)	137 (11.2 %)
Off-street Path	70.4 (5.7 %)	0 (0 %)	0 (0 %)	0 (0 %)	0 (0 %)	70.4 (5.7 %)
Total	70.4 (5.7 %)	850.7 (69.5 %)	153 (12.5 %)	131.4 (10.7 %)	19 (1.6 %)	1224.5 (100 %)

The study area has a relatively high number of off-street paths with 70.4 miles of this kind of facility. There are nearly 140 miles of bike lanes throughout the region as well, or nearly double that of off-street paths. Bike routes, those street facilities with a bike boulevard or shared lane marking designation, are a small proportion of the total network with only 12.5 miles of his kind of facility. Major arterials are summarized in Table 4.6 above but no counts were collected on these facility types and so estimates of bike travel were completed by assuming they would perform like a minor arterial. Freeways, ramps and highways are not included in this summary because they did not have bicycle counts collected on them so no information exists regarding how those facility types influence bicycle travel. The percentages presented in the table above are the proportion of the total network represented in each cross classification category. For instance, local streets without a bicycle facility represent about 70% of the total network miles while the 40.1 miles of minor arterial streets without a bicycle facility represent about 3% of the total network miles.

4.8 BICYCLE MILES TRAVELED (BMT) RESULTS

The section below summarizes BMT results from applying models 1 through 3 to the entire network within the study region. The section then details results from applying just model 2. Model 2 was selected as the ‘optimal’ model because of its balance of relatively low amount of error in the validation tests and high explanatory power as measured by pseudo r-squared. Model 2 also exhibited relatively low standard error, also presented in Table 4.4 above.

4.8.1 Estimated Total Bicycle Miles Traveled for all Models

Figure 4.9 below shows the total BMT for models 1 through 3 since the Strava data necessary to apply models 4 and 5 is not appropriately formatted for the entire network precluding there broader application. In additional to the BMT estimates are the confidence interval shown in the error bars. Lower and upper limits of bicycle volumes estimation are provided in this research in order to demonstrate the certainty at which estimates are provided. These highest and lowest intervals capture 95% of the true value had repeated samples been drawn from the estimation data. These confidence intervals are calculated by the exponential function of the fitted value plus the critical value multiplied by the fitted value’s standard error. The equation below summarizes this calculation.

$$\boldsymbol{CI} = \mathbf{exp}(\boldsymbol{fit}\ (+)\ \mathbf{1.96} \times \boldsymbol{Standard\ Error}) \tag{4-3}$$

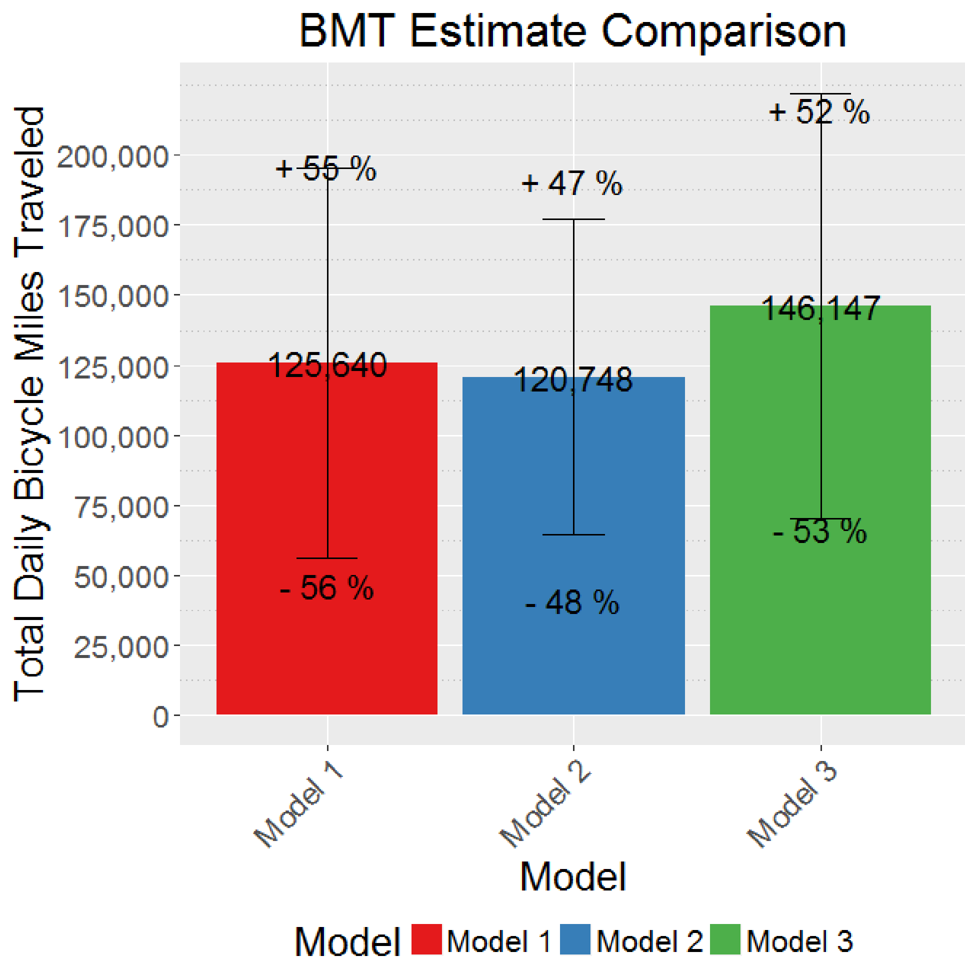


Figure 4.9: BMT estimate comparison

As expected the final total BMT estimates are similar across models thought the confidence intervals (95%) vary with model 2 producing an estimate with marginally less spread in these intervals. The confidence intervals show that the BMT estimates are within 120,748 daily bicycle miles traveled, plus or minus 47% and 48% respectively in the case of model 2 results.

To make further summaries and analysis simpler and since model 2 had the least amount of spread in the final BMT estimate additional summaries and analysis will use results from that model. The model using Strava did produce less error in the validation tests but problems with how Strava rider counts were assigned to the underlying network data prohibit using these data in further analyses.

4.8.2 Model 2 BMT Estimate Details and Comparison

To understand how well model 2 may be predicting BMT an independent estimate of BMT will be used to compare. This work represents a first generation model system for bicycle miles traveled estimation so very little independent information exists for an independent comparison. The best available information available as an independent data source is the Oregon Household

Activity Survey (OHAS), a travel survey performed throughout Oregon from 2009 to 2011. In the study region, over 1,800 households participated in the survey with 700 bicycle trips logged. The information for these bicycle trips is limited in a few ways. The first limitation is that the trip distance is simplifies and is not the actual path but instead the shortest path. The second limitation to the bicycle trip information is that though some recreational trips were recorded, it the survey likely misses most recreational travel activity. A third limitation of the OHAS data is that it does not include many students from the local university whom are likely to bicycle for many of their trips. The last limitation of the OHAS estimate is that it only accounts for travel by study region residents and does not include travel activity from tourists or other visitors. These limitations are likely to bias the OHAS-based BMT estimate downward and under account for bicycle activity in the region.

The total BMT shown in Table 4.7 below reflect annual BMT by multiplying the daily estimate presented above by 365 days of the year. This results comparison shows that the counts based model estimates a higher amount of bicycle travel compared to the OHAS derived estimate which would be expected based on the limitations of the survey data. This comparison shows the counts based estimate is at least within a reasonable range of the OHAS estimate, estimating 73% more bicycle miles traveled.

Table 4.7 – Comparison of BMT Estimates

Measure	Counts Model	OHAS	Difference
Total BMT	44,072,656	25,454,140	73.1%
Annual per Capita	174.4	103.9	
Daily per Capita	0.48	0.28	

Another version of the results is featured in the figure below that describes the estimated AADBT for each link in the network for the study region.

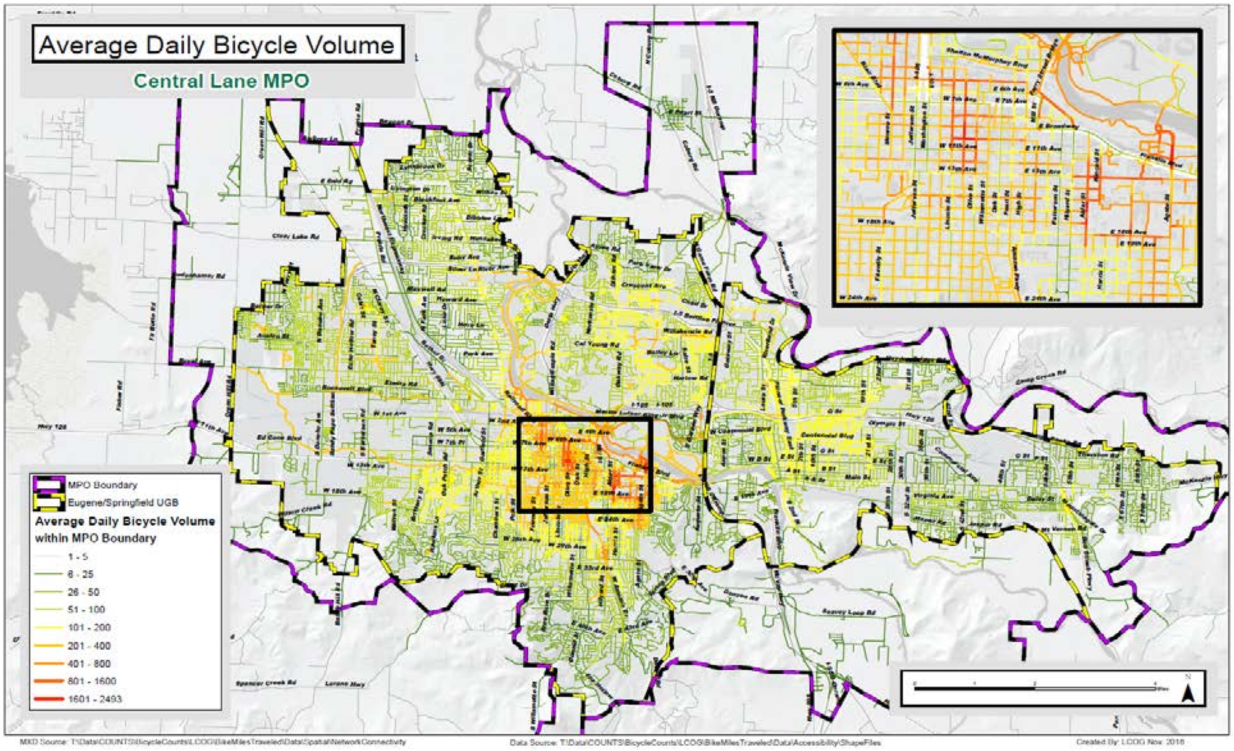


Figure 4.10: AADBT for study region network

The next table details the proportion of BMT represented in each cross classification of functional classification and bicycle facility types. These estimates show that nearly 20% of the BMT occurs on the off-street path system while 59% of the activity occurs on the local street network with most of that happening on streets with no bike facility. Streets with bicycle lanes exhibit just over 9% of the BMT with just over half of that occurring on minor arterials. BMT for major arterials are estimated even though no bicycle counts were collected on streets with this functional classification. Instead it was assumed that these facilities would perform like minor arterials and was thus designated as such for purposes of applying the models. The resulting estimates show the very little bicycle travel occurs on these facilities, just over one percent.

Table 4.8 - Proportion of Total BMT – Model 2

Bicycle Facility Type	Path	Local	Collector	Minor Arterial	Major Arterial	Total
No Bike Facility	17.5%	53.0%	4.9%	1.9%	0.7%	78.0%
Bike Blvd.	0.0%	3.4%	0.2%	0.0%	0.0%	3.6%
Bike Lane	0.0%	1.9%	4.2%	10.8%	1.5%	18.4%
Total	17.5%	58.2%	9.4%	12.7%	2.2%	100.0%

Figure 4.11 shows the per capita daily miles of travel for vehicle and bicycle traffic. This figure is calculated by dividing the total annual amount of travel for both modes which equals roughly 44 million and 15.9 *billion* for bicycle and vehicle travel respectively, and dividing by the study population of roughly 252,000. These values indicate that bicycle travel represents approximately 2.8% of total travel for both of these modes.

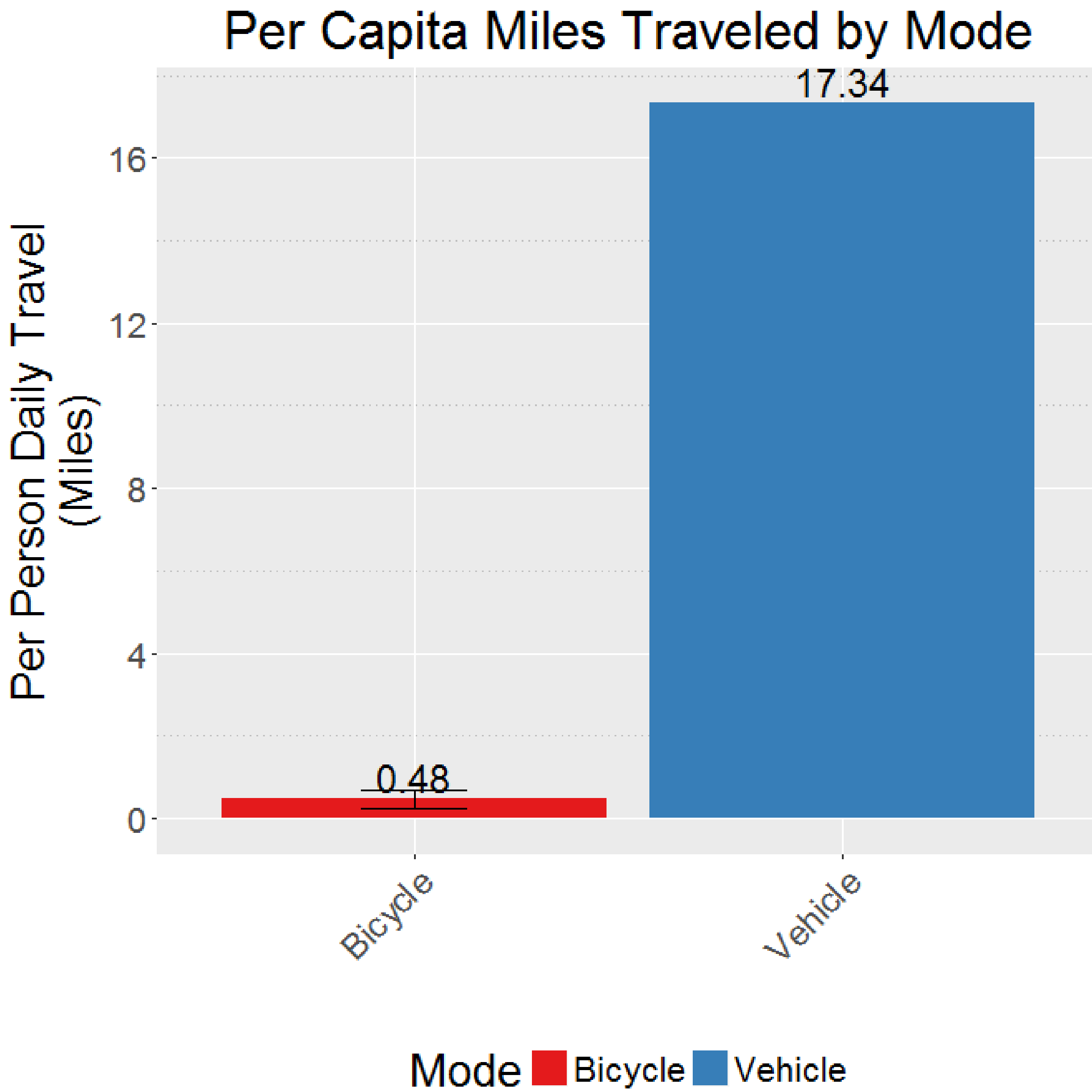


Figure 4.11: Per capita travel by mode

4.9 BICYCLE ACTIVITY ESTIMATION SUMMARY

Section 4 demonstrated the development and application of statistical models for estimating bicycle travel on an entire bicycle network showing the results of bicycle miles traveled and associated confidence intervals. Results for one of these models was explored in more detail to reveal how the model performed, including a comparison with the best available independent data from a household travel survey as well as a comparison with vehicle miles traveled. The results seem reasonable compared to the survey and with the calculated confidence intervals, should be usable as inputs into further analyses. Further analyses using the BMT estimates from model 2 will be explored below in Section 5 (Crash) and Section 6 (Health) below.

5.0 CRASH ANALYSIS

The availability of network wide estimate of BMT presents opportunities for better understanding crash outcomes for people riding bicycles. Bicycle crash analyses are typically limited by a lack of measured bicycle traffic which forces researchers and practioners to ignore exposure completely or use proxy measures. An often reported method for comparing jurisdictions is to use population based rates. This method of rate calculation is not the same as one that uses miles of travel and instead represents the injury or crash harm burden on the population, similar to how the public health sector related burden of disease.

A critical element to risk analysis is inclusion of a suitable measure of exposure to the risk under investigation. In highway safety studies, vehicle miles traveled is a near universal measure available to practioners that help them to understand which locations have higher crash risk while controlling for the number of vehicles. Similar to crashes that involve vehicles, non-motorized crashes are influenced by the amount of travel activity and should be controlled for in any crash analyses. The use of the BMT estimates derived above will be implemented at various levels to demonstrate the crash risk for people riding bicycles in the study region and help to understand how different infrastructure types impact the crash risk for people riding bicycles. This application of the BMT estimate will also help practioners understand the limitations of the current BMT estimate as it's applied for these purposes.

5.1 AGGREGATE BICYCLE CRASH RISK LITERATURE REVIEW

Only minimal research has attempted to describe the bicycle crash risk on the aggregate, system wide level. Using data from the National Household Travel Survey for 2001, Pucher and Dijkstra (2003) showed that fatal bicycle crash rates are 12 times higher than vehicle occupants. The authors also found that bicycle crash rates in the U.S. are double those in Germany and three times higher than kilo-meter based rates in the Netherlands. Beck et al. (2007) used data from 2001 National Household Travel Survey and fatal crash information from the Fatal Accident Reporting System (FARS) and non-fatal crash data from the general Estimates System (GES) to calculate person trip crash rates for multiple modes of travel. The researchers found that fatal crash rates for people riding bicycles were more than double passenger vehicle rates and non-fatal injury rates for bicyclists were nearly double those of passenger vehicle rates. Teschke et al. (2013) use a travel survey of British Columbia, Canada to calculate fatal and injury crash rates per kilometer for automobile users and people who ride bicycles. They found that fatal crash rate for bicyclists was over double that of automobile users and injury crash rates were nearly three and a half times higher for people riding bicycles.

This research relies on travel surveys for calculating travel distance which is many times self-reported and may have some error. Additionally, travel surveys do not typically account for recreational trips which can make up a large proportion of bicycle travel for a given region. These two limitations may bias the previous crash rate estimates upward since they do not fully account for the full value of the denominator.

There is some debate about whether distance based exposure measures should be used versus time based measures. Hakkert and Brainmaister (2002) examine this debate and conclude that deciding between distances versus time based risk depends on the issue being examined. They point out but don't examine fully one contradiction in a time based approach where an increase in speed would lower a given mile of travels time based risk. However, it is commonly understood that speed increases risk, especially at the upper margins of vehicle speeds when the driver's ability to react is further limited. Though an interesting philosophical debate, this research will rely on distance based metrics for the crash analyses presented below.

5.2 BICYCLE INFRASTRUCTURE IMPACT OF CRASH RISK

A complete literature review of the impact of bicycle infrastructure on crash risk is not provided here but two summaries of existing literature are discussed. The first review is by DiGioia et al. (2017) and examines what research exists that document 22 bicycle treatments using information presented in three guidebooks (AASHTO *Guide for the Development of Bicycle Facilities*, 2012; National Association of City Transportation Officials *Urban Design Guide*, 2012; Institute of Transportation Engineers *Traffic Calming State of the Practice*, 1999) and 19 peer-reviewed papers (from a pool of 81 initially selected papers). The authors conclude that bike lanes may be beneficial to improving safety conditions but results are mixed and some even show a slight increase in crashes. Bicycle boulevards improve safety likely due to the lower speed and traffic volume of the facilities. Cycle tracks show a reduction in crash risk but one-way cycle tracks appearing safer at intersections compared to two-way cycle tracks. For intersection treatments bike boxes have proven effective as were raised bicycle crossings. Figure 5.1 below reproduces a summary graphics from DiGioia et al. (2017) that condenses the literature review and reported findings related to crash reduction potential which the authors convert to relative risk ratios to make comparisons more meaningful.

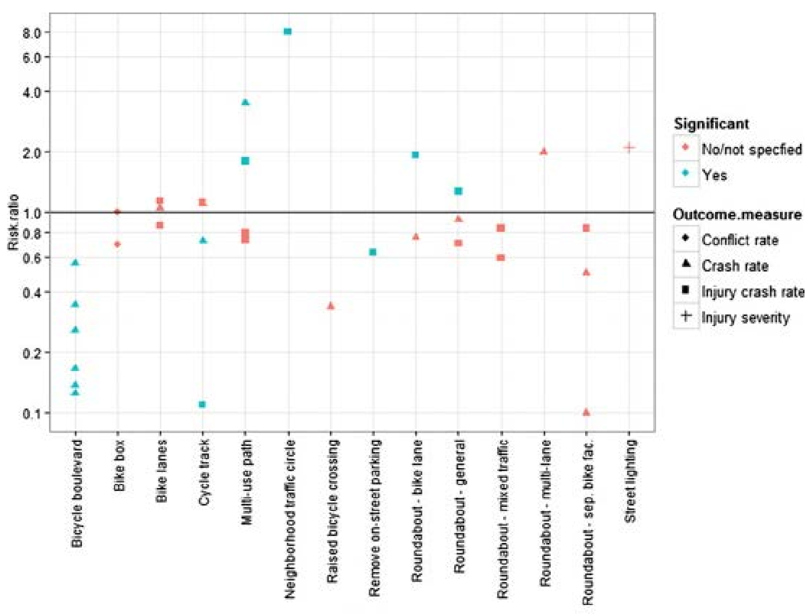


Figure 5.1: Summary of risk ratios for bicycle infrastructure treatments from DiGioia et al (2017)

DiGioia et al. (2017) expand on a previous review of pedestrian infrastructure treatments by Retting et al. (2003) stating that in order to reduce the severity and frequency of non-motorized crashes, treatments need to accomplish one or more of the following objectives:

- Increase separation of bicycles and motor vehicles in time and space
- Increase visibility and conspicuity of non-motorized users
- Improve sight between the modes
- Reduce the number of interactions between modes
- Reduce motor vehicle speeds

A thorough review of these risks and others can be found in *Risk Factors for Pedestrian and Bicycle Crashes Final Report* (ODOT 2016). The report authors present past research on six categories of risk factors including roadway, intersection, traffic characteristics, land-use, demographic and behavioral, and weather and lighting. Discrete factors for roadways and intersections include roadway geometry and cross section as well as operations while the traffic characteristics include speed limit, peak-hour traffic and daily traffic volumes. This review found 10 studies that identified speed or traffic volume of motorized vehicles as a risk factor for bicycle or pedestrian crashes.

5.3 CRASH DATA SUMMARY

Crash data for this analysis comes from the Oregon Department of Transportation's Crash Analysis and Reporting Unit which creates and maintains these data. Crash data is limited to those self-reported to the Department of Motor Vehicles or those reported by law enforcement following a crash. These data are likely to under report crashes for non-motorized users since only crashes involving a vehicle are subject to rules for reporting.

As mentioned above, the inclusion of exposure data is essential to fully understanding the crash risk for certain infrastructure designs. For example, Figure 5.2 below shows the total number of crashes on minor arterials with and without a bicycle lane for the study region. This figure shows that more crashes are reported on minor arterials with bike lanes, which at first glance might seem to indicate higher risk of crashes for people riding a bicycle. Below these crash outcomes will be controlled for using the BMT estimate to more fully understand the difference in crash risk.

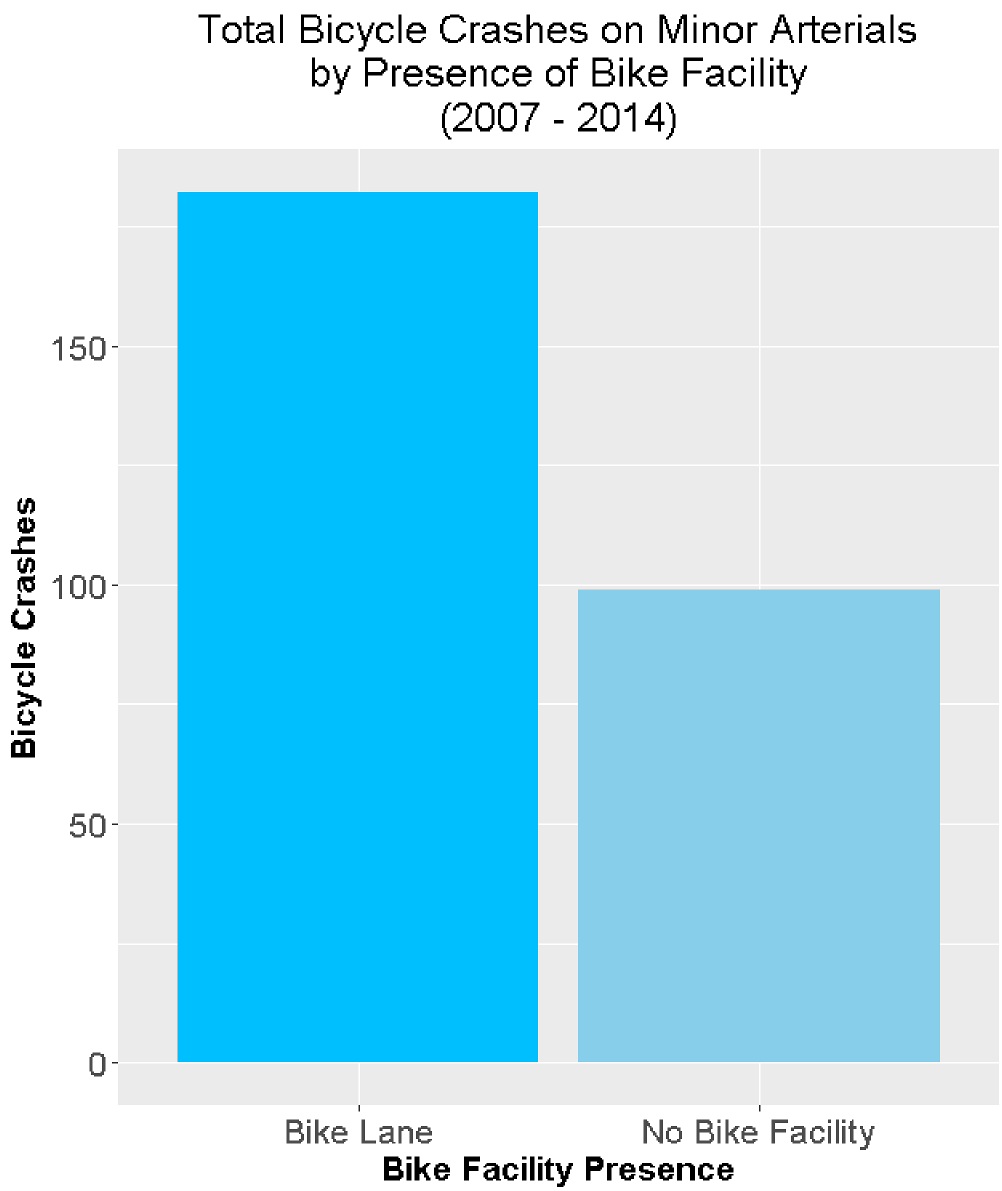


Figure 5.2: Crash count by presence of bicycle facility

Table 5.1 below summarizes the crashes by year, by injury severity for the study region. The table also shows the calculated average for all years and then years 2013 through 2015, the years of crash data used in creation of the crash rates. These years are selected because they overlap with the years in which the bicycle traffic counts data were collected. Table 5.1 shows that for some injury severities the average is lower than the longer term average and in others it is higher. Bike fatal and severe injuries are lower in the select years (2013-2015) compared to the longer term average while the total injury average is higher in the select years compared to the longer term average.

Table 5.1 – Persons Injured by Mode, Injury Severity, and Year

	Injury Severity					
	Fatal		Severe		All Injuries	
Year	**Bike**	**Motorized**	**Bike**	**Motorized**	**Bike**	**Motorized**
2002	2	5	5	36	72	1,204
2003	1	4	9	23	93	622
2004	2	5	6	16	68	572
2005	2	6	5	29	111	1,026
2006	1	12	5	50	74	1,255
2007	2	4	8	57	79	1,521
2008	1	7	13	30	89	1,459
2009	0	11	1	26	64	1,483
2010	0	2	5	49	91	1,564
2011	3	7	6	64	83	1,704
2012	0	7	4	62	76	1,901
2013	0	5	4	47	102	1,663
2014	1	5	7	55	128	1,711
2015	1	8	3	70	91	2,286
All Year Total	16	88	81	614	1,221	19,971
All Year Average	1.14	6.3	5.8	43.9	87.2	1426.5
2013-2015 Average	0.7	6.0	4.7	57.3	107.0	1886.7

5.4 CRASH RATE COMPARISON – BICYCLE AND MOTORIZED VEHICLE CRASHES

Without exposure information crash counts by mode leaves some questions unanswered. Table 5.1 above shows that the number of people riding a bicycle that have been fatally injured is *only* 16 compared to 88 people using a motor vehicle[3]. Bicycle rider fatal injuries comprise roughly 15% of the total between these two modes though as described above bicycle miles traveled makes up just 2.4% of per capita miles traveled (or 3.5% if the upper bound estimate of BMT is used). Figure 5.2 below shows the calculated crash rate for the study area and for both modes. Two categories of injuries are presented, fatal and severe injury and non-fatal injury. These

[3] Of the 88 fatal injuries for motorized vehicles users/occupants, 12 or about 13%, were people using a motorcycle. Motorcycle risk has long been recognized as having a much higher risk than vehicle travel with Beck et al. (2007) finding the crash rate for motorcycle trips being 58 times higher compared to passenger vehicle travel. Additionally, for the years 2002-2015, there were 59 pedestrian fatal injuries in the study area.

injury severity categories align with the KABCO injury classification scheme where fatal and severe injuries includes *K* and *A* while non-fatal injuries include *A*, *B*, and *C*.

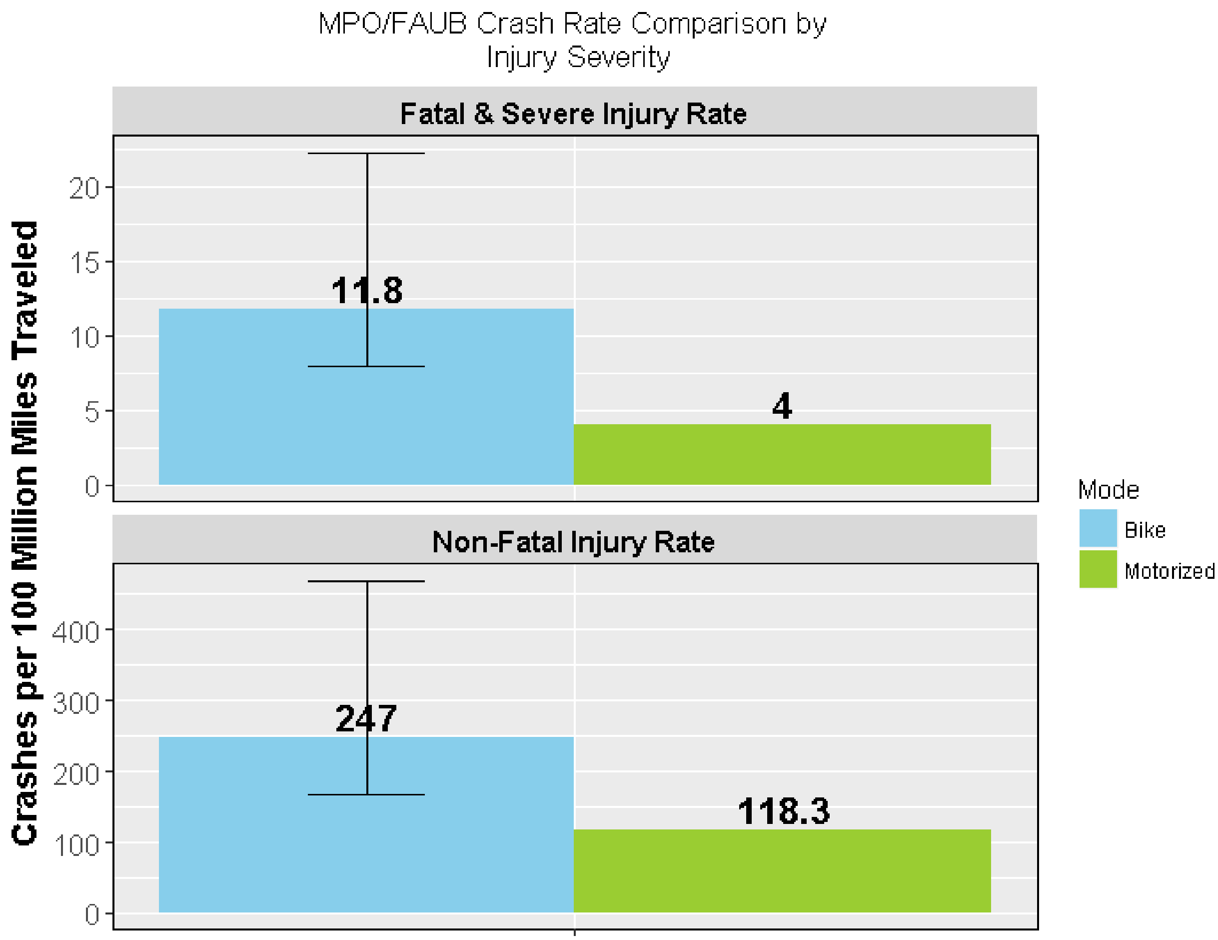


Figure 5.3: Crash rate comparison for study area

Figure 5.3 shows the crash rate for the above described injury severity categories along with the lower and upper bound estimate derived from the lower and upper bound estimate of bicycle miles traveled. The figure shows that the fatal and severe injury rate for people on bicycles is nearly three times the rate for motorized travel. Even at the lowest bound error (higher BMT estimate) the bicycle crash rate is double that of the motorized crash rate. The non-fatal crash rate for bicycle riders is also higher at 247 non-fatal injuries per 100 million miles compared to 118 for motorized travel. The lower bound estimate is also reveals a significant discrepancy with a bicycle crash rate of 167, over 40% higher than the motorized non-fatal injury crash rate.

Because of the uncertainty in the BMT estimate, higher level crash rate comparisons are the most dependable, though more detail can still be gleaned by looking at crash rates on different functional classifications for bicycle and motorized travel. Figure 5.3 disaggregates the travel activity and crash data by function classification to see how the risk varies across these categories. The same injury categories are used as above and include fatal and severe injury and non-fatal injury. The summary below shows that for both injury and mode categories risk generally increases as the functional classification increases from local to collector and up to minor arterials. Of the functional classifications analyzed, minor arterials have the highest crash rate for both motorized and bicycle travel followed by collectors and local streets. This is likely an indication of the higher speeds on these higher functional classification streets coupled with more conflicts at intersections and driveways. Lastly, the results in Figure 5.3 show that a risk disparity between motorized and bicycle travel with bike crash rates consistently higher compared to motorized travel. Even if comparisons are made using the lower bounds of the calculated bicycle crash rate the risk is almost always greater for people riding bicycles.

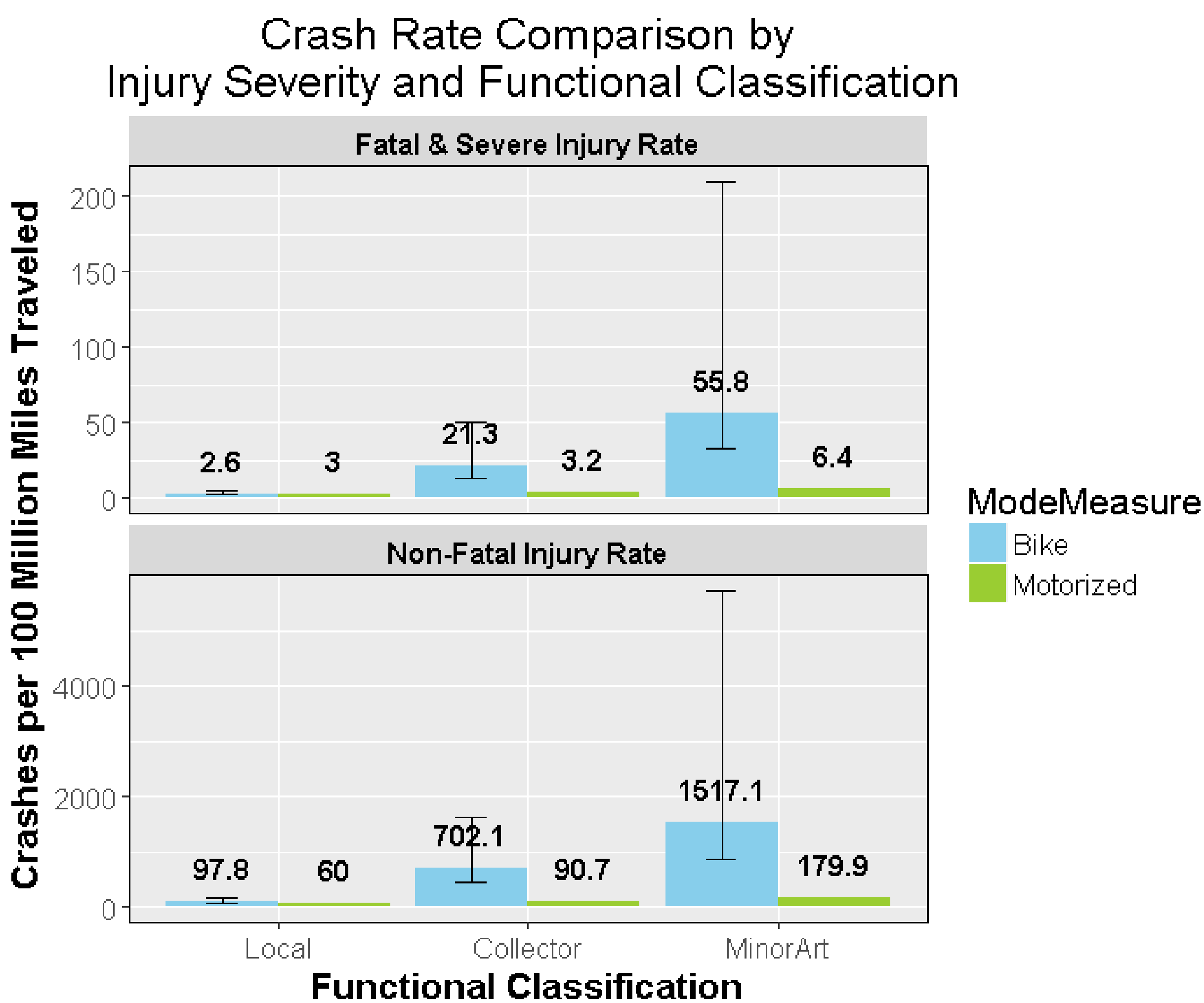


Figure 5.4: Crash rate comparison by functional classification

5.5 CRASH RATE COMPARISON – BICYCLE FACILITY TYPES

Bicycle crash rates are calculated and presented in Figure 5.5 below and show these rates show the difference between streets with bicycle lanes and those streets without bicycle lanes as well as the showing these differences on each of three functional classifications. Unfortunately because the range in error for the BMT estimates are so large, meaningful differences between streets without bicycle lanes and those without are difficult to determine. However, the point estimates describe a consistent trend where bicycle lanes have higher crash rates compared to streets without bicycle lanes for all functional classifications and injury severities. For readers interested in more detail, Table 5.2 summarizes the information presented in Figure 5.4.

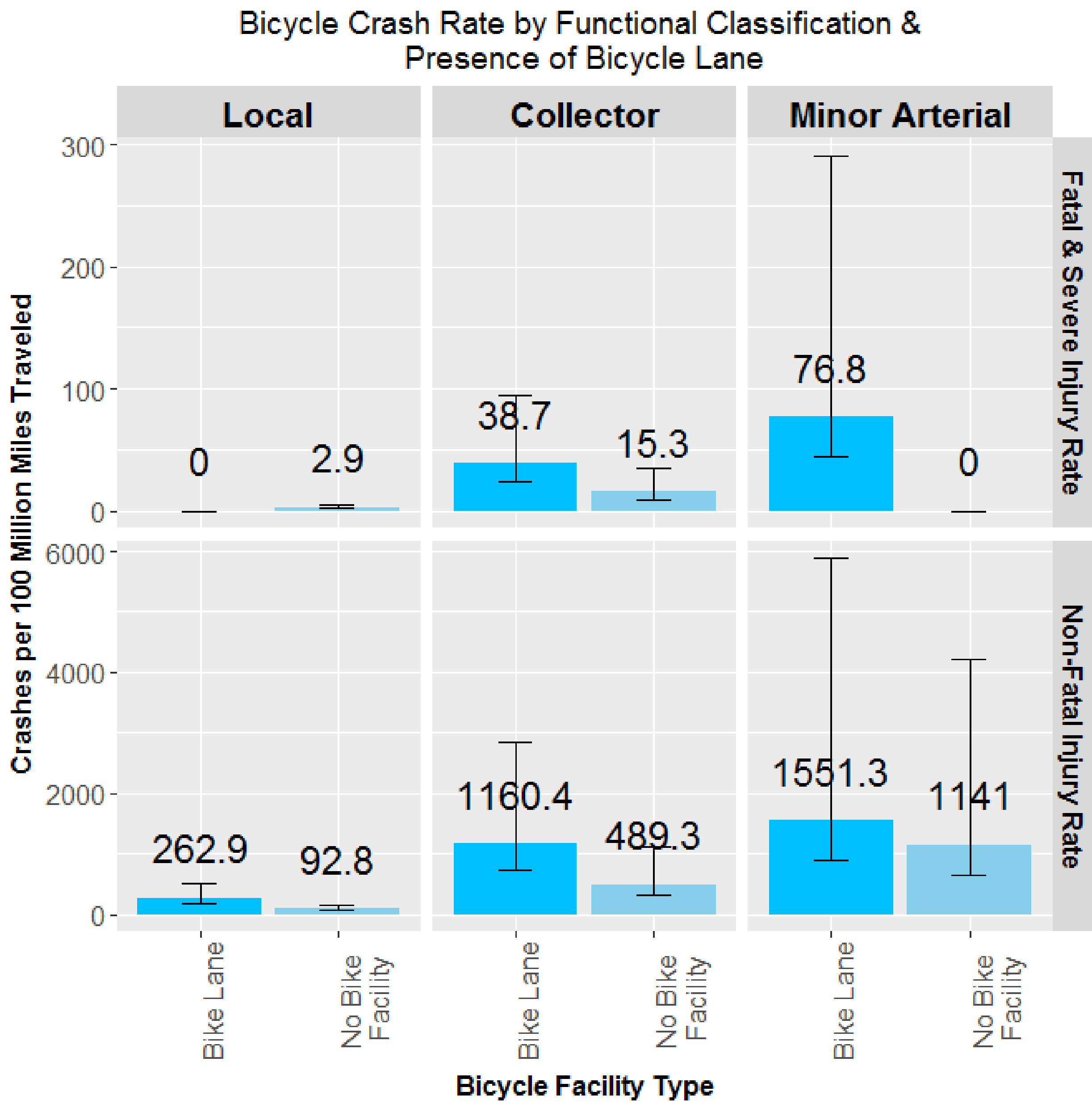


Figure 5.5: Crash rate comparison by functional classification and presence of bicycle lane

Table 5.2 – Crash Rate Comparison by Functional Classification and Presence of Bicycle Lane

Bicycle Facility	Functional Classification	Crash Rate			Injury Severity
		Estimate	Lower	Upper	
No Bike Facility	Local	1.7	1.2	2.8	Fatal & Severe Injury Rate
Bike Lane	Local	0	0	0	
No Bike Facility	Collector	9.2	5.9	21.1	
Bike Lane	Collector	46	29	114	
No Bike Facility	Minor Arterial	49	28	181	
Bike Lane	Minor Arterial	83	48	314	
No Bike Facility	Local	83	60	138	Non-Fatal Injury Rate
Bike Lane	Local	210	142	406	
No Bike Facility	Collector	376	240	864	
Bike Lane	Collector	975	612	2392	
No Bike Facility	Minor Arterial	1027	594	3798	
Bike Lane	Minor Arterial	1355	780	5134	

5.6 SAFETY PERFORMANCE FUNCTIONS FOR BICYCLE CRASHES

There is a need for better tools to understand and mitigate bicycle crashes as cities and states seek to increase the amount of bicycling by residents and visitors. The Highway Safety Manual (HSM) published in 2010 formalized a host of methods for practioners to use to better understand safety performance for transportation networks and to estimate the impact of upgrades based on evidence based treatments. The Safety Performance Functions (SPF) is a key tool for identifying opportunities to improve traffic safety. SPFs utilize historic crash data and traffic conditions as well as various design features in statistical models to determine the impacts of traffic exposure and roadway design elements on crash frequency. The HSM (2010) did not feature bicycle crash-prediction SPFs, and is thus limited for understanding safety performance of this mode.

This section builds on the previous section’s presentation of system wide crash rate development by constructing and applying safety performance functions (SPF) for bicycle-vehicle crashes on segments and intersections in the Eugene-Springfield area in Oregon. There is wide understanding that crash rates for non-motorized and motorized transport alike, are non-linear and a certain safety in numbers effect exists (Elvik 2017). Previous work creating SPFs for bicycle travel has been limited by the lack of bicycle traffic data. Past research has used proxies for non-motorized traffic such as percent of population using public transport or presence of a bike facility. Others have used short term bicycle traffic counts extrapolated to either a longer short term count (Dolatsara 2014) or to an annual estimate (Nordback 2013) for use in bicycle SPF development. Using proxies for bicycle traffic renders the interpretation of those variables' regression model results difficult, since untangling the impact of the traffic volume from the design treatment, as in the case of using bike lane presence is impossible.

This research benefits from the availability of annual average daily bicycle traffic (AADBT) estimates on most segments in the regional travel network for the study area. Using AADBT and annual average daily traffic for motorized vehicles, as well as available information on design features, SPFs will be created for three and four leg intersections and roadway segments. These SPFs will then be utilized to perform a systemic bicycle crash risk assessment of the entire bicycle travel network to determine priority locations for potential treatments.

5.6.1 Safety Performance Function Literature Review

Brüde and Larsson (1993) author one of the first papers that attempt to construct a predictive crash model for bicycles and pedestrians. The authors use police reported crash data from six years (1983 to 1988) for intersections in Sweden where at least 100 daily bicycles or pedestrians were observed. Non-motorized traffic volumes were derived from single weekday counts though no factoring process is described. For the bicycle crash models, 377 intersections with 432 crashes are pooled from 30 towns across Sweden. The researchers also use vehicle traffic volumes in their crash models but do not control for any other design features of the intersections under examination. The results show that bicycle crashes increase as the bicycle and vehicle traffic volume increases but the bicycle crash rate decreases as the number of bicycles increases. The paper also reports the crash rate for different intersection types and speeds but found no obvious pattern of risk between the featured categories.

Miranda-Moreno et al. use a detailed inventory of 753 intersections in Montreal, Quebec, Canada combined with vehicle and bicycle traffic flow data to understand the bicycle crash risk of various turning movements and geometric designs. Bicycle traffic volume is derived from 8-hour peak period counts (morning, afternoon, evening) and include all flows for each turning movement in the intersection. Crash data were derived from ambulance calls for multiple years from 2000 to 2008. The authors employ a negative binomial regression specification to estimate the effects of aggregate and disaggregate traffic flows on bicycle crash risk while also assessing the impact on crash risk from geometric and built environment variables. Results of the analysis found that both total bicycle and vehicle traffic volumes increased the frequency of bicycle crashes while the disaggregate models showed right-turn lane vehicle volume traffic was the strongest predictor of bicycle crashes.

Turner et al. (2011) analyze bicycle-vehicle crashes for segments and intersections using data in New Zealand and Australia using data from 102 intersections and 97 segments. Bicycle traffic exposure is derived from one and two hour counts factored to annual traffic estimates. Two types of analyses are performed including a before-and-after control impact analysis and the construction of safety performance functions. The safety performance functions included variables to understand the impact of geometric conditions of study sites including the width of the bicycle lane and bike-box length and whether or not the bike lane is painted. Different crash types were analyzed including crossing, right and left turn, and same direction. Results found an overall neutral effect of bicycle lanes and that painted bicycle lanes decreased crashes for most crash types. Additionally, the research found that sites with exclusive left-turn and through lanes have higher crash rates but benefited most from painted bicycle lanes.

Nordback et al. (2014) creates safety performance functions for intersections in Boulder, CO. The researchers use crash data from two time periods, 2001 to 2005 and 2008 to 2011 due to their availability. Annual bicycle volume traffic data was estimated using two different methods. This first method applied a traditional procedure from the TMG (2001) where peak hour bicycle traffic volumes are combined with factors from permanent bicycle count sites to estimate annual bicycle traffic. The second approach uses a negative binomial statistical model to estimate annual traffic by relating the hourly weather information like temperature and solar radiation as well as daily conditions like day of the week to the hourly count. In locations where both methods could be used the average of the two results were used as the AADBT for that location. The authors report bicycle traffic volume error from these estimates between 38% to 40% absolute percent error. Growth factors were used to adjust the traffic volumes data for each of the years to match the vintage of the crash data. The authors use the natural log of both bicycle and vehicle traffic as inputs into the SPF for signalized intersections in the study region. Results of the SPF show that AADT for vehicles and AADBT are both associated with an increase in bicycle-vehicle crashes but also find that as the number of daily bicyclists increases the bicycle crash rate decreases. The authors state that due to the AADBT estimation error results should not be taken as definitive.

Vandenbulke el at. (2014) attempt to predict bicycling risk and the influence of road infrastructure on risk for a transportation network in Brussels. Using a case-control approach, the authors quantify bicycle traffic exposure using population census based measures of bicycling activity combined with a gravity model to estimate a ‘Potential Bicycle Traffic Index’. This metric is created for spatial units and combined with crash and network information within the zones. Bicycle-vehicle crash data comes from police records and include 644 crashes from 2006 to 2008. The authors employ an autoregressive and auto logistic modeling approach with controls for spatial effects and find that bicycle and vehicle traffic measures increase the probability of bicycle crashes. Their findings suggest a non-linear effect on crashes from bike activity suggesting a safety in numbers impact.

Park et al. (2015) create safety performance functions for multiple bicycle and all crash injury severity levels using data from Florida. A primary aim of the research is to determine the variation in crash modification factors due to heterogeneity of roadway conditions like vehicle traffic and median width. The authors estimate SPFs using vehicle traffic volumes, segment length and also include socio-economic variables. The authors then estimate crash modification functions to determine how the crash reduction potential of adding bicycle lanes changes as geometric and population density changes. The results suggest that bike lanes can reduce crashes and bike crashes but the impact varies across geometric and population density. For instance, as vehicle volumes increase the ability to reduce all crashes diminishes. The authors do not account for bicyclist exposure with bicycle traffic counts and the number of bicycle crashes included in the study was very small and include only 44 total crashes.

Thomas et al. (2017) develop SPFs for three types of bicycle crashes including all intersection crashes, bicyclists opposite direction, and bicyclists, angle crashes using eight years of crash police crash data from Seattle, WA. Bicycle traffic volume data is estimated using a direct demand model through a so-called "ball park' method that relates short-term and automated counter data at 46 intersections to factors correlated with bicycle activity. Vehicle traffic volume was unavailable and functional classification was used instead. The authors employ a Conditional Random Forest (CRF) regression analysis to uncover eligible crash predictors before specifying an SPF using negative binomial regression. The safety performance function uses the natural log of bicycle volume as well as estimates of annual average daily pedestrian traffic in conjunction with intersection variables like the presence of signals, entering segment legs, parking, lanes, and transit stops. The authors also include the amount of commercial building space within a specified buffer.

Thomas et al. (2017) find that an increase in motor vehicle volumes as measured by the functional classification increases the risk for bicycle crashes for all crash types. Intersections with traffic signals increased the risk of bicycle crashes as did the presence of parking. This research also found the presence of bicycle lane and shared markings had a positive correlation with bicycle crashes. The authors apply the estimated SPFs using three approaches including an unadjusted prediction of bicycle crashes, Empirical Bayes adjusted prediction of bicycle crashes, and a Potential for Safety Improvement (Persaud et al. 1999) where the difference between the EB expected and SPF predicted crashes is calculated. The authors conclude that the data and methods used in the analysis offer a way for cities to prioritize locations for further investigation and likely treatments.

5.6.2 Model Description

This research implements methods suggested in the HSM (2010) for predictive modeling of crashes. Specifically, this work utilizes negative binomial regression to estimate bicycle crashes on segments and at intersections in the study area. The negative binomial is commonly used in SPF estimation because crash data is often found to be over-dispersed, meaning the sample variance exceeds the sample mean. The relationship between the dependent variable and the independent variable is described in the equation below:

$$\boldsymbol{\mu_i = EXP(\beta X_i + \varepsilon_i)} \tag{5-1}$$

Where:

ε = random error assumed to be uncorrelated with X while

EXP (ε_i) = Gamma-distributed disturbance term with mean 1 and variance α

β = independent variables related to μ at location i.

This statistical specification will be applied to both segment and intersections within the study area network in order to estimate SPFs that account for inherent design features of those roadway types.

5.6.3 Safety Performance Function Data Description

This research will estimate a set of SPFs for bicycle-vehicle crashes using three data sets. The first data set includes a database of bicycle crash injuries for the study area. These crash data are gathered, cleaned, and organized by the Oregon Department of Transportation's Crash Analysis and Reporting (CAR) Unit. The bicycle crash data are those incidents reported to Department of Motor Vehicles (DMV) by drivers involved in the crash or by law enforcement called to the scene. There is wide recognition that these reported incidents undercount the actual number of bicycle crash injuries (Shinar et al. 2018). The bicycle crash data represents three years of incidents from years 2013 through 2015. Bicycle crash injuries for incidents on segments are summarized in Table 5.3 and those for intersections are described in Table 5.4. A summary of these incidents by injury severity is included in Table 5.5.

Table 5.3 – Bicycle Crash Injuries by Bike Lane and Functional Classification Type

Functional Classification	Bike Lane Presence		Total
	No	Yes	
Local	19	1	20
Collector	13	12	25
Minor Arterial	4	42	46
Major Arterial	3	5	8
Total	39	60	99

Table 5.4 – Bicycle Crash Injuries by Intersection Type

Intersection Description	Bike Lane Presence		Total
	No	Yes	
3-Leg Stop Only	11	11	22
3-Leg Signalized	9	23	32
3-Leg Total	23	41	64
4-Leg Stop Only	7	10	17
4-Leg Signalized	7	57	64
4-Leg Total	27	70	97
Total Intersections	74	123	197

Table 5.5 – Bicycle Crash Injuries by Severity

Severity	Count	%
Fatal	2	0.7%
Severe	13	4.7%
Moderate	158	57.2%
Minor	103	37.3%
Total	276	100.0%

Determination of a crash between segment and intersection was made based on the location flagged in the crash data managed by ODOT's CAR unit. Segment crashes include both crashes marked as segment and also those marked as driveway crashes in this dataset. A map showing the locations of all crashes used in this analysis is below in **Figure 5.6.**

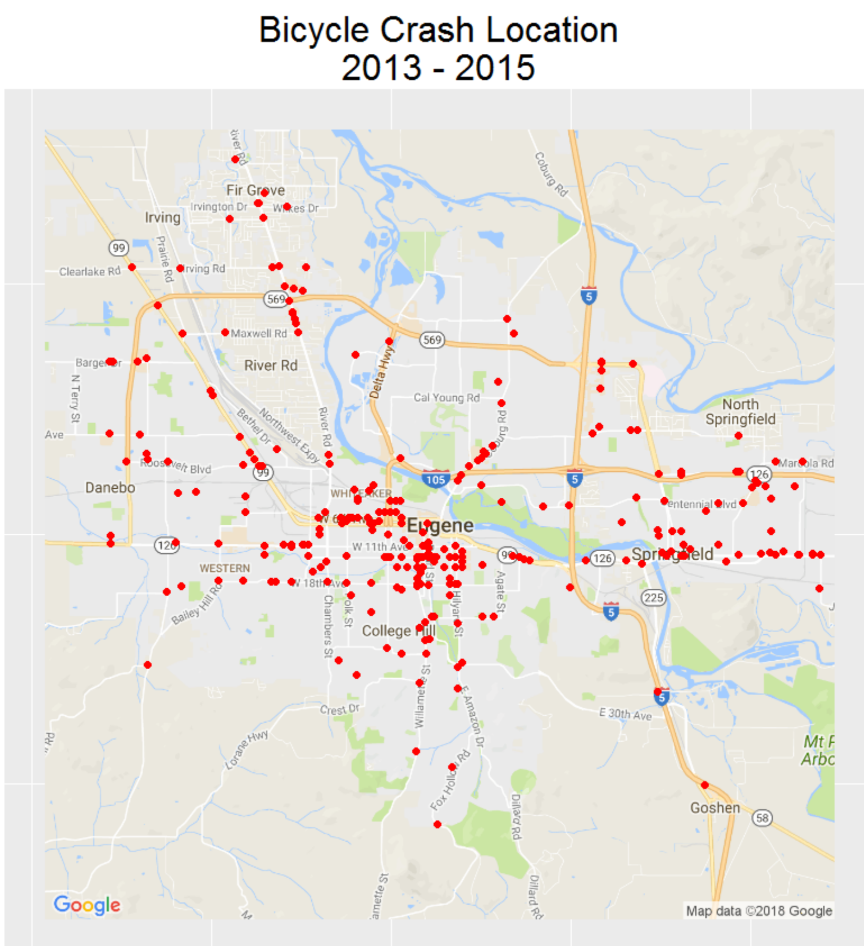


Figure 5.6: Map of bicycle-vehicle crashes in study area during study period

The second data set used in this analysis is an estimated daily bicycle traffic volume derived from bicycle counts collected using portable pneumatic tube counters. These daily bicycle traffic counts are converted into annualized bicycle traffic volumes and then used as inputs into a direct demand model. The direct demand model utilizes measures of accessibility, network connectivity and roadway characteristics such as functional classification and presence of various bicycle facilities in a statistical model that projects bicycle traffic for the entire bicycle network. Intersection traffic volumes are derived from aggregating all entering link volumes for both bicycle and vehicle volumes. Vehicle volumes are derived from the regional travel model and not traffic counts which makes their usage somewhat limited. This issue is discussed in more detail below. The table below summarizes the estimated bicycle miles traveled for a cross-classification of functional classification and bicycle facility type.

Table 5.6 – Millions of Miles of Bicycle Travel by Facility Type

Bicycle Facility	Path	Local	Collector	Minor Arterial	Major Arterial	Total
No Bike Facility	7.71	23.34	2.18	0.82	0.31	34.37
Bike Blvd.	-	1.49	0.09	-	-	1.58
Bike Lane	-	0.82	1.85	4.77	0.67	8.12
Total	7.71	25.66	4.12	5.59	0.99	44.07

The third data set is a spatial network of all streets for the study area with attributes that might affect crash risk and therefore are useful inputs into the SPF estimation process. These attributes include the functional classification, posted speed limit, annual average daily traffic (AADT) for motorized traffic, and the presence of stop signs and traffic signals. These network data are used to construct both segment and intersection data sets used in the SPF estimation process. Network summary information is presented in Table 5.7.

Table 5.7 – Network Miles by Facility Type

Bicycle Facility	Path	Local	Collector	Minor Arterial	Major Arterial	Total
No Bike Facility	70	839	119	39	11	1,078
Bike Blvd.	-	6	1	-	-	7
Bike Lane	-	6	32	93	8	138
Total	70	851	152	132	19	1,224

Due to the existence of a high quality bicycle network a large number of observations are available for model development. This will make application of estimated SPFs to the entire network for systemic system wide analysis possible as well.

Table 5.8 below summarizes network data used in this analysis and includes information on both segment and intersection units of analysis as noted in the table. Average bicycle volumes are orders of magnitude lower compared to motorized traffic volumes. The minimum speed limit is 25 miles per hour (mph) with a maximum of 60 mph on segments. Posted speed was operationalized differently at intersections where the maximum entering segment speed is used.

Table 5.8 – Variable Description

Variable	Description	Model Type	Minimum*	Maximum	Mean
ABT	Annual bicycle traffic in thousands	Both	1.00	2,400	101
ADT	Annual vehicle traffic in thousands	Both	4.00	50,970	3,108
Length_Mi	Length of segment in miles	Segment	0.0	1.76	0.07
Speed	Posted speed limit	Segment	25.0	60.0	22.93
CitySpringfield	Dummy variable for segment present in City of Springfield (0 = No, 1 = Yes)	Segment	0.00	1.00	NA
Collector	Factor variable for collector streets (base = Local)	Segment	NA		
MinorArt	Factor variable for Minor Arterial street	Segment			
MajorArt	factor variable for major arterial streets	Segment			
IsBikeLane	Dummy variable for segment having a bike lane	Segment			
BikeLaneCount	Number of segments entering intersection with bike lanes	Intersection	0.00	5.00	0.34
MaxSpeed	Speed of segment with the highest posted speed	Intersection	25.0	60.0	25.54
HasSignal	Dummy variable indicating if traffic signal is present (0=No, 1=Yes)	Intersection	0.00	1.00	NA
HasStop	Dummy variable indicating if stop sign is present(0=No, 1=Yes)	Intersection	0.00	1.00	NA
Leg_Cat	Factor variable for number of segments entering intersections(base = 3 legs)	Intersection	NA		

*Though the variables are operationalized in the model in 1000s the descriptive statistics are in average daily volumes to make interpretation simpler

5.6.4 Bicycle Crash SPF Results

Two types of SPFs were developed: one predicting segment crashes, and the other predicting intersection crashes. The segment models include bicycle crashes not at intersections but include crashes at driveways and link portions of the roadway. Intersection models were limited to four leg and three leg intersections, with an attempt to model the difference between signalized and stop controlled locations. Uncontrolled intersections were not modeled separately but results can be inferred using some of the models.

5.6.4.1 Segment Models

Multiple models were tried for estimating a bicycle crash SPF on a segment and model diagnostics are summarized in Table 5.9 below. Model diagnostics include the pseudo r-squared, Akaike information criterion (AIC), Bayesian information criterion (BIC), the over dispersion parameter, the number of crashes used in the model estimation and the number of observations (segments) used in the model. AIC is an approximation of a constant plus the comparative distance between the unknown true likelihood function of the estimation data and the fitted likelihood function of the model. A smaller value AIC can be thought of as a model that is closer to the truth. BIC is an estimate of a function of the posterior probability of a model being true under a certain Bayesian circumstance with lower values also indicating a truer model (Dziak et al. 2012). A summary of each model's estimated parameters are included below in Table 1.6 followed by a synthesis of the information presented in both Tables 5.9 and 5.10.

Table 5.9 – Segment Model Diagnostics

Model	Pseudo R2	AIC	BIC	Over-dispersion	Number of Crashes	Number of Segments
Segment_Base	21%	973.3	1011.1	4.5	94.0	14,091
Segment_Speed	21%	974.6	1019.9	4.4	94.0	14,091
Segment_City	22%	968.9	1014.2	4.0	94.0	14,091
Segment_Fc_desc	23%	969.6	1022.5	5.7	94.0	14,091
Segment_Fc_desc_BL	23%	966.7	1027.1	4.9	94.0	14,091

Table 5.10 – Segment Model Detailed Results

Model Name	Variable	Estimate	Standard Error	P value
Segment_Base	(Intercept)	-10.709	0.542	0.00
	log(ABT)	0.6178	0.142	0.00
	log(ADT)	0.9500	0.100	0.00
	Length (Miles)	4.406	0.656	0.00
Segment_Speed	(Intercept)	-10.927	0.599	0.00
	log(ABT)	0.6229	0.143	0.00
	log(ADT)	0.9451	0.100	0.00
	Length (Miles)	4.435	0.657	0.00
	Speed	0.010	0.011	0.38
Segment_City	(Intercept)	-10.945	0.552	0.00
	log(ABT)	0.686	0.147	0.00
	log(ADT)	0.9435	0.100	0.00
	Length (Miles)	4.378	0.663	0.00
	CitySpringfield	0.628	0.242	0.01
Segment_Fc_desc	(Intercept)	-7.599	0.321	0.00
	log(ABT)	0.720	0.135	0.00
	Collector	2.032	0.335	0.00
	Minor Arterial	2.455	0.305	0.00
	Major Arterial	2.888	0.419	0.00
	Length (Miles)	4.155	0.686	0.00
Segment_Fc_desc_BL	(Intercept)	-7.408	0.325	0.00
	log(ABT)	0.561	0.152	0.00
	Collector	1.754	0.362	0.00
	Minor Arterial	1.919	0.396	0.00
	Major Arterial	2.500	0.459	0.00
	Length (Miles)	3.985	0.682	0.00
	IsBikeLane	0.722	0.330	0.03

The first model, *Segment_Base* uses the natural log of bicycle and vehicle traffic (log (ABT) and log (ADT) respectively) and the length of the segment. All variables are significant at the 0.05 level. The *Segment_Speed* model adds the posted speed limit but that variable is not significant. *Segment_City* adds a dummy variable for the city of Springfield which is a positive and significant predictor of bicycle injury crashes.

Since the posted speed limit data is not significant but may be due to those data having some reliability issues, functional classification was used as a proxy for speed and vehicle traffic volume in the *Segment_Fc_desc* model. All parameters in this model are significant at the 0.05 level and have expected values and signs. The functional classification variable is a categorical variable with the base value set to a local street. The variables can be interpreted by comparing their estimated parameter value to a local street. This model result shows that compared to a local street, collectors increase bicycle crash injuries, though less than minor arterials which in turn do not increase the frequency of crashes by as much as major arterials. The final model, *Segment_Fc_desc_BL* uses the same parameters as *Segment_Fc_desc* but adds a variable for the presence of a bike lane. All variables remain significant though the bike lane variable increases the frequency of bicycle crashes even considering the increase in ABT which is somewhat unexpected.

Applying the model parameters in sensitivity tests below show how certain model parameters affect crash prediction outcomes when all other variables are held constant. The figures below present results using estimated models which included crash data from three years therefore the predicted crash outcomes reflect three years. Figure 5.6 shows the predicted crash counts using the *Segment_Fc_desc_BL* model and varying the vehicle and bicycle traffic volume and shows the effect of bike lanes. As described above in the model parameter discussion, the figure shows how the functional classification increases the number of predicted crashes while also showing the impact of the bicycle lane variable on predicted crashes.

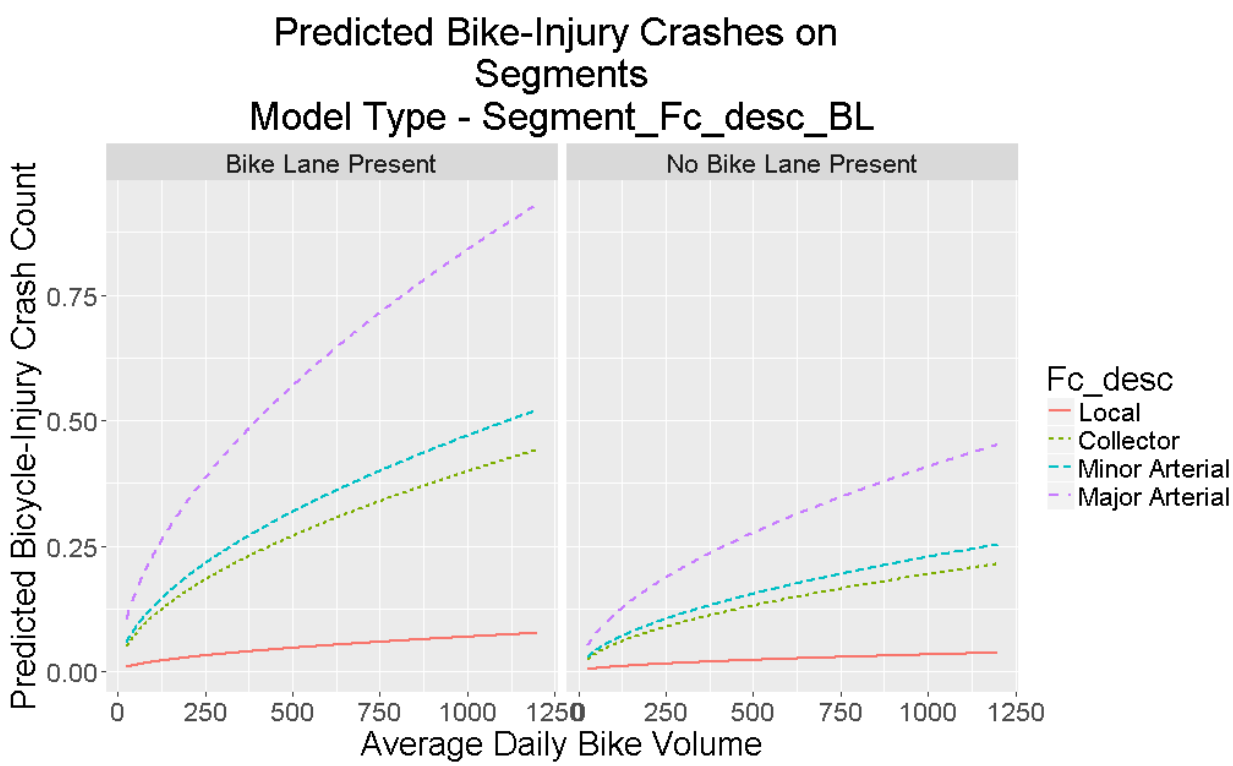


Figure 5.7: Segment_Fc_desc_BL model safety performance function sensitivity test

In the next figure, predicted crash counts are converted to crash rates by combining the crash count estimates with AADBT. Figure 5.8 also includes confidence intervals using the standard errors to highlight the uncertainty in the effect of the bicycle lane variable. Figure 5.8 shows that the presence of a bike lane does not appear to have a difference of effect outside the confidence interval.

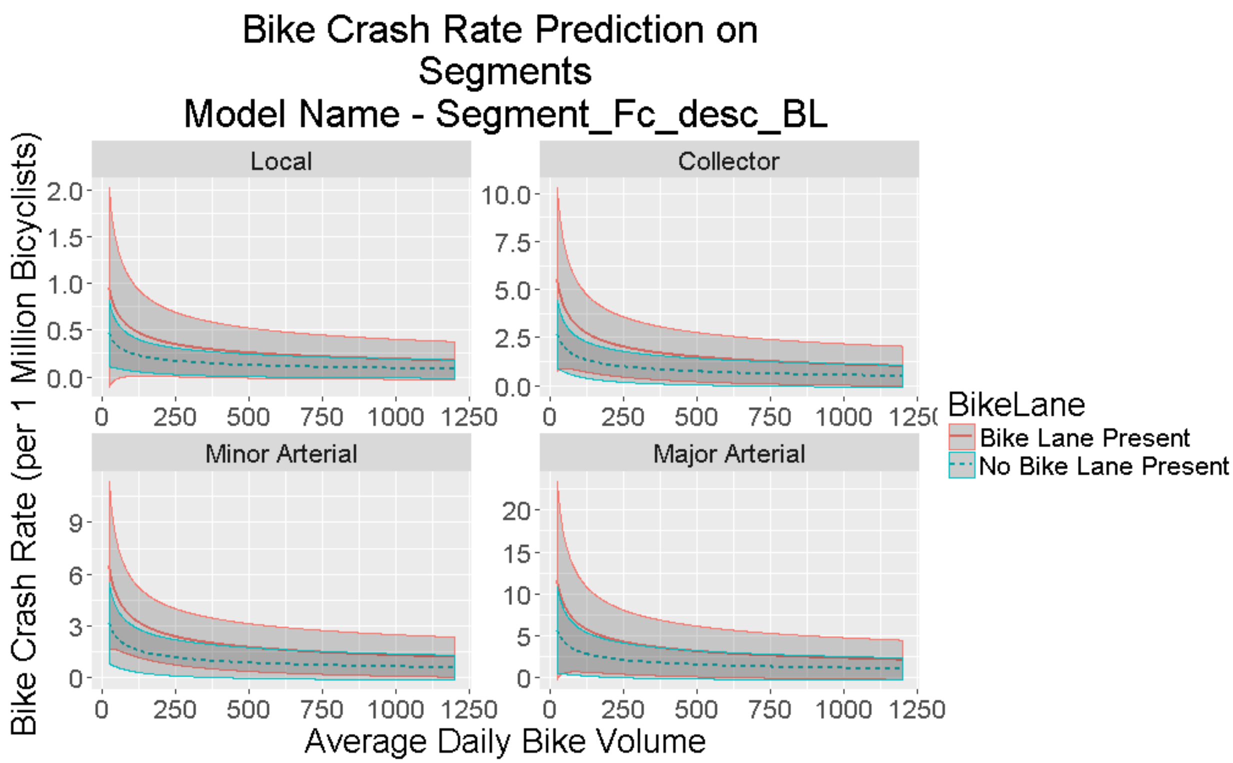


Figure 5.8: Segment_Fc_desc_BL model safety performance function sensitivity test

Applying the model results from the Segment_Fc_desc to a sensitivity test is presented below in Figure 5.8. This model does not include a variable for bike lane and primarily shows the difference between predicted crash counts with different bicycle volumes on different functional classifications.

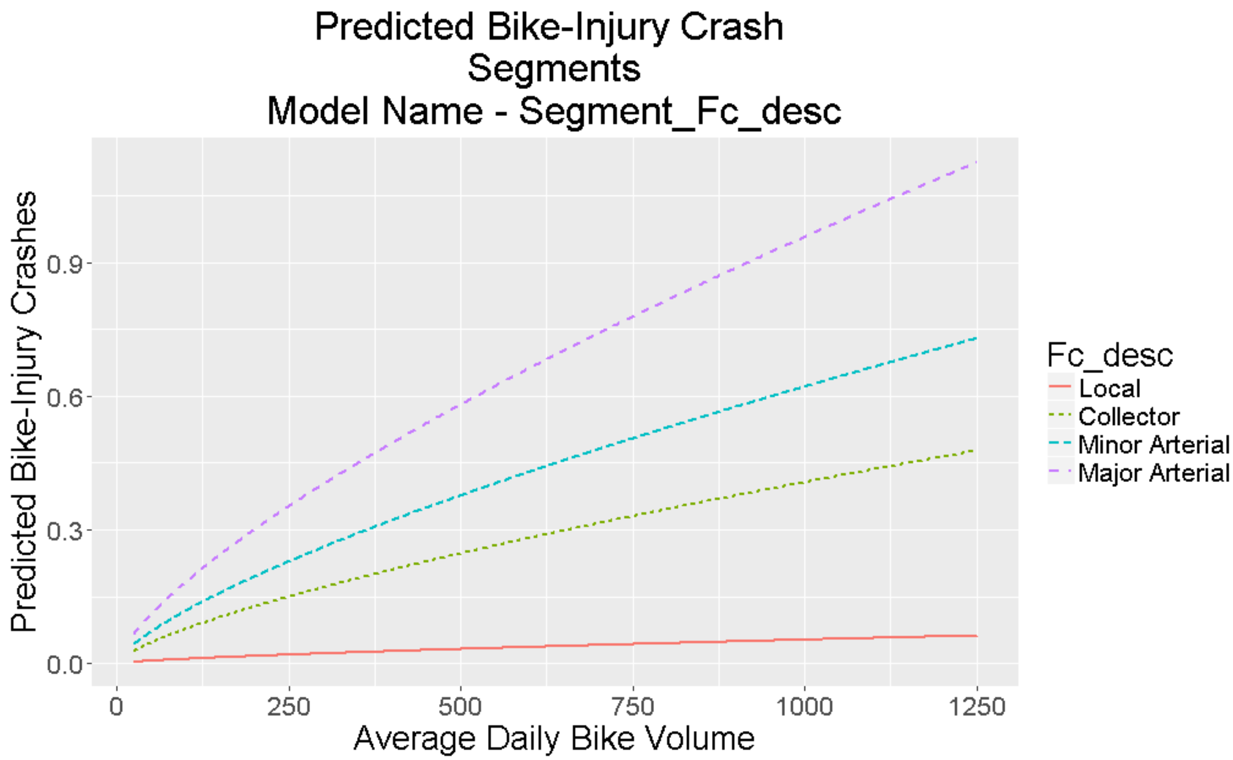


Figure 5.9: Segment_Fc_desc crash count model safety performance function sensitivity test

Figure 5.10 shows bicycle crash rates using the estimated model parameters and shows a significant decrease with initial increases in average daily bicycle volume. For instance, in the Segment_Fc_desc model, bicycle crash rates decrease by 51% when ABT increases by 100 going from 25 to 125 while the crash rate decrease is only 20% when the average ABT goes from 125 to 225 ABT.

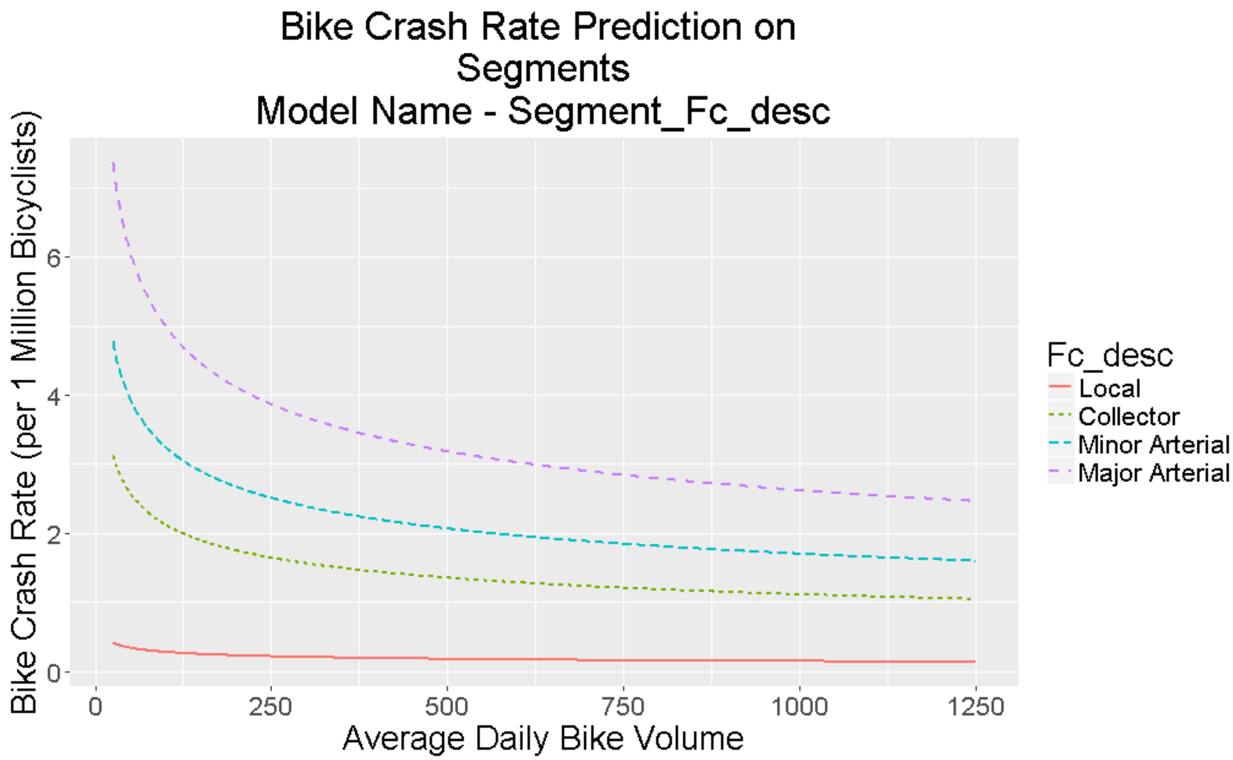


Figure 5.10: Segment_Fc_desc crash count model safety performance function sensitivity test

5.6.4.2 Intersection Models

A total of 22 models were tried for the intersection SPF including separate models for intersections with three and four legs and additional models separating intersections with signal controllers and stop signs. Models were also tried that pooled all the intersections and added terms for presence of signals and stop signs and number of legs. Only 11 of the models are presented below in Table 5.11 though full results can be found in Appendix B. Caution should be used when comparing model diagnostics in the table below since the AIC and BIC are not comparable across models that use different data. For instance the AIC and BIC metrics can be compared between Four_Leg_Base and Four_Leg_SignalStop since they both use the same intersections and crashes but those model diagnostics cannot be compared with Four_Leg_Signal since that model only uses data for four leg intersections that have a signal controller. A summary of each model's estimated parameters are included below in Table 5.12.

Table 5.11 – Intersection Model Diagnostics

Model	Pseudo R2	AIC	BIC	Over-dispersion	Number of Crashes	Number of Intersections
Four_Leg_Base	30%	623.9	645.6	1.57	100	1,689
Four_Leg_SignalStop	31%	624.3	656.9	1.51	100	1,689
Four_Leg_Signal_Term	31%	622.3	649.5	1.5	100	1,689
Four_Leg_Signal	14%	340.8	356.1	1.9	67	338
Four_Leg_Signal_BL	17%	337.4	356.5	1.5	67	338
Three_Leg_Base	28%	593.8	620.8	3.8	66	6,195
Three_Leg_MaxSpeed	30%	583.1	616.7	3.1	66	6,195
Three_Leg_Signal_Term	30%	588.0	621.7	3.4	66	6,195
Three_Leg_Stop	16%	245.9	269.0	1.7	24	2,366
Composite_Int_1	36%	1209.3	1258.1	1.8	166	7,884
Composite_Int_2	37%	1201.5	1257.3	1.6	166	7,884

Table 5.12 – Intersection Model Results

Model Name	Variable	Estimate	Standard Error	P value
Four_Leg_Base	(Intercept)	-11.15339	0.88686	0.00
	log(ABT)	0.77346	0.14310	0.00
	log(ADT)	0.9714235	0.12853	0.00
Four_Leg_BL	(Intercept)	-10.05889	0.94262	0.00
	log(ABT)	0.63954	0.14570	0.00
	log(ADT)	0.80839	0.14112	0.00
	BikeLaneCount	0.27554	0.09271	0.00
Four_Leg_Signal_Term	(Intercept)	-10.10275	1.01802	0.00
	log(ABT)	0.72613	0.14558	0.00
	log(ADT)	0.78690	0.15582	0.00
	HasSignalTRUE	0.57306	0.30148	0.06
Four_Leg_Signal	(Intercept)	-9.59292	1.91023	0.00
	log(ABT)	0.53289	0.20960	0.01
	log(ADT)	0.88583	0.23918	0.00
Four_Leg_Signal_BL	(Intercept)	-9.19088	1.89625	0.00
	log(ABT)	0.37234	0.20941	0.08
	log(ADT)	0.82558	0.24281	0.00
	BikeLaneCount	0.27309	0.11168	0.01
Three_Leg_Base	(Intercept)	-13.01665	0.92990	0.00
	log(ABT)	0.57755	0.22160	0.01
	log(ADT)	1.24282	0.14178	0.00
Three_Leg_MaxSpeed	(Intercept)	-14.67583	1.07065	0.00
	log(ABT)	0.63864	0.22612	0.00
	log(ADT)	1.12450	0.14692	0.00
	MaxSpeed	0.07505	0.02093	0.00
Three_Leg_Signal_Term	(Intercept)	-11.93171	0.99720	0.00
	log(ABT)	0.49366	0.22514	0.03
	log(ADT)	1.05486	0.15589	0.00
	HasSignalTRUE	0.88756	0.31544	0.00
Three_Leg_Stop	(Intercept)	-11.87318	1.45390	0.00
	log(ABT)	0.73216	0.32946	0.03
	log(ADT)	0.98728	0.23451	0.00
Composite_Int_1	(Intercept)	-11.20420	0.72245	0.00
	log(ABT)	0.70483	0.11807	0.00
	log(ADT)	0.83373	0.11260	0.00
	BikeLaneCount	0.22313	0.08401	0.01
	HasSignalTRUE	0.78364	0.21926	0.00
	HasStopTRUE	0.29517	0.18407	0.11

Composite_Int_2	(Intercept)	-10.91833	0.73171	0.00
	log(ABT)	0.53351	0.12676	0.00
	log(ADT)	0.81685	0.11453	0.00
	BikeLaneCount	0.24460	0.08170	0.00
	HasSignalTRUE	0.71476	0.22485	0.00
	HasStopTRUE	0.31795	0.18676	0.09
	Leg_Cat4_Leg	0.61248	0.19248	0.00

The initial model *Four_Leg_*Base for four-leg intersections shows that both ABT and ADT (both as a natural log) variables are significant at the 0.05 level. The next model (*Four_Leg_BL*) adds a term for the number of bike lanes entering the intersection while *Four_Leg_Signal_Term* model includes a variable for if the intersection has a traffic signal. The *Four_Leg_Signal* model only uses vehicle and bike traffic as inputs and only includes four leg intersections with a traffic signal while *Four_Leg_Signal_BL* adds a term for the number of bicycle lanes entering the intersection. Most of these models' results show the parameters are significant at the 0.05 level though some have one variable significant at the 0.10 level.

The three leg intersection models include a base model that includes just entering traffic as predictors of bicycle injury crashes with results of both variables significant at the 0.05 level. The *Three_Leg_MaxSpeed* model adds a terms for the maximum speed entering the intersection which is significant at the 0.05 level. Similar to the four leg intersection models, a three leg model was estimated where a term was added to indicate that the intersection had a traffic signal (*Three_Leg_Signal_Term*). And the last three leg specific model shown in Table 5.12 uses data for three leg intersections that are stop controlled but have no traffic signal.

Models *Composite_Int_1* and *Composite_Int_2* pool all three and four leg intersections into one model and add terms for presence of signals and stop signs as well as bike lane count in the former while the latter has a term added to distinguish four leg intersections. All variables are significant at the 0.10 level in the second composite model.

Sensitivity tests are performed to demonstrate how the estimated models perform. Figure 5.10 below shows how the *Four_Leg_Base* model responds with varying levels of bicycle and vehicle traffic entering the intersection. Figure 5.11shows the calculated bicycle-injury crash rate varying the same input parameters. This graphic more clearly demonstrates the important risk reduction role an increase in the number of daily bicyclists play, showing that when the AADBT goes from 25 to 125 the crash rate decreases by 31% whereas a further increase in from 125 to 225 only decreases the crash rate by 13%.

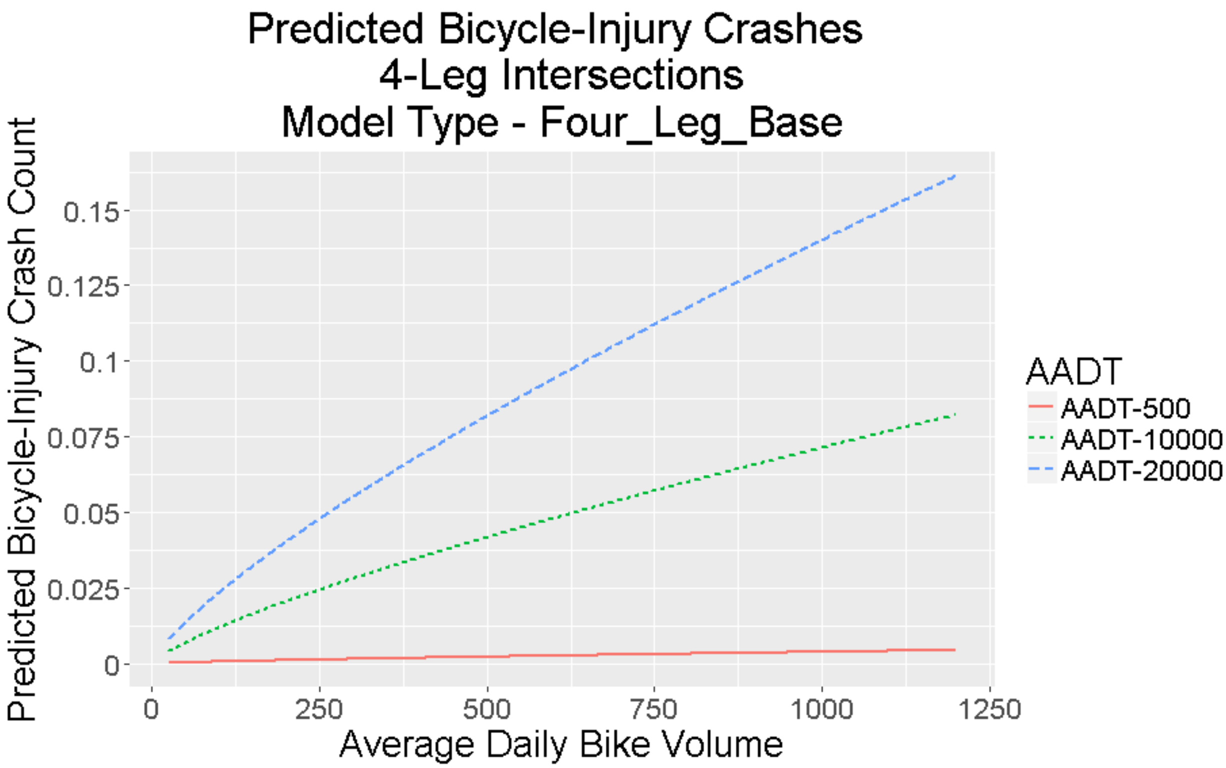


Figure 5.11: Four-leg base model bicycle-injury crash frequency prediction

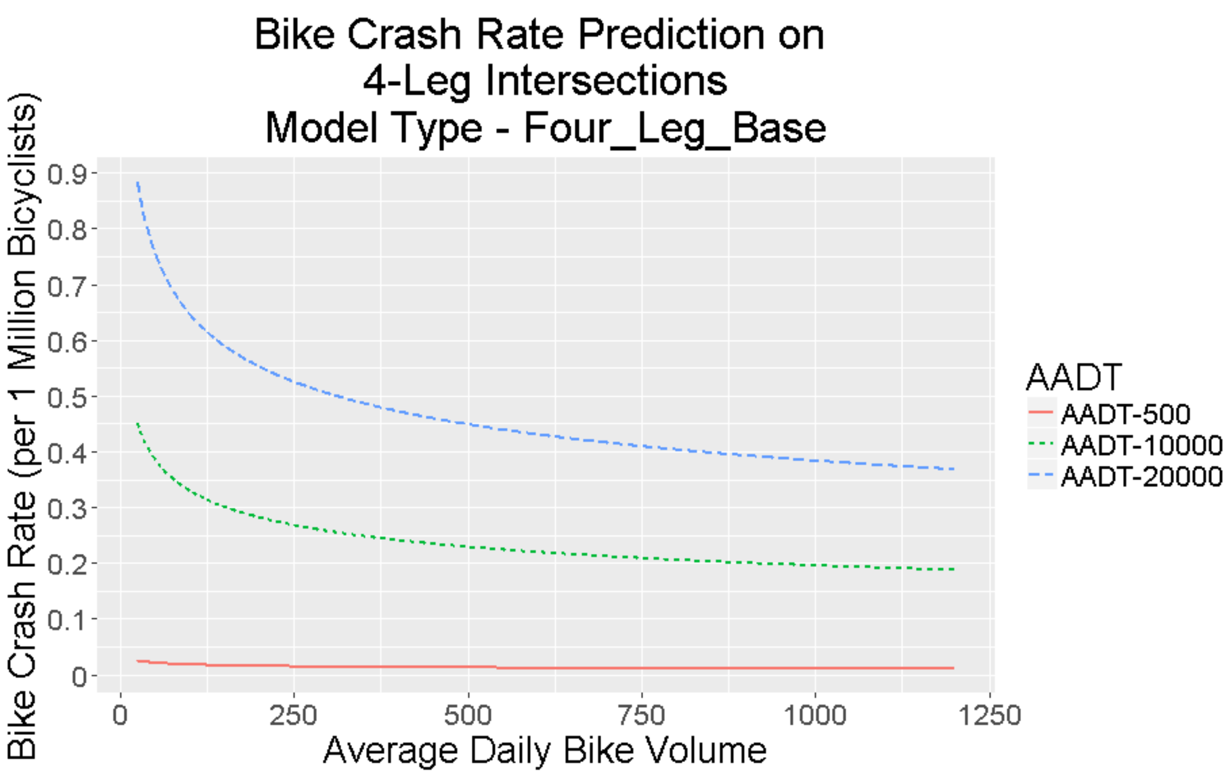


Figure 5.12: Four-leg base model bicycle-injury crash rate prediction

A similar graphic is presented for the *Four_Leg_Signal_Term* model in Figure 5.11 below. This test reveals similar findings from the base model but shows the effect that presence of traffic signals have on the crash frequency prediction revealing an increase compared to no traffic signal. Viewing these results as a crash rate, Figure 5.12 shows the reduction in risk as the number of bicyclists' increases at this type of intersection.

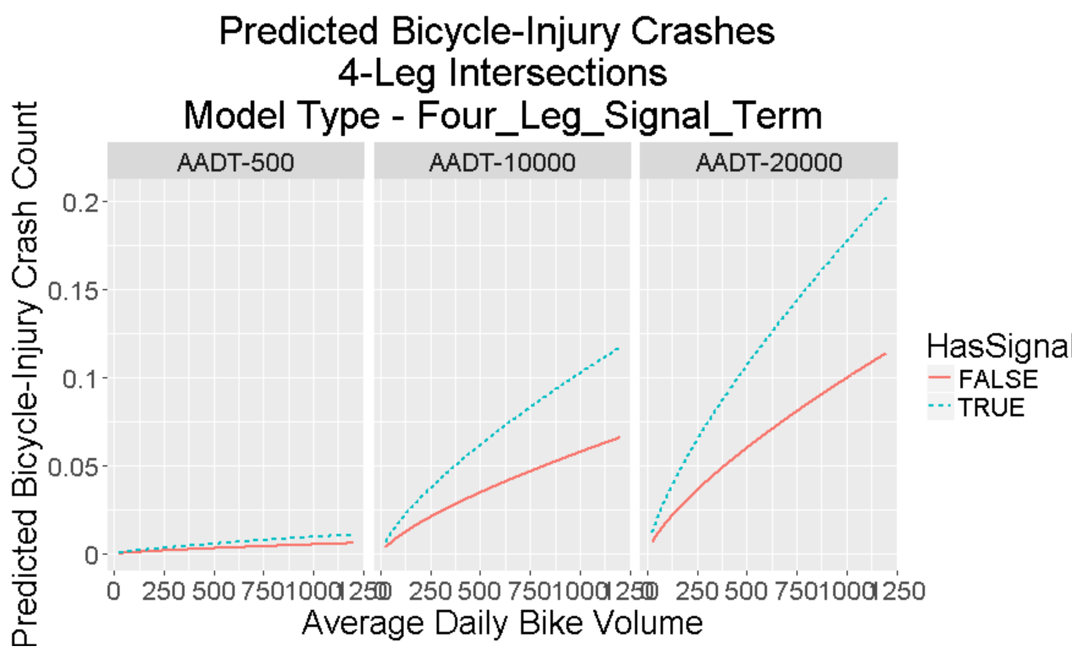


Figure 5.13: Four-leg with signal term model bicycle injury crash frequency

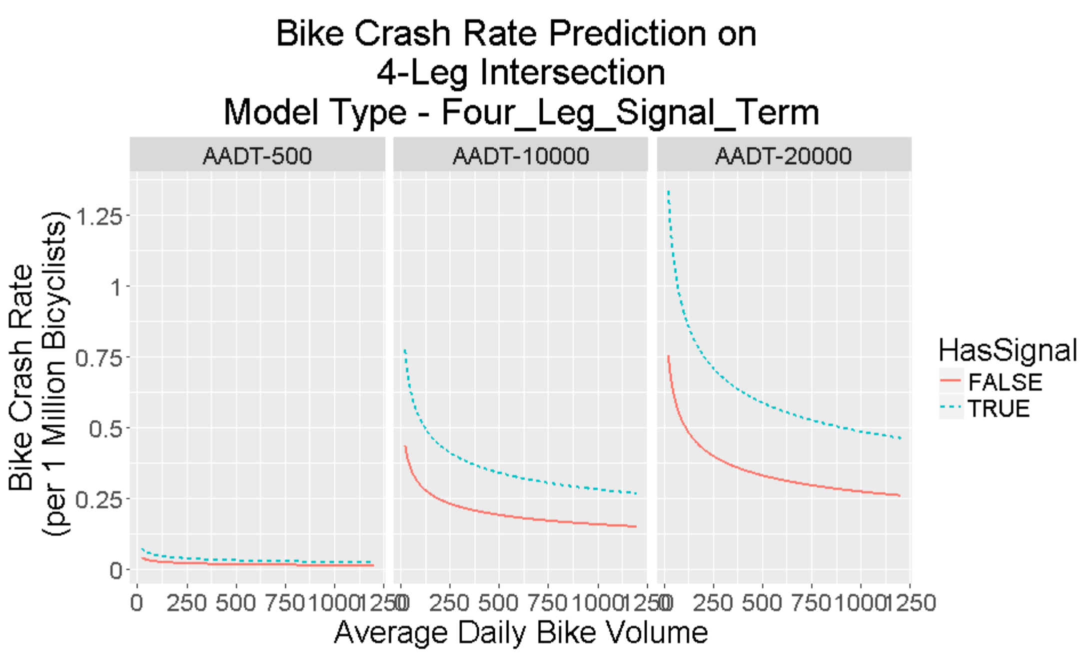


Figure 5.14: Four-leg with signal term model bicycle-injury crash rate

Figure 5.15 shows a sensitivity test of the *Three-Leg_Base* model followed by Figure 5.16 where the *Three_Leg_MaxSpeed* model is shown which includes a variable for the maximum speed of an entering leg. The base model shows the impact that exposure to vehicle volume has on crash frequency while the *Three-Leg_MaxSpeed* model shows the impact that higher entering intersection speed has on crash frequency.

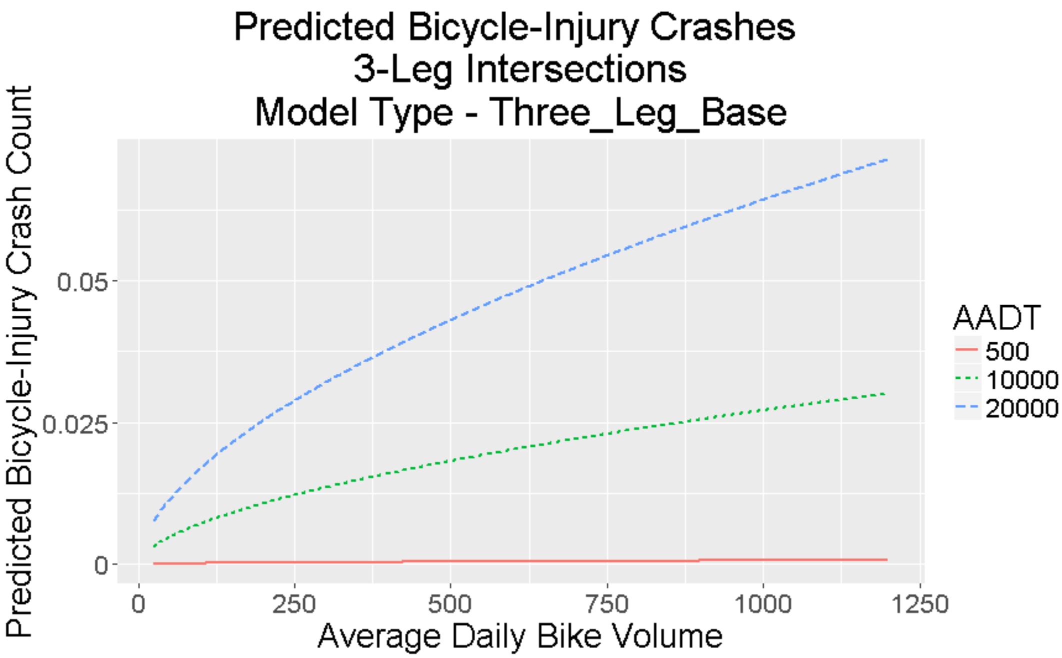


Figure 5.15: Three-leg base model bicycle-injury crash frequency

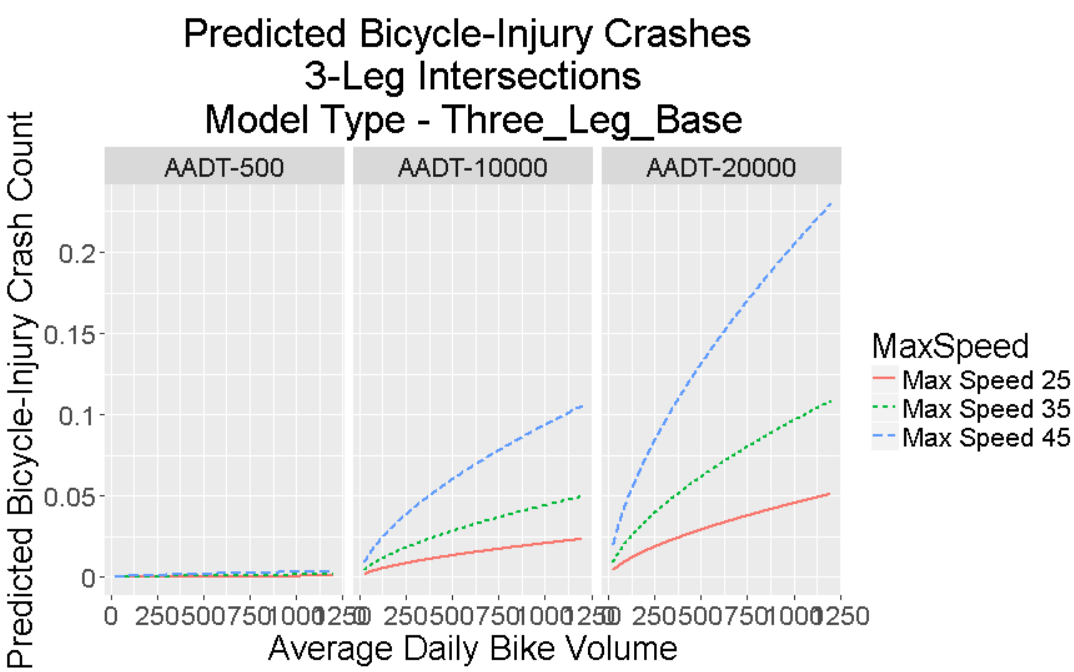


Figure 5.16: Three-leg with max speed model bicycle-injury crash frequency

Figure 5.17 shows sensitivity test results for the *Three_Leg_Signal_Term* model and shows the impact that increasing bicycle volume and vehicle volume have on predicted crash counts. Figure 5.18 then shows the bicycle injury crash rate

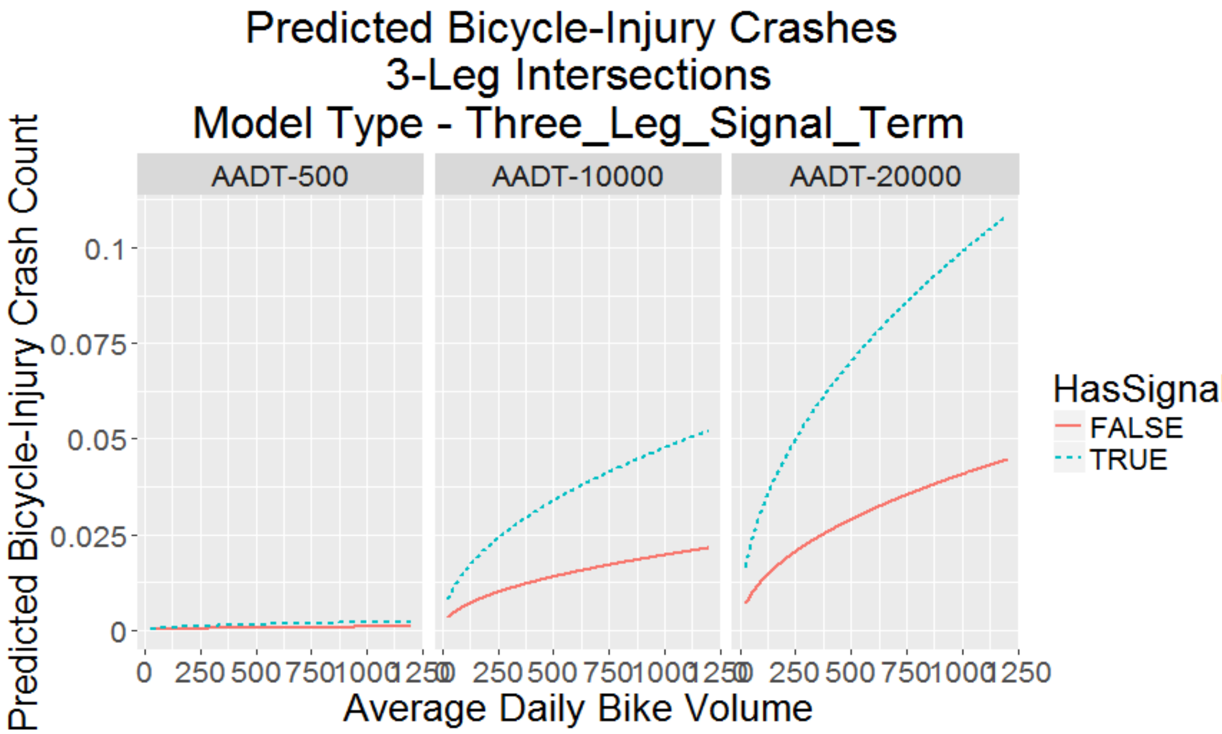


Figure 5.17: Three-leg with signal model bicycle-injury crash frequency

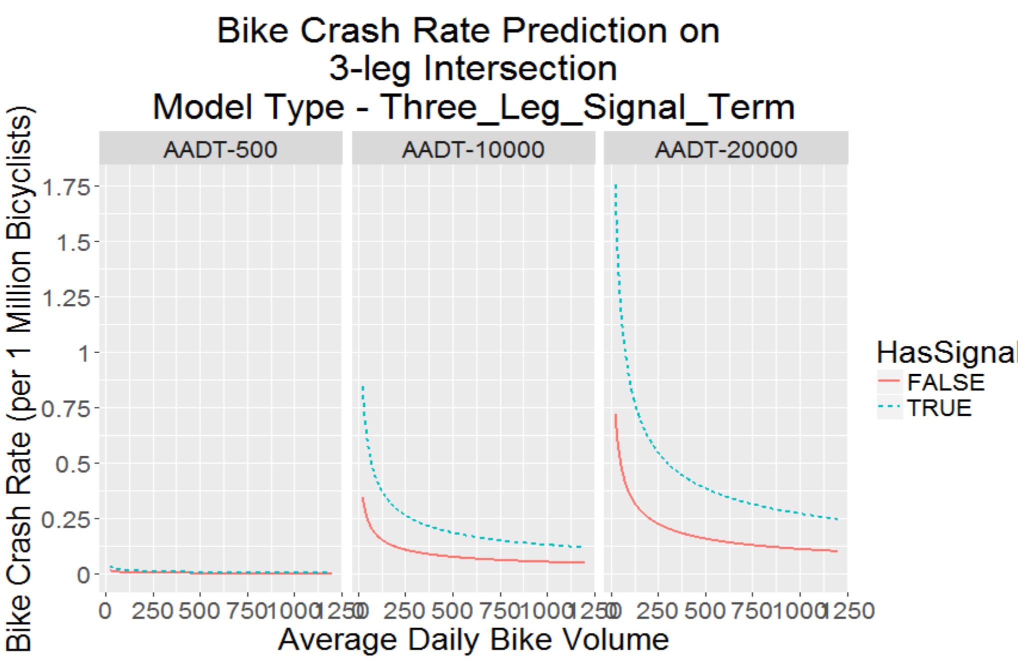


Figure 5.18: Three-leg with signal model bicycle injury crash rate

Figure 5.19 compares the application of the *Four_Leg_Signal_Term* and *Three_Leg_Signal_Term* models to make simpler comparisons of the model coefficients. The results show that four leg intersections general present larger crash frequencies all else being equal.

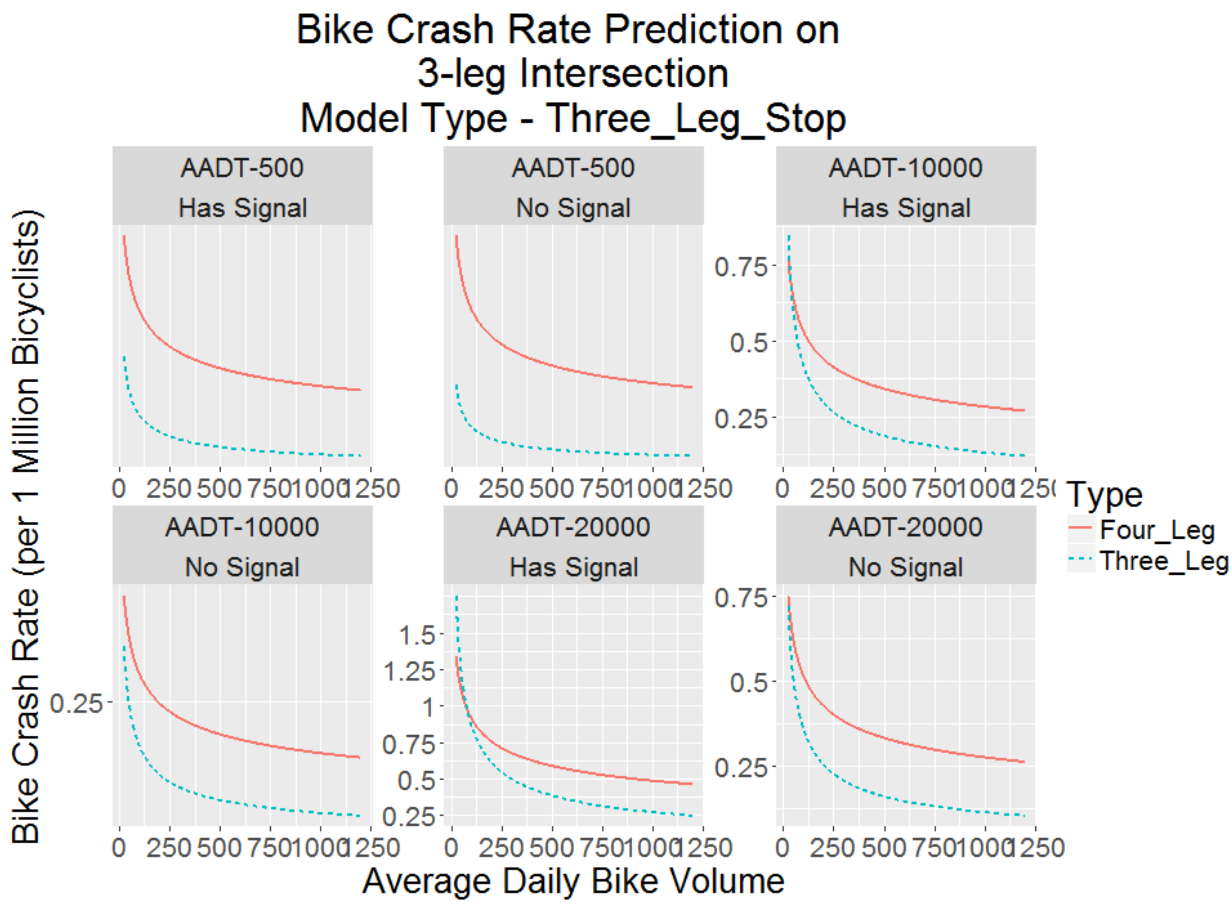


Figure 5.19: Four-leg and three-leg with signal models comparison of bicycle-injury crash rate

Lastly, a sensitivity test is performed for the second composite model (*Composite_Int_2)* where intersection data are pooled. Using estimated parameters from this model, multiple types of intersection crash counts including all combinations of three and four-leg configurations with and without signal and stop control. This model allows for bicycle-injury crash for uncontrolled intersections denoted in the figure with “No Signal-No Stop” header and typically exhibit lower crash counts all else being equal. Figure 5.20 shows the bicycle-injury crash risk and similar to the intersection model results above an increase number of daily bicyclists decreases crash risk while intersections exposed to higher vehicle volumes increase bicycle crash risk. Presence of bicycle lanes does not decrease bicycle crash risk.

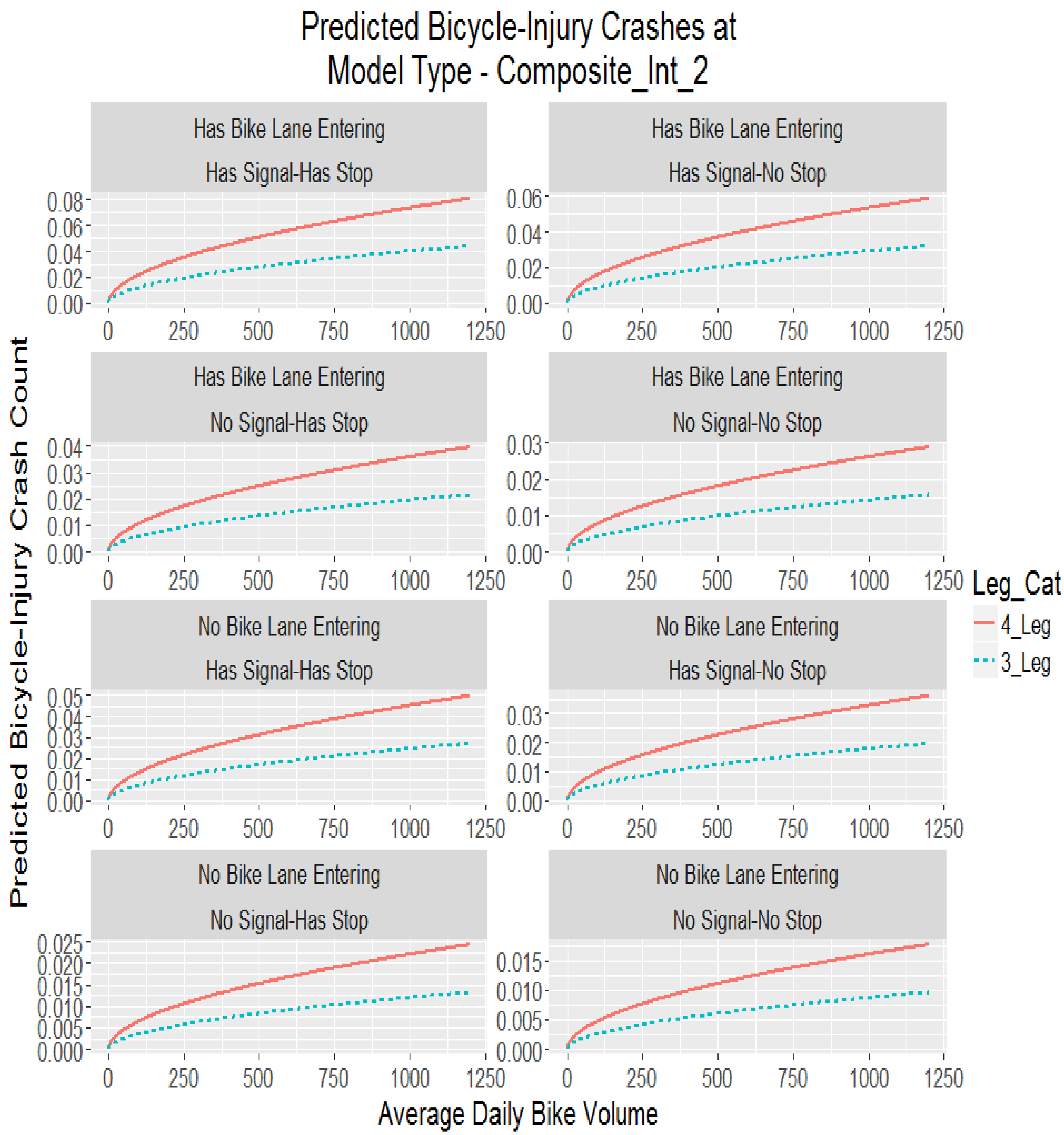


Figure 5.20: Composite model 2 bicycle-injury crash frequency

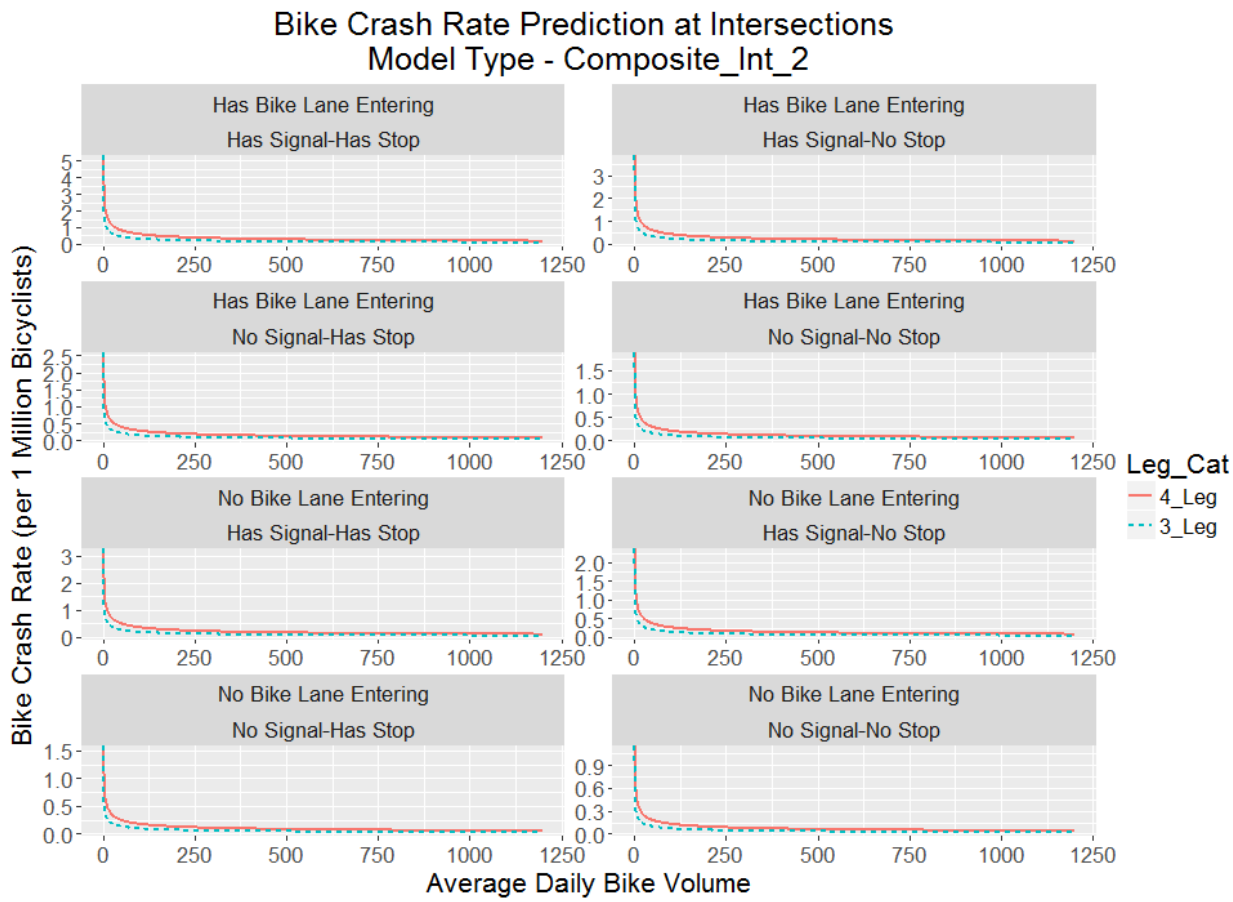


Figure 5.21: Composite model 2 model of bicycle-injury crash rate

The crash prediction models developed and demonstrated above show that increase vehicle volume and speed increased crash frequencies and risk for bicycle-injury crashes. Four leg intersections present greater risks as well as signal controlled intersections also increasing the frequency and risk of bicycle-injury crashes. Increasing the daily bicycle volume has a protective effect and reduces risk though does increase crash frequency, albeit at a diminishing rate with the inverse true of risk outcomes furthering the notion of a safety in numbers effect.

5.6.5 Application of Bicycle SPFs for Systemic Bicycle Crash Analysis

Managing roadway safety includes four basic elements; 1) identification of sites requiring safety investigation, 2) diagnosis of the safety problem, 3) selection of a feasible treatments for potential problem locations, and 4)prioritization of treatments within a limited budget (Persaud 1999). Techniques that use counts or simple rates are subject to bias due to regression-to-the-mean phenomenon in which sites that have randomly high incidents of crashes draw undue attention (Hauer et al. 2014). Misidentification of sites as problem areas can lead to an inefficient use of public resources and missing problem spots can mean continued crashes in places that could be treated.

Studies have evaluated the optimal way to identify priority investigation locations and have shown that the Empirical Bayes (EB) method consistently performs best compared to other methods such as using raw crash frequencies, equivalent property damage only crash frequency, crash rate, the proportional method, and the potential for improvement method (Montella, 2009; Cheng and Washington, 2008; Elvik, 2007, Elvik 2008). Using observed crash data from a select number of years is well understood to contain regression-to-the-mean (RTM) bias or selection bias which is likely to lead to selecting sites that might not have longer term safety issues. This limitation can be addressed by applying estimated SPFs and calculating an expected crash frequency with an Empirical Bayes (EB) adjustment. As described in the Highway Safety Manual, the expected crash frequency can be calculated using the following formula.

$$\boldsymbol{N_{expected} = w \times N_{predicted} + (1 - w) \times N_{observed}} \tag{5-2}$$

Where:

N_{expected} = expected average crash frequency for the study period

w = weighted adjustment to be placed on the SPF prediction (derived from overdispersion parameter)

$N_{\text{predicted}}$ = predicted average crash frequency using SPF for study period

$N_{observed}$ = observed crash frequency at site over the study period

The weighted adjustment factor, w, is a function of the SPF's overdispersion parameter, k, and is calculated using the following equation (HSM 2010).

$$\boldsymbol{w = \frac{1}{1+k}\left(\sum N_{predicted}\right)} \tag{5-3}$$

For the systemic crash analysis three products will be created that seek to highlight segments and intersections that could be prioritized for further investigation due to safety issues. The first product will utilize the *Segment_desc_BL* segment model since it had the lowest AIC and APE compared to the other models and it used functional classification as a proxy for vehicle speed and volume which might be easier for other cities and regions to apply. The map in Figure 5.20 shows the top 40 locations ranked from highest to lowest based on the EB adjusted bicycle-injury crash frequency. OF the top 40 segments revealed using this method, 28 are on arterial streets with the remaining 12 located on collector streets. Thirty-six of the segments are locations in the city of Eugene with the remaining four in Springfield.

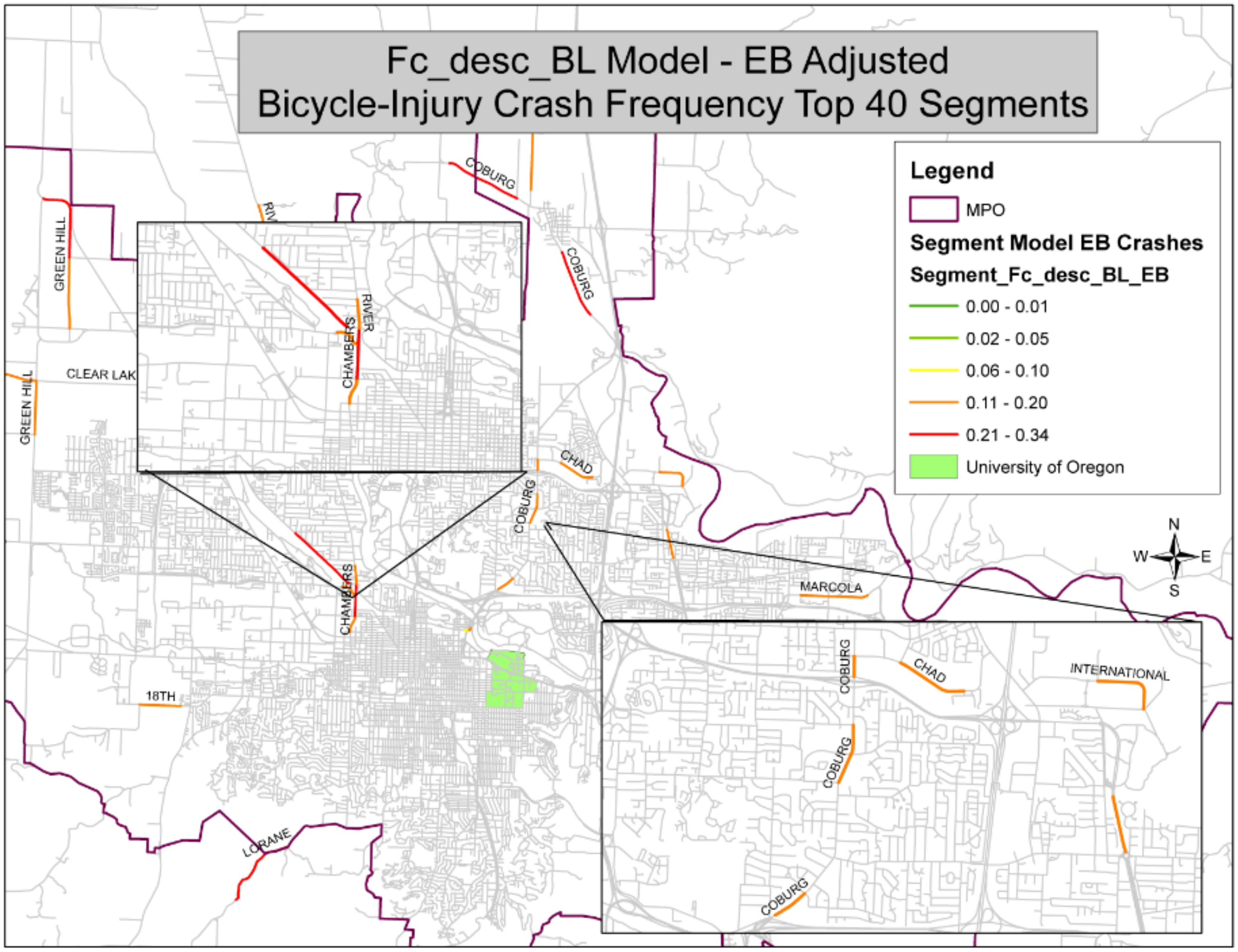


Figure 5.22: Segment model mapping results – EB adjusted bicycle-injury crash frequency

The next application of the SPFs uses the discrete models estimated above including the *Four_Leg_Signal_Term* and *Three_Leg_Signal.* These models were selected due to all variables being significant at the 0.10 level. The map featured in 5.22 shows the top 40 sites ranked based on the expected crash frequency with EB adjustment. Intersections are clustered near the downtown area of Eugene and west of the University of Oregon Campus. The intersections are mostly located at junctions of arterials and some are located near locations highlighted in the segment model. A table with additional summary information on the segments is included in Appendix C.

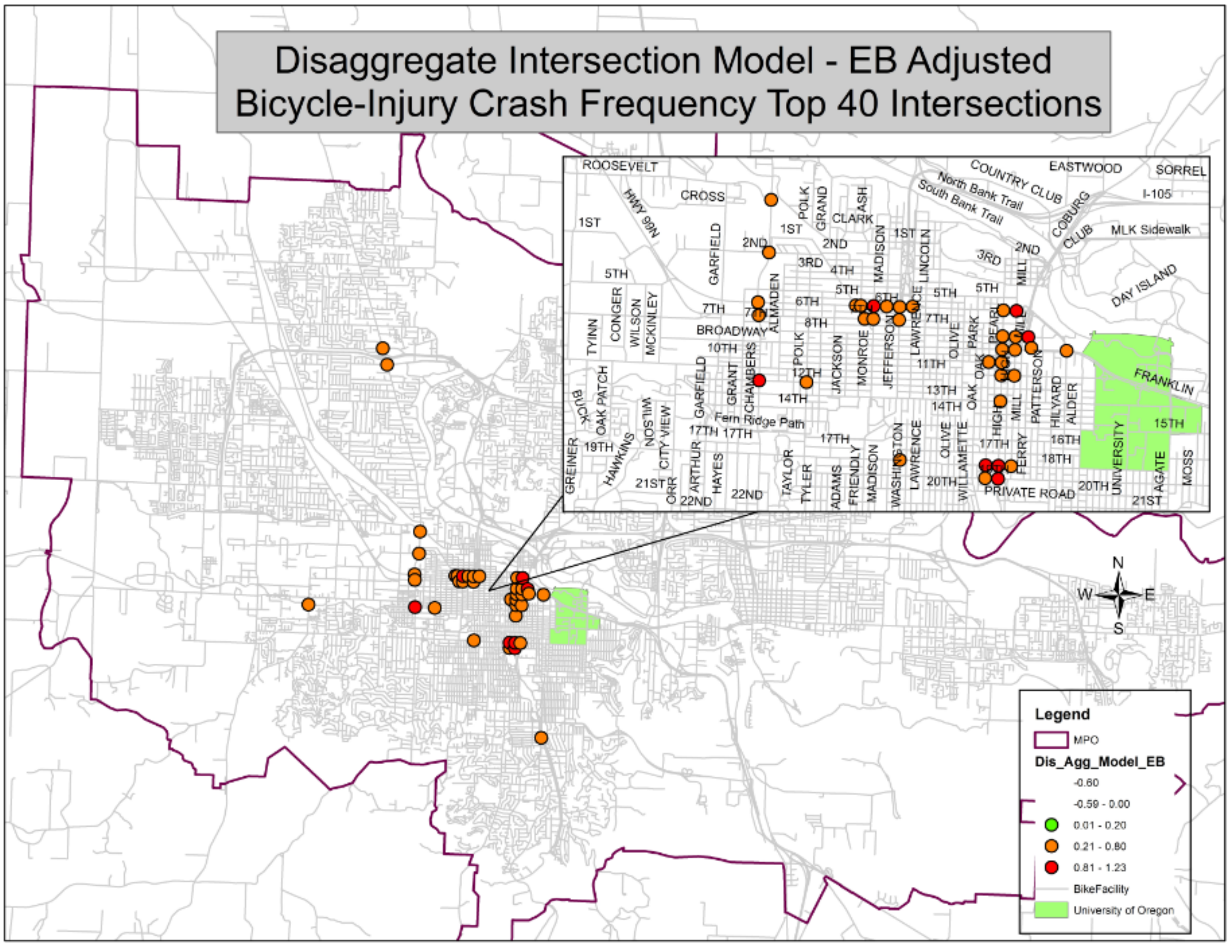


Figure 5.23: Disaggregate intersection model mapping results – EB adjusted bicycle-injury crash frequency

Lastly, the *Composite_Int_2* model is applied with the top 40 intersection locations presented in Figure 5.24 below. All the variables in this model are significant at the 0.10 level and are comprehensive and applicable to more of the intersections in the study area since it pooled all available intersections in the model. Exact locations differ compared to the disaggregate model application but some similarities emerge. Similar to the disaggregate model application in Figure 5.24, there is some overlap between these intersections and the segment model results. Also, almost every intersection includes one or more arterials entering the intersection.

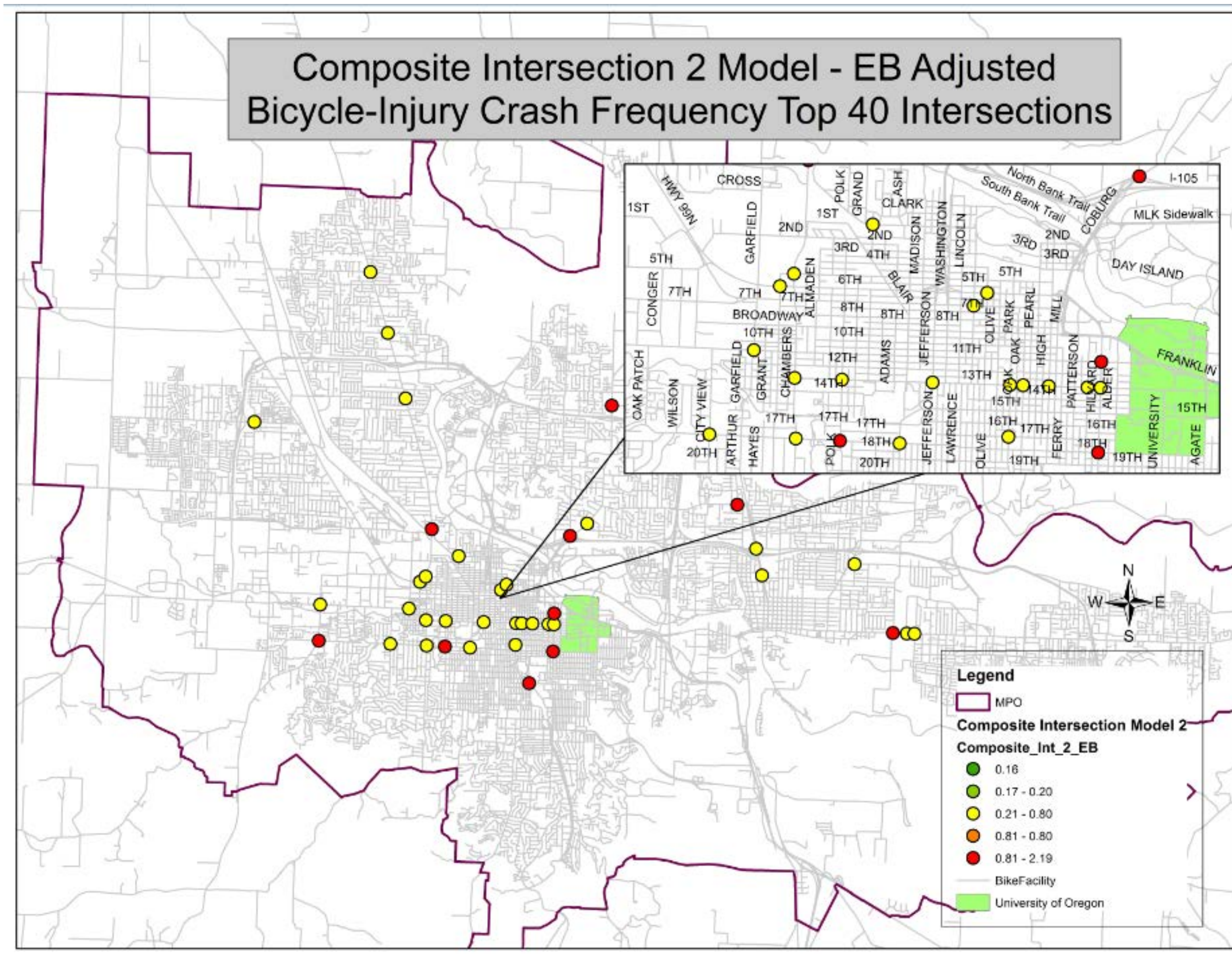


Figure 5.24: Composite 2 model mapping results – EB adjusted bicycle-injury crash frequency

Table 5.12 below summarizes the functional classification of the intersections highlighted using both of these methods. The most common intersection is a four-leg intersection with all minor arterials entering the intersection. Other high frequency locations in appear to include locations where low volume roads cross arterials. A table of the intersections and their intersection id can be found in Appendix C.

Table 5.13 – Intersection Priority Locations Functional Classification Makeup

Intersection Functional Classification Makeup	Count of Intersections		Total
	Disaggregate Intersection Model	Composite Intersection 2 Model	
MinorArt-MinorArt-MinorArt-MinorArt	7	10	17
Collector-Collector-MinorArt-MinorArt	4	4	8
Local-Local-MinorArt-MinorArt	6	2	8
Collector-Collector-MajorArt-MajorArt	6	1	7
Local-Local-MajorArt-MajorArt	3	3	6
Collector-MinorArt-MinorArt-MinorArt	2	3	5
Local-MinorArt-MinorArt-MinorArt	2	2	4
MajorArt-MajorArt-MinorArt-MinorArt	1	3	4
Collector-MajorArt-MajorArt-MinorArt	2	2	4
MinorArt-MinorArt-Path-Path	2	1	3
Collector-Local-MinorArt-MinorArt	0	2	2
Collector-Local-MajorArt-MajorArt	1	1	2
Collector-Collector-Local-Local	1	0	1
Collector-MinorArt-MinorArt	0	1	1
MinorArt-MinorArt-MinorArt	0	1	1
Collector-Collector-Collector-Local	0	1	1
MajorArt-MajorArt-MinorArt	1	0	1
Collector-Collector-Path-Path	0	1	1
Collector-MajorArt-MinorArt-MinorArt	0	1	1
Local-MajorArt-MajorArt-MinorArt	0	1	1
MajorArt-MajorArt-MajorArt-MajorArt	1	0	1
MajorArt-MinorArt-MinorArt-MinorArt	1	0	1

5.6.6 Conclusion and Discussion

The development and application of bicycle-vehicle crash specific safety performance functions fills a gap in currently available SPFs and allows for data driven bicycle crash network screening. Without further review of top 40 sites it is unclear how this prioritization process would be successful but this is the first step in using a more data driven process for initial site selection. Next steps could include, following additional examination of priority sites, identification of potential crash reduction treatments using resources such as the Crash Modification Database Clearinghouse[4] or Oregon Department of Transportation's own database of countermeasures[5]. Now that SPFs are available, base scenario crash frequencies can be estimated and potential crash modification factors applied to better understand the benefits of the treatment at different locations in the study region.

The SPFs developed above all utilize daily bicycle traffic and likely improve the performance of these tools so priority should be maintained on collection of these data. The bike volumes were generated from a facility demand model with known error and should be improved as more data becomes available. Similar issues exist however, for vehicle volumes so priority should be given to collection of these data as well.

Network data on other network design features (vehicle parking, bulb outs, speed humps, traffic diverters) could also improve these methods and deliver greater insight into how these features affect crash outcomes. Having more detailed data on bicycle lane width, on street vehicle parking, presence of medians and traffic calming devices not to mention more reliable data on observed speeds would all help to improve these models. The crash risk effect from bicycle lanes could be better assessed with more complete data but results presented in this report do not reveal an unequivocal crash risk reduction effect. The published research is mixed on the safety benefit of bicycle lanes with rigorous reviews like that of the Cochrane Library's *Cycling Infrastructure for Reducing Cycling Injuries in Cyclists* showing that more research should be completed to more rigorously document the impact of bicycle lanes. The above method uses a cross-sectional approach which is not ideal for understanding the safety impacts of a given infrastructure treatment FHWA 2013b).

The issue of showing the safety effectiveness of any bicycle infrastructure improvement is the fact that any improvement is likely to improve user's perception of safety and induce ridership. That's why controlling for non-motorized traffic is imperative but makes application of SPFs for EB adjusted expected crash frequencies tricky. This is not a phenomenon that appears in highway safety and represents an important element that future research needs to address.

The estimated coefficients lend further evidence to the inherent increase in risk that motorized traffic present to non-motorized road users. Across each model, increases in speed and vehicle volumes (or their proxies in functional classification) increased bicycle crash frequency and risk while increases in bicycle traffic demonstrated a consistent safety benefit with substantial decreases in crash risk and non-linear change in crash frequency. It's unclear how the

[4] FHWA Crash Modification Factor Clearinghouse - https://www.cmfclearinghouse.org/
[5] ODOT list of crash reduction factors - https://www.oregon.gov/ODOT/Engineering/Pages/ARTS.aspx

acknowledged underreporting of bicycle crashes would affect these estimates though it’s likely the relationships between these factors would remain consistent and overall frequencies of crashes and predicted crashes would increase.

6.0 HEALTH ANALYSIS

This following section will review relevant research related to the health benefits from physical activity and more specifically, travel by walking and riding a bicycle. Following this review will be a health impact analysis of the bicycle activity in the study region. The available evidence linking physical activity and reduction of many chronic diseases like heart disease, diabetes, and multiple types of cancer is unequivocal. There is considerable evidence linking bicycle and walking interventions to positive health outcomes though some uncertainty remains. Using the Integrated Transport and Health Impact Model (ITHIM), this section will demonstrate the health related benefits from the estimated bicycle activity in the CLMPO region and also report on the likely health care cost savings associated with reduced disease burden.

6.1 LITERATURE REVIEW OF HEALTH AND TRANSPORTATION

6.1.1 Health Impact and Physical Activity

In 1996 the US Surgeon General's report, *Physical Activity and Health* summarized evidence from a variety of studies to conclude that many chronic diseases and related health problems are associated with a lack of physical activity (CDC 1996). Since then, a significant amount of research has been done documenting the role physical activity can play in reducing the risk of developing, breast cancer (Monninkhof et al. 2007), colon cancer (Wolin et al. 2009), neurodegenerative disease (Hamer and Chida 2009), depression (Paffenbarger et al. 1994), as well as cardiovascular (Hamer and Chida 2008) and heart disease (Sattelmair et al. 2011). In a meta-analysis of data from seven studies, Kelly et al. (2015) found that if the if the recommendation of 100 minutes of moderate-intensity aerobic physical activity per week is met through bicycling, all-cause mortality is reduced by 10 percent.

6.1.2 Health Impacts and Active Travel

A number of studies have looked at the role of active commuting on health. In Mueller et al. (2015) 30 studies looking at the health impact of shifting driving trips to walking and bicycle trips finding that in 27 of those studies the benefits of increased physical activity outweighed the increased risks of traffic safety and air pollution exposure. In a recent study of over 250,000 people in the United Kingdom, researchers followed participants for up to 5 years and found that people who bicycled or bicycled and walked to work had lower risks of cardiovascular disease and cancer (Celis-Morales et al. 2017). In another study researchers looked the relationship between the percentage of workers that walk and bike to work and the percentage of adults that are obese or have diabetes. Findings from the study showed that for cities and states with higher proportion of active commuters were also places with less obesity and diabetes.

6.1.3 Health Impact Assessment and Health Impact Modeling

Health impact assessment (HIA) is a method to help decision makers understand the health-related implications of decisions across a variety of sectors. HIAs are becoming more common in transportation and land use decision making. Based on the CDC's online reporting system, over 130 land use or transport-related HIAs have been done in the US since 2006 (Pew).

Models that employ the established relationships between physical activity such as walking and bicycling and health outcomes have been implemented in a number of cases to help show the benefits of the provision of infrastructure and programs to support these activities. The Health Economic Assessment Tool (HEAT) developed by the World Health Organization (WHO) and first released in 2007 (WHO 2017). The tool incorporates established research to estimate the mortality risk reduction and related economic costs. In a number of studies (Mueller et al. 2015) have employed the HEAT tool to assess the impacts of walking and bicycle activity.

Another tool developed to assess the health impacts of the physical activity associated with walking and bicycle activity is the Integrated Transport and Health Impact Model (ITHIM). This tool uses a comparative risk assessment approach that utilizes established relationships between certain chronic diseases and exposure to variables like physical activity, air pollution and roadway crashes. For physical activity, ITHIM first converts time spent walking and biking into metabolic equivalent tasks (METs), a consistent unit of energy expenditure from exercise compared to sitting. Since its first deployment in 2009 to study the effects of greenhouse gas reduction strategies in London, England and New Delhi, India (Woodcock et al. 2009) the ITHIM tool has been deployed in numerous cities and regions throughout the US including San Francisco, California (Maizlish et al 2013), Nashville Tennessee (Whitfield et al 2017), Portland, Oregon (OHA, 2013) and once before in the current study area, Central Lane Metropolitan Planning Organization (CLMPO 2015).

ITHIM has been used to show how policies and programs aiming to decrease the amount of driving and increase walking and bicycle activity and subsequent physical activity change future health conditions of the population. Health conditions are measured using metrics commonly used in public health and include mortality and morbidity. Mortality is measured by estimating the number of premature deaths associated with a specific disease and morbidity is measured by disability adjusted life years (DALYs) (Murray 1994). DALYs are a measure of burden of disease. ITHIM works by comparing a base scenario with an alternative scenario and reports on the change in these outcomes between the two scenarios to show how the alternative scenario performs in terms of health outcomes.

The ITHIM tool also has a cost of illness (COI) module that uses population level cost estimates of different diseases to estimate the health care cost savings from modeled scenarios. Cost estimates are derived from the literature and include:

- Mariotto et al. (2011) – Cancer (breast, colon, rectum, and lung)
- Go et al. (2011) – Cardiovascular (Stroke and heart disease)
- Wimo et al. (2010) – Dementia

- Greenberg et al. (2003) – Depression
- ADA (2011) - Diabetes

Cost of illness approach aims to estimate the economic burden associated with a given illness using representative surveys of medical utilization such as the Medical Expenditure survey (Segel, 2006). Though the COI approach underestimates the full cost of illness, it accounts for the direct costs including professional services, hospital services, prescribed medications, and home health care. COI also accounts for indirect costs like lost productivity but does not include costs associated with pain and suffering nor does it include the value of a statistical life. All economic costs and benefits are in 2018 dollars after adjusting for inflation using the Bureau of Labor Statistics Consumer Price Index.

After ITHIM computes the disease burden the cost of illness is calculated by factoring the costs reported in the research to the change in attributable risk for the disease in the study area population. These costs are summed to report on the total cost of illness change compared to the base scenario. Cost of illness is an important part of communicating the health benefits of policy interventions as they put more health specific metrics like DALYs in monetary terms that practioners from other fields can more easily understand. Using ITHIM to compute health metrics including mortality and DALYs and cost of illness, the benefits of estimated bicycle activity in the study region will be summarized below.

6.2 IMPLEMENTATION OF ITHIM IN CENTRAL LANE MPO

ITHIM employs a method known as comparative risk assessment which was first applied by the WHO in 2000 as an element of the Global Burden of Disease Project (Haggerty and Hamburg, 2015). ITHIM uses inputs of travel activity including the number of miles per week of driving, walking, bicycling, and transit use as a measure of exposure for estimating health outcomes across a number of disease types. As straightforward as these inputs seem getting a complete picture of activity for walking and bicycling travel is not readily available. Travel models do well to produce the amount of driving and are well supported by traffic volume count programs. These methods are not tuned to producing reliable estimates of travel activity for people who bicycle however and thus the direct demand model documented in Section 4.0 above is utilized for this purpose.

ITHIM is set up to compare alternative scenarios against a base scenario in order to estimate the relative difference from changes in travel activity. For this implementation, a scenario where the estimated bike miles traveled (BMT) of 44 million miles (+/- 20.5 million) will be compared to a baseline scenario where zero bicycle miles are traveled and differences in mortality, morbidity and the cost of illness will be summarized. Because of the uncertainty in the BMT estimate, a lower and upper bounded estimate will also be provided to demonstrate the least and more likely benefit. A fourth scenario that uses the mid-point estimate of bike miles traveled on the off-street path system is also used to understand the health benefits of bicycle activity on this class of infrastructure.

6.2.1 Health Impact Results

Table 6.1 below summarizes the morbidity (DALY) and premature deaths (mortality) avoided due to the estimated bicycle activity in the study area. For the mid-point estimate of BMT, the total number of DALYs reduced is 241 with a large portion of those associated with a reduction in heart disease followed by diabetes, stroke, and depression. An estimated seven premature deaths were avoided due to the 44 million bicycle miles traveled in the study area with four of those deaths related to a reduction of heart disease followed by diabetes and stroke.

Table 6.1 – Mortality and Illness Change from Bicycle Activity in CLMPO

Health Outcome	Mid-point BMT Estimate		Lower Bound BMT Estimate		Upper Bound BMT Estimate		Off-Street Path System Only	
	DALY	Mortality	DALY	Mortality	DALY	Mortality	DALY	Mortality
Breast Cancer	-2	-0	-1	-0	-4	-0	-0	0
Colon Cancer	-2	-0	-1	-0	-4	-0	-0	-0
Stroke	-39	-1	-22	-1	-59	-2	-11	-0
Ischemic Heart Disease	-86	-4	-49	-2	-126	-6	-25	-1
Depression	-24	-0	-12	-0	-36	-0	-4	-0
Dementia	-6	-0	-3	-0	-13	-1	-1	-0
Diabetes	-78	-2	-44	-1	-112	-2	-23	-0
Hypertensive Heart Disease	-4	-0	-2	-0	-5	-0	-1	-0
Total Physical Activity Health Benefit	-241	-7	-134	-4	-359	-12	-66	-2

The bicycle activity on the off-street bicycle system is estimated to reduce DALYs by 66 per year with a decrease in mortality of two per year.

6.2.2 Cost of Illness Results

The table below shows the estimated health care costs savings by the reduction in disease burden from bicycle activity in the study area. The cost of illness (COI) results using the mid-point estimate of BMT is just over $14 million annually with the largest cost savings from diabetes reduction followed by heart disease and stroke. The COI estimates for the off-street path system bicycle activity is nearly $4 million annually.

Table 6.2 – Cost of Illness by Disease

Condition	Mid-point Estimate BMT	Lower Bound Estimate BMT	Upper Bound Estimate BMT	Off-Street Path System Only
Cancer				
Breast	-74,903	-39,071	$ (148,750)	-$5,151
Colon and rectum cancer	-154,568	-81,512	$ (255,393)	-$32,869
Cardiovascular				
Stroke	-975,951	-544,706	$ (1,483,830)	-$275,366
Heart disease	-5,712,990	-3,221,017	$ (8,352,153)	-$1,687,395
Mental Illness				
Dementia	-376,745	-197,355	$ (784,226)	-$37,698
Depression	-655,416	-344,828	$ (988,653)	-$117,769
Other				
Diabetes	-6,051,273	-3,400,665	$ (8,729,558)	-$1,766,745
Total Disease Cost Savings	**-14,001,848**	**-7,829,154**	**-20,742,562**	**-3,922,994**

6.2.3 Summary of Health Impact Analysis

The health impact analysis results presented above included the health outcomes and associated costs of illness but does not include the cost of bicycle crashes. A summary of the COI and roughly $4.5 million in bicycle crash related to fatal and severe injuries is included in Table 6.3 below. Even after adding the costs of fatal and severe bicycle crashes to the COI estimates an overall benefit remains with nearly $9.5 million in savings using the mid-point estimate. Even the lower bound estimate of bicycle activity and associated health and cost outcomes is considered, a considerable economic benefit of $3.3 million accrued annually. These results are further summarized graphically in Figure 6.1 below.

Table 6.3 – Summary of Bicycle Activity, Health Measures, and Cost Savings

Measure	Bicycle Activity (Miles)		Health Measures		Annual Health Care Costs Savings*
	Annual (Millions)	Weekly	DALY	Deaths Avoided	
Total System	44.1	3.5	222	6	$ 9,474,847
Lower Bound	64.6	5.1	125	4	$ 3,302,153
Upper Bound	23.5	1.8	316	10	$ 16,215,562
Off-street Path System	7.7	0.6	65	2	$ 3,922,993

*Includes $4.5 Million in Bike Crash Costs

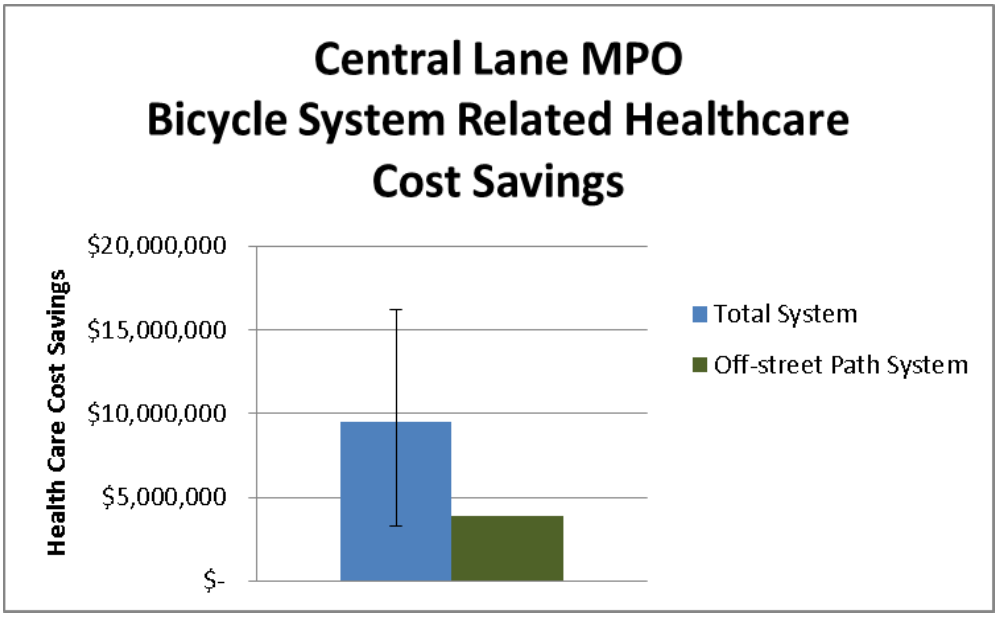


Figure 6.1: Bicycle system related health care cost savings summary

6.3 SUMMARY OF HEALTH IMPACT ANALYSIS

The above section utilizes the ITHIM tool to estimate the health benefits and associated cost savings related to 44 million bike miles traveled in the study region. The results show a significant impact at the population level on reducing certain chronic diseases like heart disease, diabetes, and stroke. The healthcare costs associated with these diseases are also reduced and represent a significant savings for the region, adding up to at least $78 million over 10 years.

Reducing health care costs related to chronic disease has been recognized as an important part of reducing overall health care spending (Brookings 2013). Health care spending now accounts for nearly 18% of the U.S. gross domestic product, or about $3.3 trillion annually (CMS 2016). On a per capita basis these costs are nearly twice the other countries in the developed world such as Britain and Germany (OECD 2018). These high costs make the U.S. worker less competitive, adding costs to the products and services produced in the U.S. and driving firms to seek workers elsewhere. Getting the prescribed physical activity through everyday activities like bicycling to work can be an important part of reducing these costs.

7.0 CONCLUSION AND LIMITATIONS

7.1 CONCLUSION

The above report details and summarizes five important elements related to bicycle transportation planning and policy including data collection strategies, annualizing daily counts, estimating system wide traffic activity, crash analysis, and health impacts of bicycle activity. Bicycle count programs are becoming more common in cities and states in the US but practioners are stills struggling to understand how to collect data and more importantly what it can be used for and what those processes look like. Four of the five sections of this report showcase the importance of data by revealing important lessons the traffic data informs either directly, or indirectly through more advanced analyses. Hopefully this report will be used to make the case for additional investment in data collection for non-motorized traffic so that even greater understanding of these modes of travel can be generated comparing cities, regions and states to one another and merging with other data sources to better inform practice and policy.

This research report shows for the first time the total amount of bicycle activity (in miles) for the study region. It uses that estimation to show a large disparity between motorized transport injury crash rates and bicycle-injury crashes and shows where risk is higher through a macro-level view. Combining estimates of bicycle traffic and detailed crash information, the report employs a data driven analytical approach to estimate safety performance functions and then applies those functions to the network to highlight areas of concern that likely require further investigation. The results of the bicycle activity estimation are used to quantify the health benefits for the study region, demonstrating the number of chronic disease avoided and a number of premature deaths eluded. Finally, the health care cost savings of these avoided negative health outcomes is presented, showing large economic benefits that would likely offset the investments in bicycle infrastructure that have been made over the decades,

7.2 LIMITATIONS

This research presents a number of outcomes that are less than perfect and observance of these limitations can help make future products and processes better. The flowing sub-sections attempts to reveal these limitations in an open and honest way.

7.2.1 Bicycle Traffic Data

The bicycle count program that guides the bicycle traffic data collection has multiple objectives. These objectives make random selection of locations improbable and introduce a measure of bias to the resulting models. Locations with known bicycle travel activity which means no daily counts of zero bicyclists exist in the observed data. Though efforts are underway to collect data on less traveled streets and off-street facilities, it is unlikely that the count program would choose to divert resources to count locations with no bicycle travel. One way this impacts the final BMT estimates is the resulting amounts of small daily bicycle volumes on local streets with low population and employment densities. There is likely some bicycle activity on these facilities throughout the year but these estimates are probably biased upwards. Depending on the use of the BMT estimates they might matter one way or the other. For instance if the BMT estimates are used for health impact assessment the health benefits would be overstated. If bicycle crash rates were calculated (with crashes as the numerator and the BMT as the denominator) the rate would be lower than it would had this bias not existed.

Another limitation in the data is that bicycle ridership on sidewalks is neither included nor estimated. The CLMPO bicycle count program has collected counts on sidewalks and as a proportion of total bicycle volume on a given roadway segment, can be as high as 30%. This means that the estimates provided as a part of this model system would be underestimating the actual bicycle travel activity.
It should be pointed out again that though no data was collected on major arterials estimates were derived for these facility types using the assumption that major arterials would perform similar to minor arterials. Depending on the use of the final estimates this assumption may be reasonable. The bicycle volumes are not likely to be higher than what this assumption would imply, however these facility types would probably exhibit sidewalk travel due to their relatively high level of stress for people riding bicycles. Current counting technology makes counting on major arterials very difficult but data collection programs should aim to collect at these types of locations when devices allow.

Another limitation with the bicycle traffic data relates to the devices used to record the bicycle traffic volumes. These devices are also known to undercount bicycle traffic (ODOT 2016, NCHRP). The devices used to collect bicycle traffic for this research are Eco Counter tube counters and have a manufacturer acknowledged undercount rate of at least 3% but perhaps as much as 5%. This under count rate grows as traffic volumes increase and the likelihood of large groups of bicyclist using counted facilities grows since occlusion, or counting each rider in a pack is a source of much of the undercounting. The other source is occlusion on mixed traffic count sites where vehicles and bicycles both travel. Careful placement of the devices is important for accurate bicycle counts.

Another limitation is the lack of a significant variable in any of the models for precipitation. Past research has found precipitation to be a significant variable negatively correlated with bicycle traffic (Hankey 2012). One hypothesis for precipitation not being a significant variable in the models estimated for this research is that there was not enough observed variation in precipitation patterns across the different day types and university in session variables. Without this variable it’s possible the estimated daily bicycle volumes are biased upward.

7.2.2 Limits of Direct Demand Models

The use of direct demand models for bicycle traffic estimation is not novel and has been in place for vehicle traffic for decades. It’s a less common approach in vehicle traffic simulation because of the lack of policy and project testing this approach allows. Forecasting future volumes is possible with this approach but the results would need to be carefully understood to not make incorrect inferences from the calculations. This model approach does not yield insights into the socio-demographics of the bicycle activity and so leaved transportation options practioners without needed information that could be used to target communities not bicycling currently.

7.2.3 Precision of Bicycle Traffic Activity Estimates

It is desirable to have more precision in both the aggregate and link level bicycle volume estimates. Due to higher than desirable standard errors in the model estimation, precision of the final estimates contain uncertainty greater than is desirable. Some of this is due to the low number of observed data used in the model estimation. In the future this may be alleviated by increased availability of counts data. Users of these estimates will have to use judgement when employing this information in practice. If the aggregate BMT estimate is used for monitoring total bicycle activity from one year to the next, these methods will have to be improved as year to year changes are likely in the 0-10% range which would be within the upper and lower limit estimates and thus be undetected. However, if a point estimate is required for a given street segment, and the practioner is okay with an estimate of daily bicycle travel of between 100 and 400 daily bicyclists these methods can be useful in practice.

7.2.4 Implications for Data Collection

The research presented in this report should give count program managers looking to do more in-depth analysis of their count data some direction in how they collect data. Many demands are placed on counting programs for any mode and bicycle and pedestrian count programs are not different. Practioners many times want to count in locations they know bicycle travel occurs or may want to be collecting on a newly finished or soon to be finished bicycle facility upgrade project. Bridges are often times counted because they are good bottlenecks that ensure all the traffic headed to certain destinations like a downtown are captured and recorded. Though these motives are reasonable count program managers should take care to collect on a variety of street designs with a diversity in functional classifications and bicycle facility types at varying levels of accessibility to population and employment. Further, many count programs desire counts to be comparable from year to year and so collect data only in a given season like in the spring during decent riding weather. If more detailed analysis of the non-motorized count data is required, it's likely that other times of the year will need to be utilized to perform data collection. The seasonal variation of the counts data is useful in its own right as it helps to establish the kinds of user types at a given location.

7.2.5 Crash Analysis

A primary limitation of the crash analyses is the uncertainty in the bicycle traffic estimates. Whereas the high level rate calculation shows the upper and lower estimated of BMT the safety performance function development only uses the mid-point estimates. Additionally number of crashes available for analysis does not meet the FHWA's guidance (FHWA 2013c) where it is directed that 300 crashes per year be used in the development process. Without meeting this threshold it is likely that additionally uncertainty is added to the results presented in this report. Meeting this threshold will be difficult for any medium sized urban area since bicycle crashes are relatively infrequent.

The crash analysis does not include all bicycle crashes and underreporting of non-motorized crashes is expected for any crash database. It's not clear how this underreporting would impact the results. If the underreporting is uniform across the network then the safety performance functions are likely just underestimating total crashes. If for some reason underreporting is more common on one facet of the network or in one part of town (like the university area) this could have implications for the performance of the crash analysis. The crash analysis, like the inputs for the direct demand model, could use better data on vehicle traffic and speeds, and design features. Currently the impact on bicycle crashes of certain design features like the number of lanes, or presence of street parking or median not known and could represent omitted variable bias into the results. The current results are still useful, but more comprehensive results could be derived with more complete data.

7.2.6 Health Analysis

The results presented in the health analysis should be viewed as indicative not necessarily empirical. The global burden of disease information used as the basis of the base line risk ratios are for urban counties throughout Oregon and were pooled because a single county has too few cases of many disease types to be statistically significant. The health care costs are estimates helpful to inform decision maker's understanding of the potential benefits from existing and future changes that would increase the amount of bicycle activity. These estimates would likely not hold up to an actuary or other financial analyst though they would be helpful starting place.

8.0 REFERENCES

American Diabetes Association. (2013). Economic Costs of Diabetes in the U.S. in 2012. *Diabetes Care*, *36*(4), 1033–1046. Doi:10.2337/dc12-2625

AMEC E&I, Inc. Sprinkle Consulting, Inc. (2011). *Pedestrian and Bicycle Data Collection*(Publication No. DTFH61-11-F-00031). Federal Highway Administration; U.S. Department of Transportation. Retrieved from https://www.fhwa.dot.gov/policyinformation/travel_monitoring/pubs/pedbikedata.pdf .

Aoun, A., Bjornstad, J., DeBose, B., Mitman, M., & Pelon, M. (2015). *Bicycle and Pedestrian Forecasting Tools: State of the Practice* (pp. 1-28, Publication No. DTFHGI-11-H-00024). Chapel Hill, NC: Pedestrian and Bicycle Information Center. Retrieved November, 2017, from https://www.pedbikeinfo.org/cms/downloads/PBIC_WhitePaper_Forecasting.pdf

Barnett, J. S. (2015). *On the Estimation of Volumes of Roadways: An Investigation of Stop-Controlled Minor Legs* (Master's thesis, Portland State University, 2015). Portland. doi:10.15760/etd.2193

Barnett, S. B., & Nurmagambetov, T. A. (2011). Costs of asthma in the United States: 2002-2007. *Journal of Allergy and Clinical Immunology, 127*(1), 145-152. doi:10.1016/j.jaci.2010.10.020

Behnam, J., & Patel, B. G. (1977). *A Method for Estimating Pedestrian Volume in a Central Business District* (Vol. 629, pp. 22-26, Publication No. 00173101). Committee on Pedestrians.

Beck, L. F., Dellinger, A. M., & O'Neil, M. E. (2007). Motor Vehicle Crash Injury Rates By Mode Of Travel, United States: Using Exposure-Based Methods To Quantify Differences. *American Journal of Epidemiology*, *166*(2), 212-218. doi:10.1093/aje/kwm064

Board, T. R., National Academies of Sciences, E., & Medicine. (2014). *Methods and Technologies for Pedestrian and Bicycle Volume Data Collection*. Washington, DC: The National Academies Press.

Board, T. R., National Academies of Sciences, E., & Medicine. (2015). *Pedestrian and Bicycle Transportation Along Existing Roads—ActiveTrans Priority Tool Guidebook.* Washington, DC: The National Academies Press.

Broach, J., Gliebe, J., & Dill, J. (2009). *Development of a Multi-class Bicyclist Route Choice Model Using Revealed Preference Data* (pp. 1-31, Publication). Portland, OR: Portland State University.

Brüde, U., & Larsson, J. (1993). Models for predicting accidents at junctions where pedestrians and cyclists are involved. How well do they fit? *Accident Analysis & Prevention, 25*(5), 499-509. doi:10.1016/0001-4575(93)90001-d

Centers for Medicare and Medicaid Services. (2016). *National Health Care Spending in 2016* (pp. 126-128, Publication). Baltimore, MD: National Health Expenditure Accounts. Retrieved May, 2018, from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/highlights.pdf .

Central Lane Metropolitan Planning Organization. (n.d.). Commute Mode Shares. Retrieved October, 2016, from https://www.thempo.org/905/Commute-Mode-Share

Celis-Morales, C. A., Lyall, D. M., Welsh, P., Anderson, J., Steell, L., Guo, Y., . . . Gill, J. M. (2017). Association between active commuting and incident cardiovascular disease, cancer, and mortality: Prospective cohort study. *Bmj, 357*(J1456). doi:10.1136/bmj.j1456

Cheng, W., & Washington, S. (2008). New Criteria for Evaluating Methods of Identifying Hot Spots. *Transportation Research Record: Journal of the Transportation Research Board, 2083*, 76-85. doi:10.3141/2083-09

Digioia, J., Watkins, K. E., Xu, Y., Rodgers, M., & Guensler, R. (2017). Safety impacts of bicycle infrastructure: A critical review. *Journal of Safety Research, 61*, 105-119. doi:10.1016/j.jsr.2017.02.015

Esawey, M. E. (2016). Toward a Better Estimation of Annual Average Daily Bicycle Traffic. *Transportation Research Record: Journal of the Transportation Research Board, 2593*, 28-36. doi:10.3141/2593-04

Esawey, M. E., Lim, C., Sayed, T., & Mosa, A. I. (2013). Development of Daily Adjustment Factors for Bicycle Traffic. *Journal of Transportation Engineering, 139*(8), 859-871. doi:10.1061/(asce)te.1943-5436.0000565

Elvik, R. (2007). *State-of-the-art approaches to road accident black spot management and safety analysis of road networks* (pp. 1-108, Publication No. 883/2007). Oslo, Norway: Institute of Transport Economics Norwegian Centre for Transport Research.

Elvik, R. (2008). Comparative Analysis of Techniques for Identifying Locations of Hazardous Roads. *Transportation Research Record: Journal of the Transportation Research Board, 2083*, 72-75. doi:10.3141/2083-08

Elvik, R., & Bjørnskau, T. (2017). Safety-in-numbers: A systematic review and meta-analysis of evidence. *Safety Science, 92*, 274-282. doi:10.1016/j.ssci.2015.07.017

Federal Highway Administration (FHWA). (2013a). *Traffic monitoring guide*. Washington, D.C.: U.S. Dept. of Transportation, Federal Highway Administration.

Federal Highway Administration (FHWA). (2013b). *Introduction to crash modification factors*. Washington, D.C.: U.S. Department of Transportation, Federal Highway Administration.

Federal Highway Administration (FHWA). (2013c). *Safety Performance Function Decision Guide: SPF Calibration versus SPF Development.* Washington, D.C.: U.S. Department of Transportation, Federal Highway Administration.

Figliozzi, M., Monsere, C., Nordback, K., Johnson, P., & Blanc, B. (2014). *Design and Implementation of Pedestrian and Bicycle-Specific Data Collection Methods in Oregon* (pp. 1-123, Publication No. FHWA-OR-RD-14-15). Salem, OR: Oregon Department of Transportation. Retrieved from https://www.oregon.gov/ODOT/Programs/ResearchDocuments/SPR754_Ped_and_Bicycle.pdf

Gadda, S., Magoon, A., Kockelman, K., & Murray, W. (2006). *Estimates of Aadt: Quantifying the Uncertainty* (Publication).

Gastaldi, M., Rossi, R., Gecchele, G., & Lucia, L. (2013). *Annual Average Daily Traffic estimation from Seasonal Traffic Counts* (Vol. 87, pp. 279-291, Publication). New York City, NY: Elsevier. doi:10.1016/j.sbspro.2013.10.610

Gecchele, G., Rossi, R., Gastaldi, M., & Kikuchi, S. (2012). Advances in Uncertainty Treatment in FHWA Procedure for Estimating Annual Average Daily Traffic Volume. *Transportation Research Record: Journal of the Transportation Research Board, 2308*, 148-156. doi:10.3141/2308-16

Go, A. S., Mozaffarian, D., Roger, V. L., Benjamin, E. J., Berry, J. D., Blaha, M. J., . . . Turner, M. B. (2013). Heart Disease and Stroke Statistics—2014 Update. *A Report From the American Heart Association*. doi:10.1161/01.cir.0000441139.02102.80

Green, M., Douglas, J. P., Main, E., Early-Alberts, J., Hamberg, A., & Dubuisson, N. (2013). *Climate Smart Communities Scenarios: Health Impact Assessment* (pp. 1-64, Publication). Salem, OR: Oregon Health Authority. Retrieved May, 2018, from https://www.oregon.gov/oha/ph/HealthyEnvironments/TrackingAssessment/HealthImpactAssessment/Documents/CSCS/FINAL_Climate Smart Communities Scenarios.pdf

Greenberg, P. E., Kessler, R. C., Birnbaum, H. G., Leong, S. A., Lowe, S. W., Berglund, P. A., & Corey-Lisle, P. K. (2003). The Economic Burden of Depression in the United States. *The Journal of Clinical Psychiatry, 64*(12), 1465-1475. doi:10.4088/jcp.v64n1211

Haggerty, B., & Hamberg, A. (2015, June). Transportation Options Health Impact Estimator User Guide. Oregon Health Impact Assessment Program.

Hakkert, A., & Braimaister, L. (2002). *The Uses of Exposure and Risk in Road Safety Studies* (pp. 1-56, Publication No. R-2002-12). The Hague, Netherlands: SWOV, Leidschendam.

Hamer, M., & Chida, Y. (2008). Physical activity and risk of neurodegenerative disease: A systematic review of prospective evidence. *Psychological Medicine, 39*(01), 3-11. doi:10.1017/s0033291708003681

Hamer, M., & Chida, Y. (2008). Active commuting and cardiovascular risk: A meta-analytic review. *Preventive Medicine*, *46*(1), 9-13. doi:10.1016/j.ypmed.2007.03.006

Hankey, S., & Lindsey, G. (2016). Facility-Demand Models of Peak Period Pedestrian and Bicycle Traffic. *Transportation Research Record: Journal of the Transportation Research Board, 2586*, 48-58. doi:10.3141/2586-06

Hankey, S., Lindsey, G., & Marshall, J. (2014). Day-of-Year Scaling Factors and Design Considerations for Nonmotorized Traffic Monitoring Programs. *Transportation Research Record: Journal of the Transportation Research Board, 2468,* 64-73. doi:10.3141/2468-08

Hankey, S., Lindsey, G., Wang, X., Borah, J., Hoff, K., Utecht, B., & Xu, Z. (2012). Estimating use of non-motorized infrastructure: Models of bicycle and pedestrian traffic in Minneapolis, MN. *Landscape and Urban Planning*, *107*(3), 307-316. doi:10.1016/j.landurbplan.2012.06.005

Hauer, E., Harwood, D., Council, F., & Griffith, M. (2002). Estimating Safety by the Empirical Bayes Method: A Tutorial. *Transportation Research Record: Journal of the Transportation Research Board, 1784,* 126-131. doi:10.3141/1784-16

Health Impact Assessments in the United States. (n.d.). Retrieved May 1, 2018, from https://www.pewtrusts.org/en/multimedia/data-visualizations/2015/hia-map

Kelly, P., Kahlmeier, S., Götschi, T., Orsini, N., Richards, J., Roberts, N., . . . Foster, C. (2014). Systematic review and meta-analysis of reduction in all-cause mortality from walking and cycling and shape of dose response relationship. *International Journal of Behavioral Nutrition and Physical Activity, 11*(1), 132. doi:10.1186/s12966-014-0132-x

Kuzmyak, J. R., Walters, J., Bradley, M. A., & Kockelman, K. (2014). *Estimating bicycling and walking for planning and project development: A guidebook.* Washington, D.C.: Transportation Research Board. doi:10.17226/22330

Lindsey, G., Wilson, J., Rubchinskaya, E., Yang, J., & Han, Y. (2007). Estimating urban trail traffic: Methods for existing and proposed trails. *Landscape and Urban Planning, 81*(4), 299-315. doi:10.1016/j.landurbplan.2007.01.004

Maizlish, N., Woodcock, J., Co, S., Ostro, B., Fanai, A., & Fairley, D. (2013). Health Cobenefits and Transportation-Related Reductions in Greenhouse Gas Emissions in the San Francisco Bay Area. *American Journal of Public Health, 103*(4), 703-709. doi:10.2105/ajph.2012.300939

Mariotto, A. B., Robin Yabroff, K., Shao, Y., Feuer, E. J., & Brown, M. L. (2011). Projections of the Cost of Cancer Care in the United States: 2010–2020. *JNCI Journal of the National Cancer Institute*, *103*(2), 117–128. Doi: 10.1093/jnci/djq495

Minge, E., Falero, C., Lindsey, G., Petesch, M., & Vorvick, T. (2017). *Bicycle and Pedestrian Data Collection Manual* (pp. 1-111, Publication No. MN/RC 2017-03). St. Paul, MN: Minnesota Department of Transportation. Retrieved from https://www.dot.state.mn.us/research/reports/2017/201703.pdf

Miranda-Moreno, L., Nosal, T., Schneider, R., & Proulx, F. (2013). Classification of Bicycle Traffic Patterns in Five North American Cities. *Transportation Research Record: Journal of the Transportation Research Board*, *2339*, 68-79. doi:10.3141/2339-08

Miranda-Moreno, L., Strauss, J., & Morency, P. (2011). Disaggregate Exposure Measures and Injury Frequency Models of Cyclist Safety at Signalized Intersections. *Transportation Research Record: Journal of the Transportation Research Board, 2236*, 74-82. doi:10.3141/2236-09

Mohamad, D., Sinha, K., Kuczek, T., & Scholer, C. (n.d.). Annual Average Daily Traffic Prediction Model for County Roads. *Transportation Research Record: Journal of the Transportation Research Board, 1617*, 69-77. doi:10.3141/1617-10

Monninkhof, E. M., Elias, S. G., Vlems, F. A., van der Tweel, I., Schuit, A. J., Voskuil, D. W., . . . TFPAC, o. b. o. (2007). Physical Activity and Breast Cancer: A Systematic Review. *Epidemiology, 18*(1), 137-157. doi:10.1097/01.ede.0000251167.75581.98

Monsere, C., Wang, H., Wang, Y., & Chen, C. (2017). *Risk Factors for Pedestrians and Bicycle Crashes* (pp. 1-99, Publication No. FHWA-OR-RD-17-13). Salem, OR: Oregon Department of Transportation. Retrieved from https://www.oregon.gov/ODOT/Programs/ResearchDocuments/SPR779_BikePedRisk.pdf

Mueller, N., Rojas-Rueda, D., Cole-Hunter, T., de Nazelle, A., Dons, E., Gerike, R., . . . Nieuwenhuijsen, M. (2015). Health impact assessment of active transportation: A systematic review. *Preventive Medicine*, *76*, 103-114. doi: 10.1016/j.ypmed.2015.04.010

Mulvaney, C. A., Smith, S., Watson, M. C., Parkin, J., Coupland, C., Miller, P., . . . Mcclintock, H. (2015). Cycling infrastructure for reducing cycling injuries in cyclists. *Cochrane Database of Systematic Reviews*. doi:10.1002/14651858.cd010415.pub2

Munro, C. (2013). *Evaluation of automatic cyclist counters* (pp. 1-108, Publication No. 0030). Retrieved from https://bicyclecouncil.com.au/files/research/EvaluationOfAutomaticCyclistCounters.pdf

Murray, C.,J., L *Quantifying the burden of disease: the technical basis for disability-adjusted life years.* WHO Bulletin OMS. Vol. 72. 1994.

Nordback, K., Marshall, W. E., & Janson, B. N. (2014). Bicyclist safety performance functions for a U.S. city. *Accident Analysis & Prevention, 65*, 114-122. doi:10.1016/j.aap.2013.12.016

Nordback, K., Marshall, W., Janson, B., & Stolz, E. (2013). Estimating Annual Average Daily Bicyclists. *Transportation Research Record: Journal of the Transportation Research Board, 2339*, 90-97. doi:10.3141/2339-10

Nordback, K., Sirisha, K., Figliozzi, M., Phillips, T., Gorecki, C., & Schrope, A. (2016). *Investigation of Bicycle and Pedestrian Continuous and Short Duration Count Technologies in Oregon* (pp. 1-154, Publication No. FHWA-OR-RD-16-15). Salem, OR: Oregon Department of Transportation.

Nosal, T., Miranda-Moreno, L., & Krstulic, Z. (2014). Incorporating Weather. *Transportation Research Record: Journal of the Transportation Research Board, 2468*, 100-110. doi:10.3141/2468-12

Oregon Department of Transportation. (n.d.). Welcome Page. Retrieved October, 2016, from https://www.oregon.gov/ODOT/TD/TDATA/Pages/tsm/hpms.aspx

Organisation for Economic Co-operation and Development. (n.d.). Health resources - Health spending - OECD Data. Retrieved May, 2018, from https://data.oecd.org/healthres /health-spending.htm

Paffenbarger, R. S., Lee, I., & Leung, R. (1994). Physical activity and personal characteristics associated with depression and suicide in American college men. *Acta Psychiatrica Scandinavica,89*(S377), 16-22. doi:10.1111/j.1600-0447.1994.tb05796.x

Park, J., Abdel-Aty, M., Lee, J., & Lee, C. (2015). Developing crash modification functions to assess safety effects of adding bike lanes for urban arterials with different roadway and socio-economic characteristics. *Accident Analysis & Prevention, 74*, 179-191. doi:10.1016/j.aap.2014.10.024

Patel, K. (2017, May 10). Containing Health Care Costs: Recent Progress and Remaining Challenges. Retrieved May, 2018, from https://www.brookings.edu/testimonies /containing-health-care-costs-recent-progress-and- remaining-challenges/

Persaud, B., Lyon, C., & Nguyen, T. (1999). Empirical Bayes Procedure for Ranking Sites for Safety Investigation by Potential for Safety Improvement. *Transportation Research Record: Journal of the Transportation Research Board, 1665*, 7-12. doi:10.3141/1665-02

Pucher, J., & Dijkstra, L. (2003). Promoting Safe Walking and Cycling to Improve Public Health: Lessons From The Netherlands and Germany. *American Journal of Public Health, 93*(9), 1509-1516. doi:10.2105/ajph.93.9.1509

Roll, J. F. (2013). *Bicycle Traffic Count Factoring: An Examination of National, State and Locally Derived Daily Extrapolation Factors* (Master's thesis, Portland State University, 2013). Portland.

Roll, J., & Adkisson, L. (2015). *Central Lane Scenario Planning HIA: A Health Impact Assessment of Regional Health Impacts and Related Cost Savings from Greenhouse Gas Reductions. Lane County Public Health* (Rep.). OR: Lane County Public Health. Retrieved May, 2018, from https://www.oregon.gov/oha/ph/HealthyEnvironments/TrackingAssessment/HealthImpactAssessment/Documents/Central Lane HIA.pdf

Roll, J. F., & Proulx, F. R. (2018). *Estimating Annual Average Daily Bicycle Traffic Without Permanent Counter Stations* (pp. 1-15, Publication No. 18-05673). Eugene, OR. Retrieved from https://trid.trb.org/view/1496894

Sattelmair, J., Pertman, J., Ding, E. L., Kohl, H. W., 3rd, Haskell, W., & Lee, I. M. (2011). Dose response between physical activity and risk of coronary heart disease: a meta-analysis. *Circulation, 124*(7), 789-795. doi:10.1161/circulationaha.110.010710

Schoner, J. E., & Levinson, D. M. (2014). The missing link: bicycle infrastructure networks and ridership in 74 US cities. *Transportation, 41*(6), 1187-1204. doi:10.1007/s11116-014-9538-1

Segel, J. E. (2006). *Cost-of-Illness Studies - A Primer* (pp. 1-36, Publication). RTI International. Retrieved from https://pdfs.semanticscholar.org/3bbf/0a03079715556ad816a25ae9bf232b45f2e6.pdf .

Sharma, S. C., Gulati, B. M., & Rizak, S. N. (1996). Statewide Traffic Volume Studies and Precision of AADT Estimates. *Journal of Transportation Engineering, 122*(6), 430-439. doi:10.1061/(asce)0733-947x(1996)122:6(430)

Shinar, D., Valero-Mora, P., van Strijp-Houtenbos, M., Haworth, H., Schramm, A.De Bruyne, G…Tzamalouka, G. (2018). Under-reporting bicycle accidents to police in the COST TU101 international survey: Cross-country comparisons and associated factors. *Accident Analysis and Prevention*. 110, 177-186. doi:(https://linkinghub.elsevier.com/retrieve/pii/S0001457517303391

Souleyrette, R. R., Howell, B. K., Green, E. R., & Staats, W. N. (2016). *Estimation of Average Daily Traffic on Local Roads in Kentucky* (Vol. 1549, pp. 1-69, Publication No. KTC-16-13/FRT201-15-1F). Lexington, KY: Kentucky Transportation Center. doi:10.13023/KTC.RR.2016.13

Staats, W. N., & Souleyrette, R. R. (2016). *Estimation of annual average daily traffic on local roads in Kentucky* (Unpublished master's thesis). University of Kentucky. doi:10.13023/ETD.2016.066

Teschke, K., Harris, M., Reynolds, C., Shen, H., Cripton, P., & Winters, M. (2013). Exposure-based Traffic Crash Injury Rates by Mode of Travel in British Columbia. *Can J Public Health, 104*(1), e75-e79. doi:10.17269/cjph.104.3621

Thomas, L., Lan, B., Sanders, R. L., Frackelton, A., Gardner, S., & Hintze, M. (2017). Changing the Future? *Transportation Research Record: Journal of the Transportation Research Board, 2659*, 212-223. doi:10.3141/2659-23

Tsapakis, I., William Schneider, I., Bolbol, A., & Skarlatidou, A. (2011). Discriminant Analysis for Assigning Short-Term Counts to Seasonal Adjustment Factor Groupings. *Transportation Research Record: Journal of the Transportation Research Board, 2256*, 112-119. doi:10.3141/2256-14

Turner, S., Wood, G., Hughes, T., & Singh, R. (2011). Safety Performance Functions for Bicycle Crashes in New Zealand and Australia. *Transportation Research Record: Journal of the Transportation Research Board, 2236*, 66-73. doi:10.3141/2236-08

Vandenbulcke, G., Thomas, I., & Panis, L. I. (2014). Predicting cycling accident risk in Brussels: A spatial case–control approach. *Accident Analysis & Prevention, 62*, 341-357. doi:10.1016/j.aap.2013.07.001

Vickerman, R. W. (1974). Accessibility, Attraction, and Potential: A Review of Some Concepts and Their Use in Determining Mobility. *Environment and Planning A: Economy and Space, 6*(6), 675-691. doi:10.1068/a060675

Wachs, M., & Kumagai, T. (1973). Physical accessibility as a social indicator. *Socio-Economic Planning Sciences, 7*(5), 437-456. doi:10.1016/0038-0121(73)90041-4

Wang, J., Hankey, S., Wu, X., & Lindsey, G. (2016). Monitoring and Modeling of Urban Trail Traffic. *Transportation Research Record: Journal of the Transportation Research Board, 2593*, 47-59. doi:10.3141/2593-06

Wang, X., Lindsey, G., Hankey, S., & Hoff, K. (2014). Estimating Mixed-Mode Urban Trail Traffic Using Negative Binomial Regression Models. *Journal of Urban Planning and Development,140*(1), 04013006. doi:10.1061/(asce)up.1943-5444.0000157

Whitfield, G. P., Meehan, L. A., Maizlish, N., & Wendel, A. M. (2017). The integrated transport and health impact modeling tool in Nashville, Tennessee, USA: Implementation steps and lessons learned. *Journal of Transport & Health, 5*, 172-181. doi:10.1016/j.jth.2016.06.009

Wimo, A., Jonsson, L., Bond, J., Prince, M., & Winblad, B. (2013). The worldwide economic impact of dementia 2010. *Alzheimers Dement, 9*(1), 1-11.e13. doi:10.1016/j.jalz.2012.11.006

Wolin, K. Y., Yan, Y., Colditz, G. A., & Lee, I.-M. (2009). Physical activity and colon cancer prevention: a meta-analysis. *British Journal of Cancer, 100*(4), 611–616. DOI: 10.1038/sj.bjc.6604917

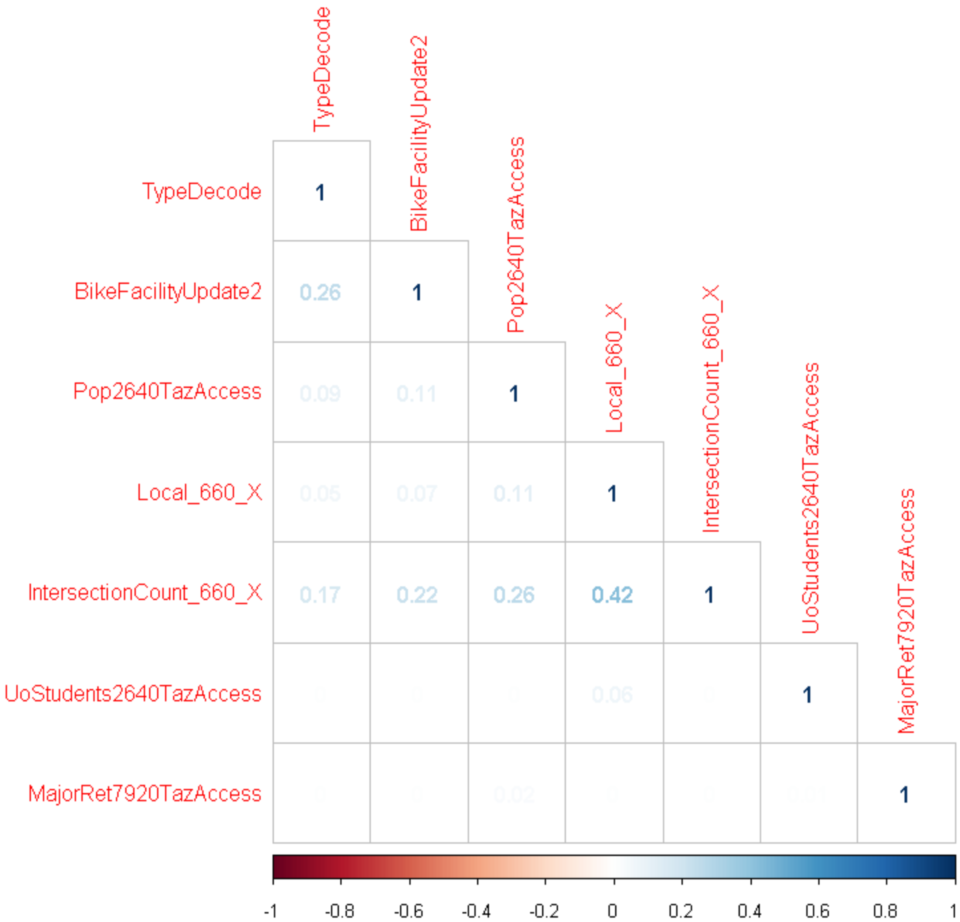
Woodcock, J., Edwards, P., Tonne, C., Armstrong, B. G., Ashiru, O., Banister, D., . . . Roberts, I. (2009). Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. *The Lancet, 374*(9705), 1930-1943. doi:10.1016/S0140-6736(09)61714-1

World Health Organization. (n.d.). HEAT 4.0; Health Economic Assessment Tool. Retrieved May, 2018, from https://www.heatwalkingcycling.org/#homepage

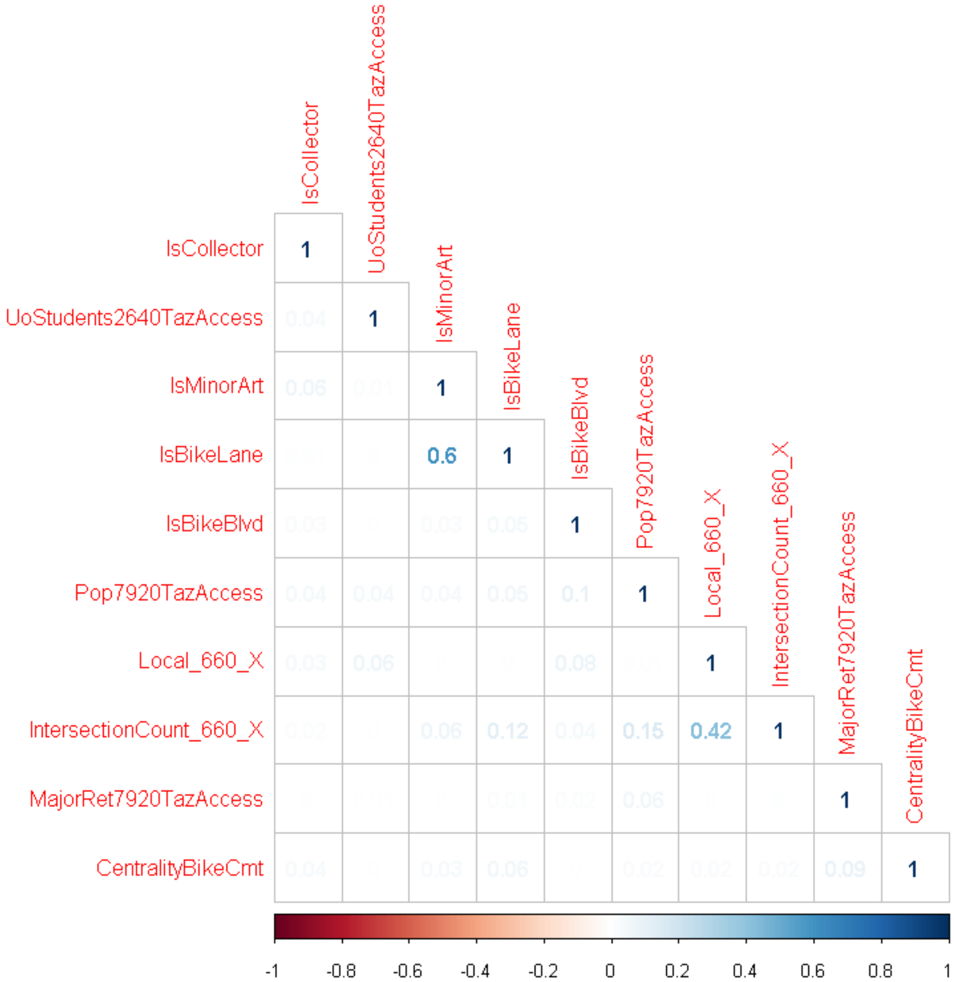
Xia, Q., Zhao, F., Chen, Z., Shen, L., & Ospina, D. (1999). Estimation of Annual Average Daily Traffic for Nonstate Roads in a Florida County. *Transportation Research Record: Journal of the Transportation Research Board, 1660,* 32-40. doi:10.3141/1660-05

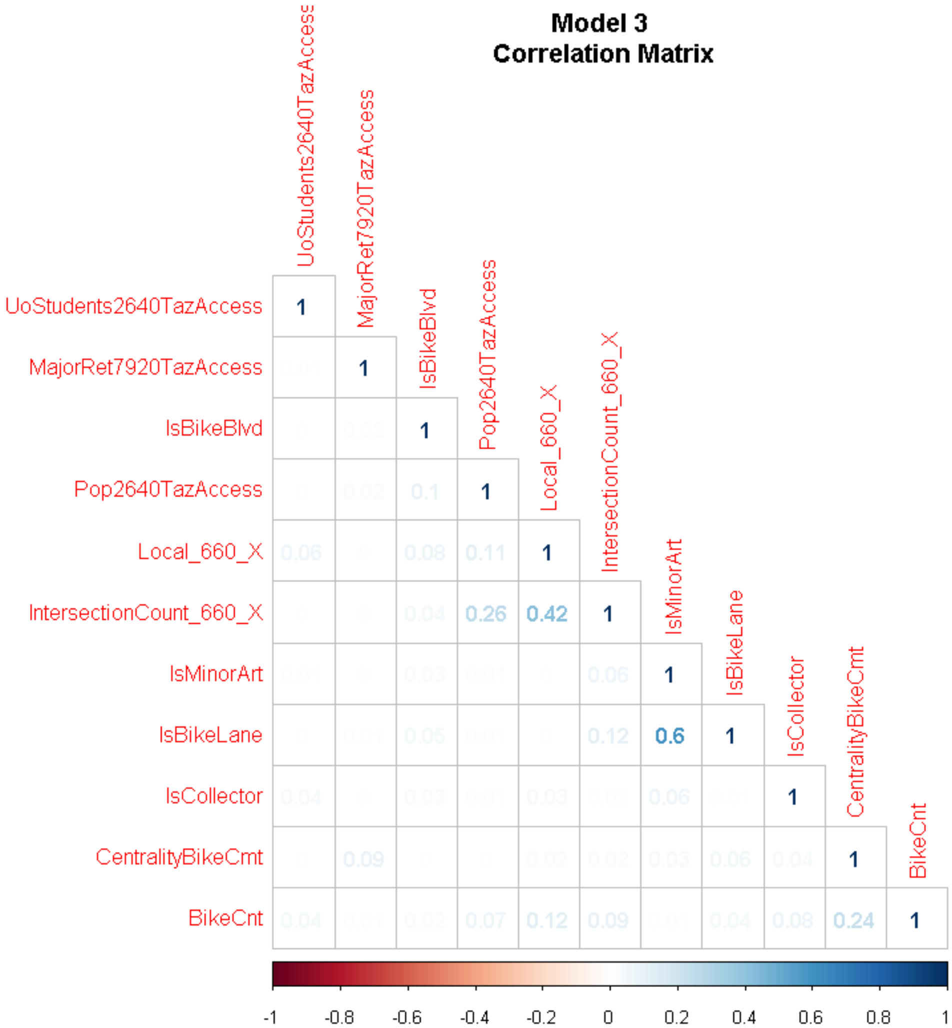
APPENDIX A – CORRELATION MATRICES

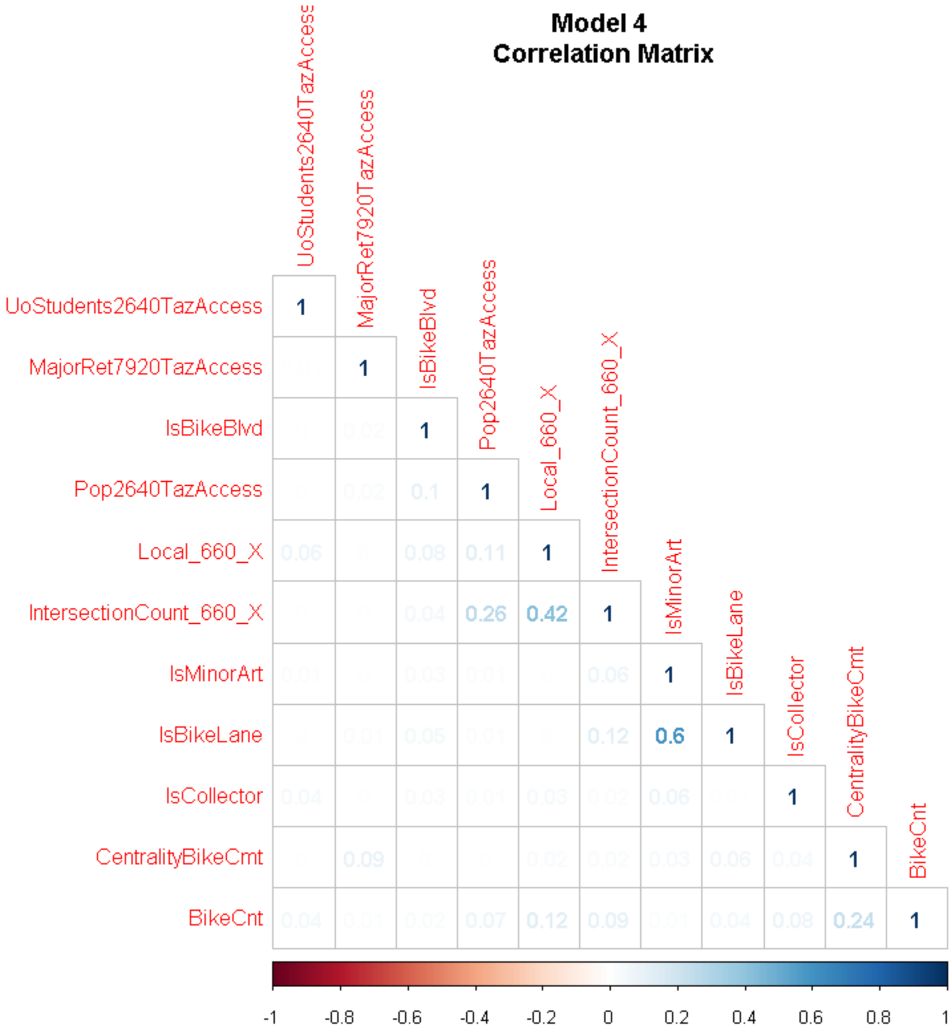
Model 1
Correlation Matrix



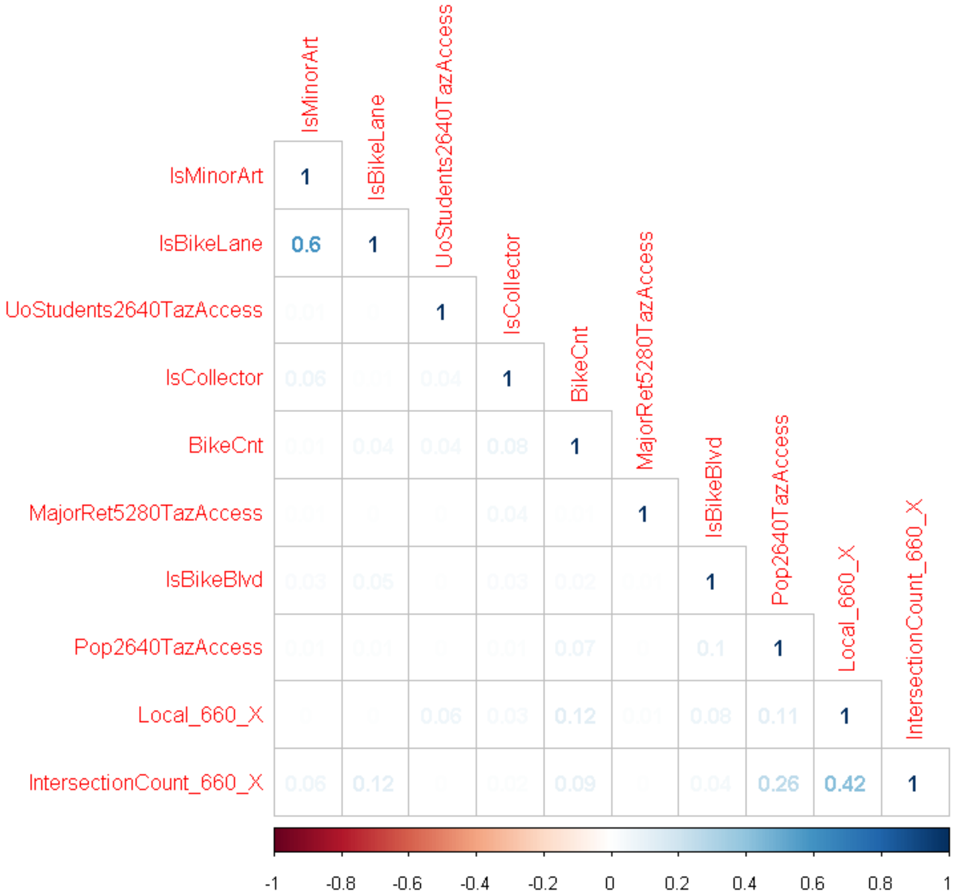
Model 2
Correlation Matrix




Model 3
Correlation Matrix
UoStudents2640TazAccess
MajorRet7920TazAccess
IsBikeBlvd
Pop2640TazAccess
Local_660_X
IntersectionCount_660_X
IsMinorArt
IsBikeLane
IsCollector
CentralityBikeCmt
BikeCnt
1
0.1
0.06
0.08
0.11
0.26
0.42
0.6
0.12
0.06
0.09
0.24
0.12
0.07
0.09
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1


Model 4
Correlation Matrix
UoStudents2640TazAccess
MajorRet7920TazAccess
IsBikeBlvd
Pop2640TazAccess
Local_660_X
IntersectionCount_660_X
IsMinorArt
IsBikeLane
IsCollector
CentralityBikeCmt
BikeCnt
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1

Model 5
Correlation Matrix



APPENDIX B - ALL SPF MODEL RESULTS FOR INTERSECTION

Model Name	Variable	Estimate	Standard Error	P value
Four_Leg_Base	(Intercept)	-11.15339	0.88686	0.00
	log(ABT)	0.77346	0.14310	0.00
	log(ADT)	0.9714235	0.12853	0.00
Four_Leg_BL	(Intercept)	-10.05889	0.94262	0.00
	log(ABT)	0.63954	0.14570	0.00
	log(ADT)	0.80839	0.14112	0.00
	BikeLaneCount	0.27554	0.09271	0.00
Four_Leg_BL_MaxSpeed	(Intercept)	-10.43737	1.04116	0.00
	log(ABT)	0.66868	0.15087	0.00
	log(ADT)	0.77129	0.14801	0.00
	BikeLaneCount	0.26526	0.09281	0.00
	MaxSpeed	0.01826	0.02129	0.39
Four_Leg_MaxSpeed	(Intercept)	-11.61957	0.97542	0.00
	log(ABT)	0.80089	0.14635	0.00
	log(ADT)	0.91302	0.13843	0.00
	MaxSpeed	0.02560	0.02165	0.24
Four_Leg_Signal_Term	(Intercept)	-10.10275	1.01802	0.00
	log(ABT)	0.72613	0.14558	0.00
	log(ADT)	0.78690	0.15582	0.00
	HasSignalTRUE	0.57306	0.30148	0.06
Four_Leg_SignalStop	(Intercept)	-10.13820	1.05732	0.00
	log(ABT)	0.72671	0.14564	0.00
	log(ADT)	0.78820	0.15625	0.00
	HasSignalTRUE	0.58969	0.33050	0.07
	HasStopTRUE	0.03249	0.27033	0.90
Four_Leg_Signal	(Intercept)	-9.59292	1.91023	0.00
	log(ABT)	0.53289	0.20960	0.01
	log(ADT)	0.88583	0.23918	0.00
Four_Leg_Signal_BL	(Intercept)	-9.19088	1.89625	0.00
	log(ABT)	0.37234	0.20941	0.08
	log(ADT)	0.82558	0.24281	0.00
	BikeLaneCount	0.27309	0.11168	0.01
Four_Leg_Stop	(Intercept)	-8.45522	1.49364	0.00
	log(ABT)	0.98954	0.20941	0.00
	log(ADT)	0.38827	0.24802	0.12
Four_Leg_Stop_BL	(Intercept)	-7.86452	1.60686	0.00
	log(ABT)	0.97409	0.21248	0.00
	log(ADT)	0.27198	0.27358	0.32

	BikeLaneCount	0.20233	0.20238	0.32
Three_Leg_Base	(Intercept)	-13.01665	0.92990	0.00
	log(ABT)	0.57755	0.22160	0.01
	log(ADT)	1.24282	0.14178	0.00
Three_Leg_BL	(Intercept)	-12.31203	1.03359	0.00
	log(ABT)	0.44260	0.23731	0.06
	log(ADT)	1.13554	0.16153	0.00
	BikeLaneCount	0.25348	0.16096	0.12
Three_Leg_BL_MaxSpeed	(Intercept)	-14.10868	1.16235	0.00
	log(ABT)	0.54523	0.24004	0.02
	log(ADT)	1.05853	0.16041	0.00
	MaxSpeed	0.07075	0.02081	0.00
	BikeLaneCount	0.17407	0.15632	0.27
Three_Leg_MaxSpeed	(Intercept)	-14.67583	1.07065	0.00
	log(ABT)	0.63864	0.22612	0.00
	log(ADT)	1.12450	0.14692	0.00
	MaxSpeed	0.07505	0.02093	0.00
Three_Leg_Signal_Term	(Intercept)	-11.93171	0.99720	0.00
	log(ABT)	0.49366	0.22514	0.03
	log(ADT)	1.05486	0.15589	0.00
	HasSignalTRUE	0.88756	0.31544	0.00
Three_Leg_SignalStop	(Intercept)	-12.01152	1.00936	0.00
	log(ABT)	0.48338	0.22659	0.03
	log(ADT)	1.03818	0.15798	0.00
	HasSignalTRUE	0.94592	0.31734	0.00
	HasStopTRUE	0.33464	0.27627	0.23
Three_Leg_Signal	(Intercept)	-6.93393	1.92745	0.00
	log(ABT)	0.26527	0.33427	0.43
	log(ADT)	0.54589	0.25761	0.03
Three_Leg_Signal_BL	(Intercept)	-6.69706	1.98429	0.00
	log(ABT)	0.10880	0.36681	0.77
	log(ADT)	0.51731	0.27025	0.06
	BikeLaneCount	0.24002	0.22249	0.28
Three_Leg_Stop	(Intercept)	-11.87318	1.45390	0.00
	log(ABT)	0.73216	0.32946	0.03
	log(ADT)	0.98728	0.23451	0.00
Three_Leg_Stop_BL	(Intercept)	-12.43236	1.73807	0.00
	log(ABT)	0.79083	0.33743	0.02
	log(ADT)	1.08366	0.28373	0.00
	BikeLaneCount	-0.16211	0.28083	0.56
Composite_Int_1	(Intercept)	-11.20420	0.72245	0.00

	log(ABT)	0.70483	0.11807	0.00
	log(ADT)	0.83373	0.11260	0.00
	BikeLaneCount	0.22313	0.08401	0.01
	HasSignalTRUE	0.78364	0.21926	0.00
	HasStopTRUE	0.29517	0.18407	0.11
Composite_Int_2	(Intercept)	-10.91833	0.73171	0.00
	log(ABT)	0.53351	0.12676	0.00
	log(ADT)	0.81685	0.11453	0.00
	BikeLaneCount	0.24460	0.08170	0.00
	HasSignalTRUE	0.71476	0.22485	0.00
	HasStopTRUE	0.31795	0.18676	0.09
	Leg_Cat4_Leg	0.61248	0.19248	0.00

APPENDIX C - SEGMENT PRIORITY LOCATIONS

LinkId	EB Adjusted Crash Frequency	Street Name	Functional Classification	City	Rank
18762	11.933	Clear Lake Rd	Collector	Eugene	1
20445	0.620	Beacon Dr	Collector	Eugene	2
14318	0.337	Northwest Expressway	MinorArt	Eugene	3
11382	0.330	Chambers St	MajorArt	Eugene	4
1425	0.301	Lorane Hwy	Collector	Eugene	5
20340	0.284	Coburg Rd	MinorArt	Eugene	6
20688	0.253	Green Hill Rd	Collector	Eugene	7
20727	0.229	Coburg Rd	Collector	Eugene	8
12157	0.227	Chambers St	MajorArt	Eugene	9
12322	0.197	River Rd	MajorArt	Eugene	10
5824	0.191	W 18th Ave	MinorArt	Eugene	11
11845	0.186	Marcola Rd	MinorArt	Springfield	12
20304	0.185	Green Hill Rd	Collector	Eugene	13
14435	0.175	Martin Luther King Jr Pkwy	MinorArt	Springfield	14
19610	0.174	Northwest Expressway	MinorArt	Eugene	15
15164	0.156	Coburg Rd	MajorArt	Eugene	16
12063	0.141	Roosevelt Blvd	MinorArt	Eugene	17
11114	0.140	Chambers St	MajorArt	Eugene	18
20768	0.133	N Coburg Rd	Collector	Eugene	19
15755	0.130	Coburg Rd	MajorArt	Eugene	20
20665	0.123	River Rd	MinorArt	Eugene	21
12801	0.123	River Rd	MajorArt	Eugene	22
12502	0.118	River Rd	MajorArt	Eugene	23
12554	0.114	River Rd	MajorArt	Eugene	24
12598	0.112	River Rd	MajorArt	Eugene	25
12653	0.111	River Rd	MajorArt	Eugene	26
16894	0.111	Chad Dr	Collector	Eugene	27
12366	0.109	River Rd	MajorArt	Eugene	28
18936	0.108	Clear Lake Rd	Collector	Eugene	29
12933	0.108	River Rd	MajorArt	Eugene	30
12334	0.105	River Rd	MajorArt	Eugene	31
10551	0.105	E 4th Ave	Collector	Eugene	32
16595	0.103	International Way	Collector	Springfield	33
18761	0.103	Green Hill Rd	MinorArt	Eugene	34
16980	0.102	Coburg Rd	MajorArt	Eugene	35
11847	0.101	Marcola Rd	MinorArt	Springfield	36
13014	0.101	River Rd	MajorArt	Eugene	37
12822	0.101	River Rd	MajorArt	Eugene	38
12418	0.101	Coburg Rd	MajorArt	Eugene	39
10426	0.100	E 4th Ave	Collector	Eugene	40

APPENDIX D - INTERSECTION PRIORITY LOCATIONS

Disaggregate Model			Composite Intersection Model 2		
Intersection Id	EB Adjusted Crash Frequency	Rank	Intersection Id	EB Adjusted Crash Frequency	Rank
8252	1.230	1	7886	2.19	1
8064	1.105	2	9170	2.04	2
8650	0.928	3	5714	1.66	3
5589	0.914	4	9747	1.43	4
6666	0.911	5	9224	1.29	5
8255	0.891	6	12634	1.14	6
8520	0.813	7	2760	0.98	7
8321	0.787	8	14118	0.96	8
5582	0.767	9	5980	0.94	9
6662	0.732	10	8369	0.90	10
8709	0.713	11	10626	0.82	11
8310	0.707	12	5598	0.79	12
8512	0.704	13	7621	0.75	13
8331	0.648	14	10130	0.74	14
5680	0.642	15	7453	0.74	15
8315	0.638	16	5434	0.73	16
8301	0.625	17	5583	0.73	17
9232	0.612	18	13038	0.72	18
5574	0.595	19	4550	0.68	19
6791	0.591	20	8481	0.66	20
8506	0.577	21	9209	0.66	21
10594	0.569	22	14159	0.65	22
6951	0.561	23	6901	0.64	23
8059	0.560	24	5569	0.60	24
8107	0.545	25	7919	0.60	25
5705	0.533	26	14191	0.58	26
8287	0.532	27	1596	0.58	27
6945	0.531	28	12950	0.57	28
7182	0.515	29	7891	0.56	29
2782	0.513	30	4080	0.55	30
6582	0.498	31	2789	0.55	31
4831	0.490	32	5038	0.52	32
9131	0.484	33	5145	0.52	33
6011	0.483	34	13871	0.51	34
6937	0.480	35	6568	0.47	35
8490	0.479	36	8971	0.46	36
6531	0.474	37	8094	0.46	37
4715	0.462	38	6319	0.46	38
6485	0.461	39	4630	0.45	39
8456	0.452	40	6007	0.45	40