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MTI MINETA TRANSPORTATION INSTITUTE

A Micro-Scale Analysis of Cycling Demand, Safety, and Network Quality

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MINETA TRANSPORTATION INSTITUTE

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REPORT 20-20

A MICRO-SCALE ANALYSIS OF CYCLING DEMAND, SAFETY, AND NETWORK QUALITY

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16. Abstract

This research uses a unique database of cycling volumes from the San Diego region to estimate cycling demand and cycling collision models. Continuous cycling count data collected from 34 automated counters are used to extrapolate over 1,400 short duration counts to average annual daily bicycle volumes (AADB). Network characteristics, built environment, and socio-economic characteristics are primary independent variables employed in the modeling. A key contribution of this research is to incorporate both a whole-network measure (betweenness centrality) and a network quality measure (LTS) in estimating cycling volumes. This research also improves upon cycling risk assessment by using more rigorous exposure measures, meaning that not only is the number of collisions at a particular location taken into consideration, but the overall cyclist volume is also considered. A final key contribution is to assess the correlation between ad hoc cycling propensity models used by practicing planners in San Diego and actual AADB. The research findings show that betweenness centrality is significant in estimating cycling volumes, meaning that as the centrality or importance of a roadway segment increases, cycling volumes also increase. It is important for long-range bicycle planners and local government traffic engineers to understand that key connections in the network draw cyclists as well as drivers and should have cycling infrastructure of adequate quality. In many instances, when connections are critical and constrained, cycling infrastructure is the first design element to be dropped. The rate of cycling collisions is found to be significantly related to proximity to freeways (higher collision rates closer to freeways), to lower income neighborhoods (higher cycling collision rates in lower income neighborhoods), and to higher density neighborhoods. In the case of San Diego's ad hoc bicycle planning tools, this research shows that indeed, high cycling propensity is related to higher bicycle volumes. A critical policy implication of this research is that local government mobility planners should more holistically consider cycling networks in their long-range plans and short-range implementation efforts, and that network-based performance measures can be more informative than demand-based performance metrics for the cycling mode. Network-based performance metrics need to be explored more rigorously in local planning as they are easy to calculate and shown to be statistically significant predictors of cycling demand.

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EXECUTIVE SUMMARY

This research uses a unique database of cycling volumes from the San Diego region to estimate cycling demand and cycling collision models. Continuous cycling count data collected from 34 automated counters are used to extrapolate over 1,400 short duration counts to average annual daily bicycle volumes (AADB). Network characteristics, built environment, and socio-economic characteristics are primary independent variables employed in the modeling. A key contribution of this research is to incorporate both a whole-network measure (betweenness centrality) and a network quality measure (LTS) in estimating cycling volumes. In this research, the term 'whole network measures' generally refers to metrics that take into consideration the shape of a network across a study area or the relationships between a single network segment and the surrounding network segments across a study area. In contrast, network quality measures consider only characteristics of the segment itself, without consideration of a larger study area. This research also seeks to improve cycling risk assessment with improved exposure measures, meaning that not only is the number of collisions at a particular location taken into consideration, but the overall cyclist volume is also considered. This has been an important missing factor in understanding cycling risk across a network. A final key contribution is to assess the correlation between ad hoc cycling propensity models used by practicing planners in San Diego and actual AADB. Given the absence of information on actual cycling volumes, many jurisdictions have developed tools for estimating the likelihood for cycling based upon density, infrastructure presence, and other variables thought to be related to the demand for cycling. This research, as it estimates bicycle flows along a number of networks segments, presents a unique opportunity to compare the relationship between estimated cycling propensity scores and volumes. A key question considered in this study was whether the propensity models are doing a good job reflecting cycling volumes?

The research findings show that betweenness centrality is significant in estimating cycling volumes, meaning that as the centrality or importance of a roadway segment increases, cycling volumes also increase. It is important for long-range bicycle planners and local government traffic engineers to understand that key connections in the network draw cyclists as well as drivers and should have cycling infrastructure of adequate quality. In many instances, when connections are critical and constrained, cycling infrastructure is the first design element to be dropped.

The rate of cycling collisions is found to be significantly related to proximity to freeways (higher collision rates closer to freeways), to lower income neighborhoods (higher cycling collision rates in lower income neighborhoods), and to higher density neighborhoods.

In the case of San Diego's ad hoc bicycle planning tools, this research shows that indeed, high cycling propensity is related to higher bicycle volumes. Academic researchers need to insert themselves into planning practice more aggressively to assess and improve ad hoc tools, especially in the realm of active travel planning, which suffers broadly from underdeveloped planning tools.

A critical policy implication of this research is that local government mobility planners should holistically consider cycling networks in their long-range plans and short-range implementation efforts, and that network-based performance measures can be more informative than demand-based performance metrics for the mode of bicycling. Network-based performance metrics need to be explored more rigorously in local planning as they are easy to calculate and shown to be statistically significant predictors of cycling demand.

I. INTRODUCTION

The 2008 California Complete Street Act delivered a mandate to carry out long-range planning for cycling, walking, and transit, in addition to vehicular-oriented systems, when any local government embarks on a general plan update.[1] Two major challenges exist for implementing this mandate, including a lack of consistently collected bicycle and pedestrian data, and, importantly, a lack of standardized metrics and planning tools for assessing infrastructure needs related to walking and cycling. This research builds from recent advances in the San Diego region in the arena of active travel data collection as well as long-range planning methods. Specifically, this project seeks to examine relationships between cycling demand, bicycle network indices, network quality, and safety. The project draws upon rich cycling count data collected between 2008 and 2018 in San Diego County from automated counters, as well as from about 1,500 short duration manual counts conducted during the same period.

The State of California has ambitious goals to double walking and triple cycling trips by 2020, as well as reducing bicycle and pedestrian fatalities by ten percent each year.[2] Long-range planning processes conducted at the local and regional levels are critical to achieving these goals. A major, persistent barrier, however, is the lack of rigorous planning metrics that can effectively justify the need for non-motorized infrastructure, especially when these modes are compared side-by-side with motorized modes. This research seeks to help cities and regional planning agencies achieve the state's active travel mode share goals by bolstering the planning toolbox available to consultants and agency staff. This research assists in meeting the following CSUTC objectives:

- CSUTC Objective 1: Leverage new technologies […] and innovative processes to achieve a seamless, multimodal surface transportation system that integrates with other "smart city" investments.

  The current research proposes enhanced processes for local, long-range bicycle planning using a state-of-the-art bicycle count data collection system in San Diego County. The deployment of an automated bicycle detection system in San Diego is highly unique, and this research is critical to showing how the data collected from such a system can be used in practice to support decisions at the local level related to non-motorized infrastructure investments.

- CSUTC Objective 4: Create safer communities, increased access to transit, and greater opportunities for use of active transportation modes (i.e., biking and walking) through complete streets and innovative land use planning so that people of all abilities and socio-economic levels enjoy the same opportunities for learning, living, labor, and leisure.

  The current project builds from previous literature by integrating network-related indicators in estimating cycling demand. In fact, bicycle network deficiencies are so pronounced in most California cities relative to automobile infrastructure that comparing levels of demand between the two modes in a performance evaluation context is ineffective. Low cycling demands are often used as an argument against allocation of funding to cycling infrastructure. This research seeks to broaden the bicycle planning toolbox by developing metrics that more accurately assess what is likely a leading factor in pervasively low cycling mode shares—namely poor network density, connectivity and quality facilities[3].

This project's key objectives are as follows:

1. Use a large network of automated count data in San Diego (34 automated count sites which have been collecting continuous data since 2012), combined with a large sample of short duration manual counts (approximately 1,500 short duration counts in the City of San Diego over the previous five years), to estimate Average Annual Daily Bicycle Volumes (AADB) across the city of San Diego's bikeable roadway network.

2. Improve bicycle demand estimation models by integrating betweenness centrality and network quality indicators.

3. Improve cycling crash rate calculations using more broadly available exposure data, specifically by normalizing crash frequency using a combined denominator of average daily bicycle volumes and vehicular volumes.

4. Assess and validate bicycle planning practices, specifically bicycle propensity models, to assist San Diego planners who are actively working on community plan updates, and work to define the transferability of these methods to other cities in California and other states.

II. LITERATURE REVIEW

This literature review summarizes key recent research on cycling demand and cycling safety.

CYCLING DEMAND

There is a large literature which finds a positive relationship between cycling infrastructure and rates of cycling.[4] Research on individuals' stated preferences for high quality cycling infrastructure and its role in the individual's choice to ride a bike is also widespread.[5] Much of the research investigating stated preferences identifies a broad preference for a bicycle facility separated from motor travel lanes.[6]

There is an increasing focus among transportation researchers on the relationship between bicycle network characteristics and the demand for cycling.[7] Network characteristics can be divided into two types: network quality and whole-network measures. Whole-network measures such as network size, density, connectivity, fragmentation, and directness have been examined in previous research and shown to be correlated with cycling demand.[8] For instance, Osama et al.[9] developed zonal-level models relating whole-network indices and bicycle kilometers traveled. Schoner and Levinson[10] developed models of whole-network indices and commuting bike trips assessed at the city level. Buehler and Pucher[11] present a city-level analysis of bikeway network miles and rates of bike commuting. One highly relevant network measure, however, has not been examined: namely, betweenness centrality. This measure assesses the relative importance of each segment in the network, expressed as the number of shortest paths passing through each segment. Some research from the general transportation planning literature examines the role of betweenness centrality to explain traffic flow and other network problems.[12] Betweenness centrality could form the basis for a powerful bicycle planning tool in the US, since a large number of our cities have very underdeveloped bicycle networks, and planners are typically overwhelmed by the pervasive need for bicycle infrastructure, as well as by the need to justify their choices of where to plan and build bicycle infrastructure. Measures of betweenness centrality can provide a prioritization metric for ranking links in the bikeable roadway network according to their relative contribution to traversing the network. This information is useful for substantiating arguments for providing bicycle facilities where none currently exist, or for enhancing existing bicycle facilities along these critical links. This research attempts to contribute to the recent academic literature by integrating whole-network and network quality measures in cycling demand estimation.

In terms of network quality, Fagnant and Kockelman[13] assessed relationships between short duration bicycle counts along segments and network quality measures such as Bicycle Level of Service (BLOS). Other researchers have examined the relationship between Level of Traffic Stress (LTS) and travel behavior. Results have been inconsistent, with one study showing no relationship between LTS and bicycle mode share but revealing a positive relationship between LTS and number of bicycle trips.[14] Fitch et al.[15] found a positive relationship between LTS and school children's bike trips. Harvey et al.[16] examined how differences in LTS measurement may affect its validity as a network quality metric. They compared multiple approaches to calculating LTS with user preference data collected through a crowd sourcing app called Ride Report. Overall, study results did indicate that the presence of cycling infrastructure and the reduction of roadway widths and traffic volumes served to reduce the level of stress for cyclists and increase user satisfaction.

CYCLING SAFETY

There were about 36,560 vehicle-related fatalities in the US in 2018, including incidents related to trucks, passenger cars, motorcyclists, cyclists, and pedestrians, which is down about 2.4% since 2017. Although bicycle–vehicle fatalities represent a very small percent of all vehicle-related fatalities, their growth is much greater than that of vehicle-related fatalities at roughly 6.3% between 2017 and 2018. For pedestrian-related fatalities, there was a 3.4% increase between 2017 and 2018. Given the improving safety for drivers (vehicle–vehicle fatalities decreased by 4.1%), the increased rates of fatalities for cyclists and pedestrians is of grave concern.

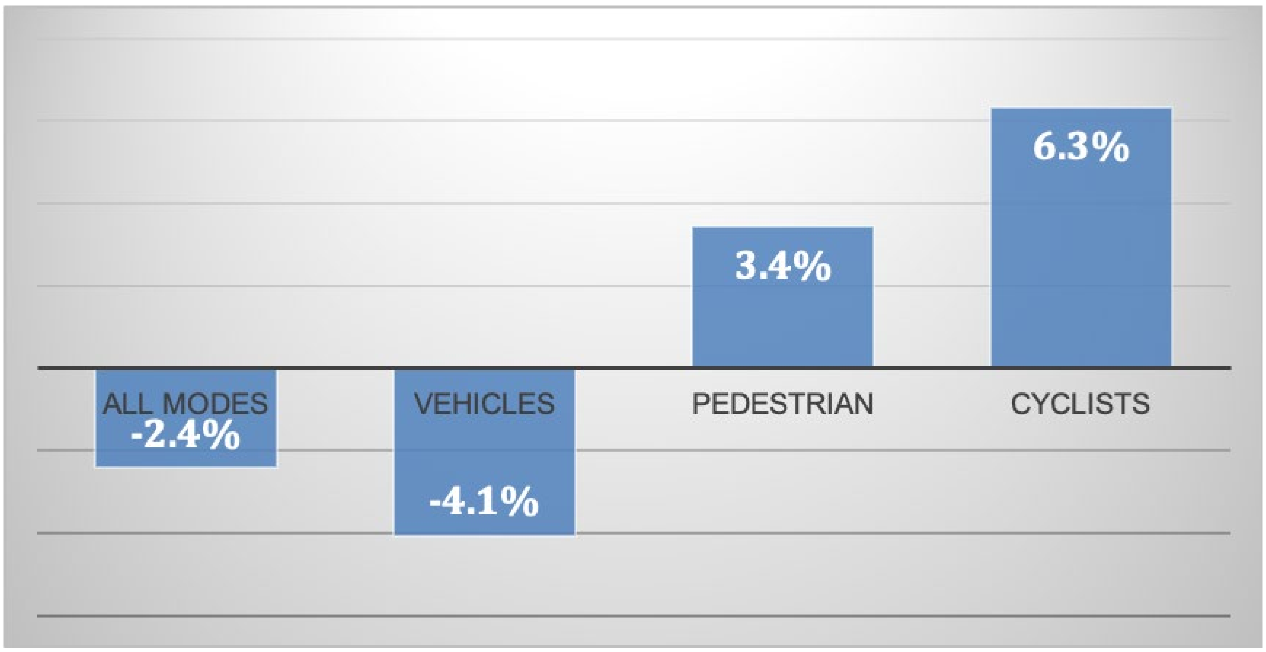

Figure 1. Change in Fatality Rates by Mode (2017 to 2018)

Source: NHTSA, October 2019

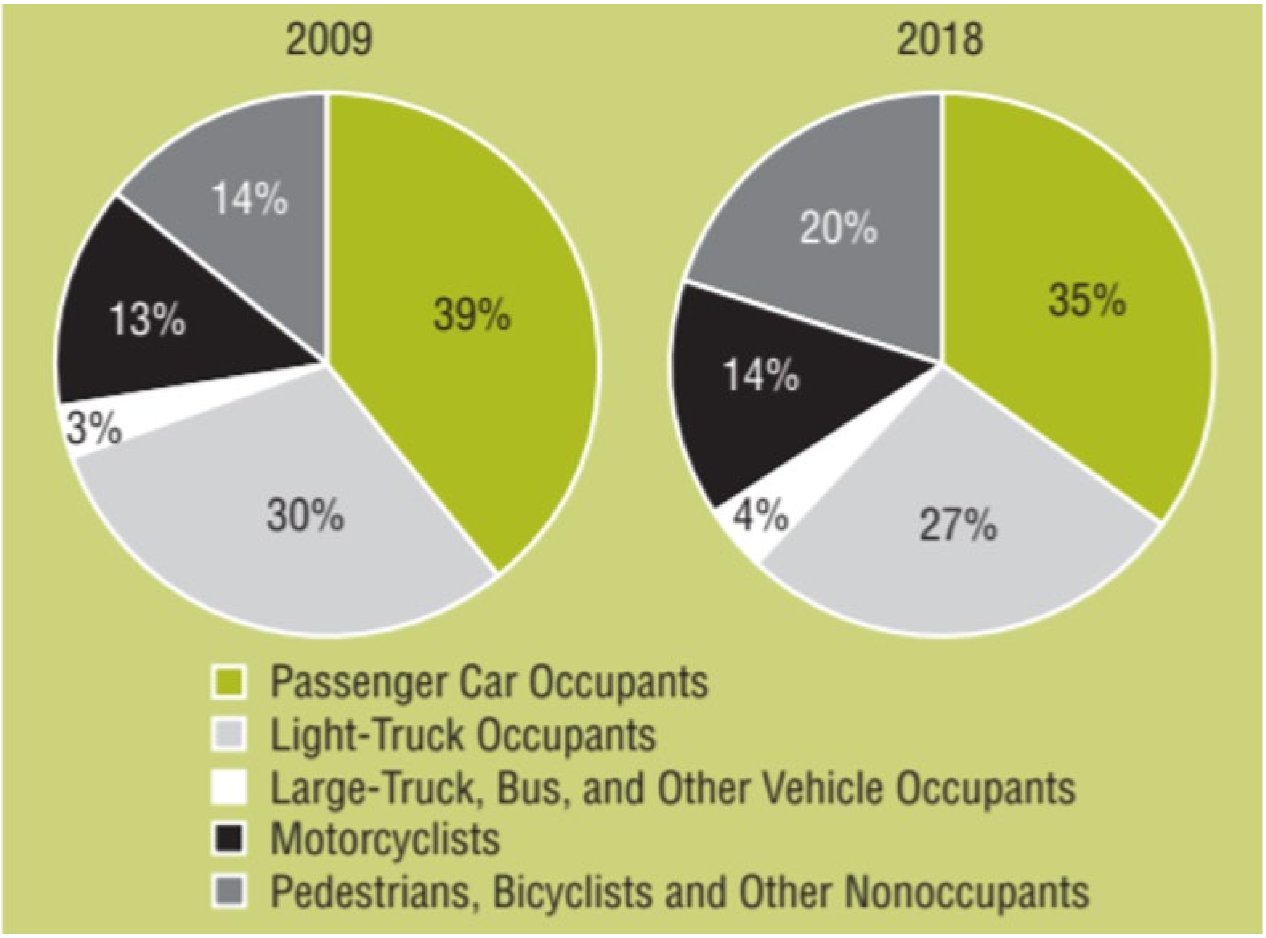

Figure 2. Fatality Composition, 2009 and 2018

Source: NHTSA, October 2019

Further, this trend has been consistent over the past decade, when between 2009 and 2018, passenger car fatalities decreased by about 4%, while cyclist and pedestrian fatalities increased by about 6%.

Many safety-related programs such as Vision Zero, Sustainable Communities, and Complete Streets have been launched nationally and at the local level in an effort to address this trend. But their success remains questionable based upon the growing proportion of pedestrian and cycling collisions relative to vehicle-vehicle collisions as shown in Figure 2.

The literature on cycling safety examines the role of vehicle and cycling infrastructure, weather, socio-economics, and other factors in estimating cycling collision rates. Pucher and Buehler[17] find that cycling infrastructure is associated with reduced bicycling collisions. Osama and Sayed[18] examine multiple factors including topography and roadway network characteristics in explaining cyclist–motorist collisions. Lusk et al.[19] show a relationship between cycle tracks and reduced cycling collisions. Kmet et al.[20] show that demographic variables, accessibility variables, bus route length, and number of intersections were positively associated with cyclist–vehicle collisions. Wei and Lovegrove[21] modeled cyclist–vehicle collisions and found that they are associated with total lane kilometers, bike lane kilometers, bus stops, traffic signals, intersection density, and percent of arterial–local intersections. Kaplan and Prato[22] found that bike paths are associated with fewer crashes.

DENSITY AND INCOME

Density as measured by population density, job density, or intersection density is typically considered as being positively related to cycling demand. Nehme et al. [23] used 2009 National Household Travel Survey (NHTS) data and found that, across the entire US, utilitarian or non-recreational cycling is positively associated with population density, and with being white and male. Earlier studies, such as Cervero and Kockelman[24] showed that density is associated with reduced vehicle miles traveled, with the implication being that in denser environments, more trips can be made by walking and cycling because the distances between sustenance land uses or opportunities is shorter and more conducive to non-motorized travel. In contexts where recreational cycling is more prevalent than utilitarian or work commute cycling, the role of density is questionable, since in this case, travel is occurring for travel's sake (leisure or physical activity) and not to minimize travel distance.

In terms of income, both community income and individual income have been considered. Lusk et al.[25] showed that lower income neighborhoods have lower quality cycling environments due in part to weaker planning practices and political advocacy to instigate the design and construction of high quality bike networks. Other studies have shown high rates of cycling among white, affluent males.[26] In the general travel literature, higher incomes are associated with more trip-making and higher vehicle miles traveled. It is uncertain whether this finding translates to cycling for transportation. To the extent that cycling is for leisure, it could be expected that higher income individuals would make more cycling trips. [27]

III. METHODS

STUDY AREA

The study area comprises the City of San Diego. San Diego has not been very progressive in its implementation of separated bicycle facilities, and only in the previous two years has it built small segments of Class IV Cycle Track. Table 1 and Figure 3 show the distribution of bicycle infrastructure by facility type for the year 2018. As shown, the majority of cycling infrastructure consists of bike lanes, at 60% of total facility lane miles, followed by bike routes at 26% of total facility miles, and finally multi-use paths at about 15%.

Table 1. 2018 Miles of Bicycle Facility by Type and Percent of Total

Facility Type	Miles	Percent of Total
Multi-Use Path	87	14.7%
Bike Route	151	25.7%
Bike Lane	352	59.7%
Total	**590**	**100.0%**

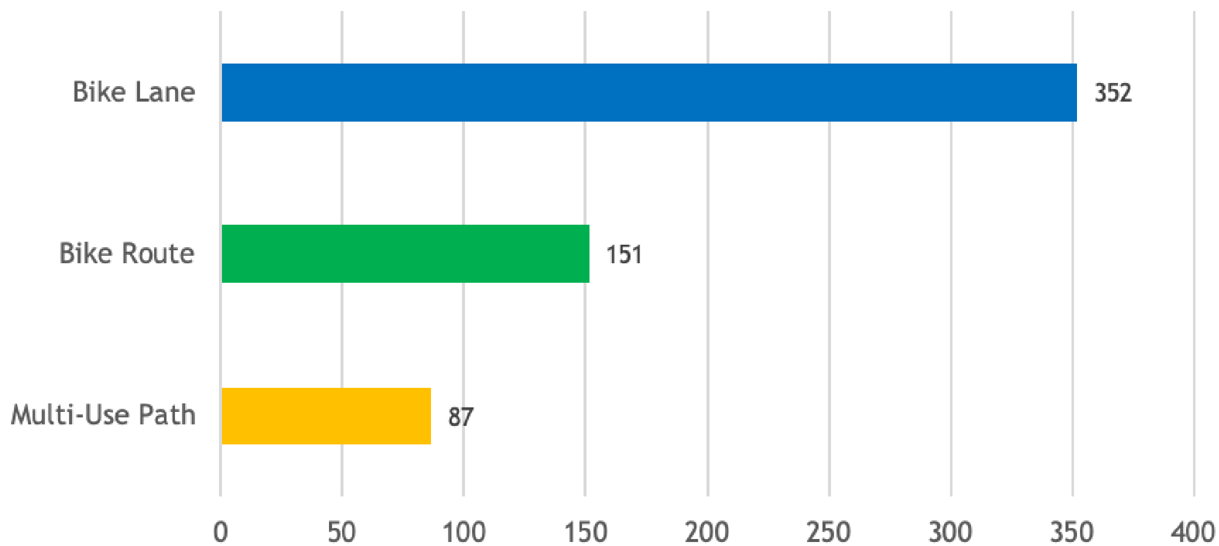

Figure 3. 2018 Miles of Bicycle Facility by Type in City of San Diego

Figure 4 shows that cycling infrastructure in San Diego is highly fragmented and disconnected. There is a strong tendency on the part of city staff to prioritize vehicular travel over bicycle travel, so, for example, if the right-of-way narrows and there is inadequate room for both vehicle lanes and a bicycle lane, the bike lane will be dropped. Another strategy on the part of city staff is to reduce bike lanes to bike routes when right-of-way is insufficient. The legacy of prioritizing vehicle travel over cycling shows up strongly in the city's bike map.

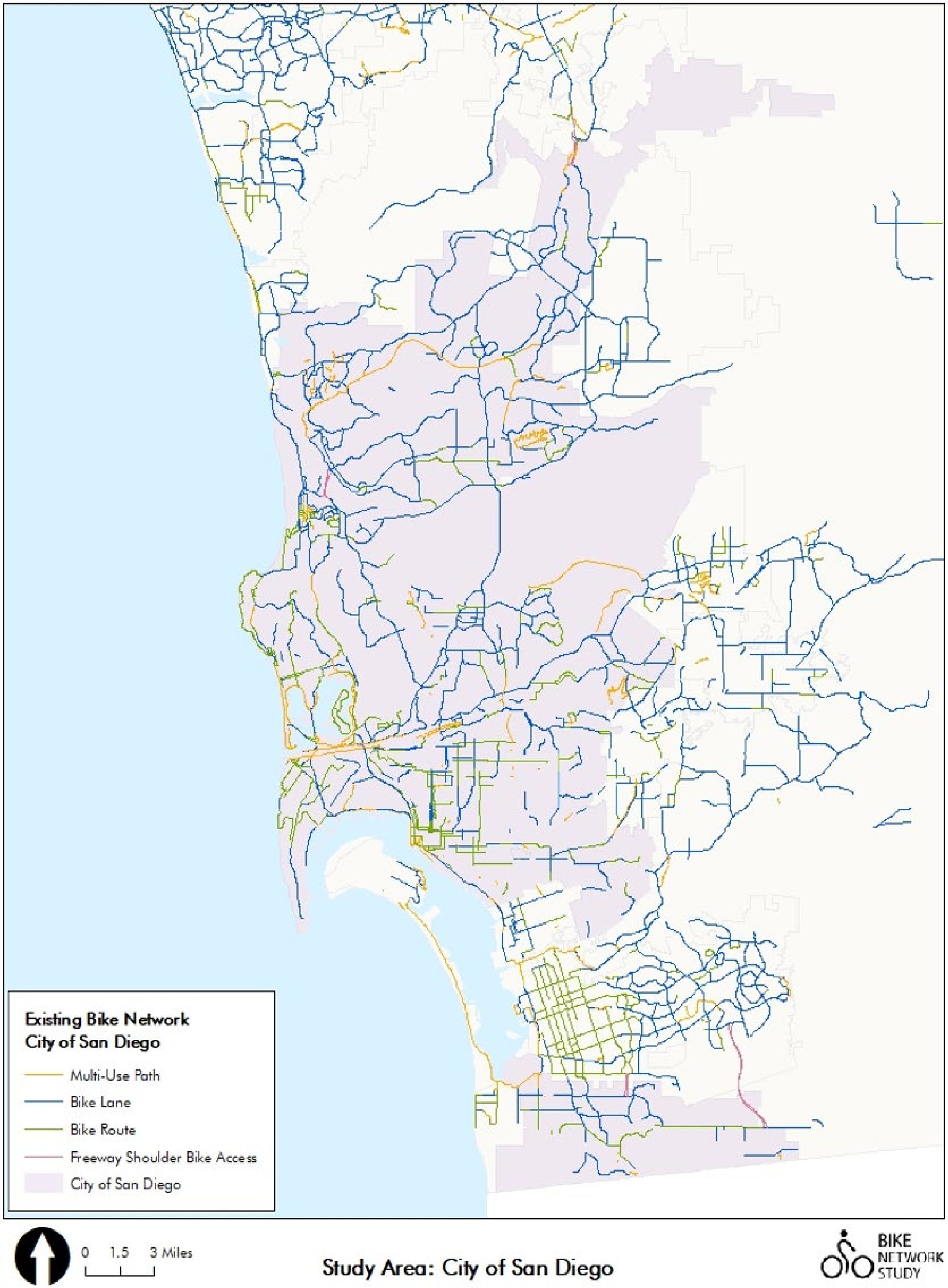

Figure 4. Study Area: City of San Diego

DATA

Table 2 shows the key variables analyzed in this research, while Table 3 presents descriptive statistics for each of these variables. As shown, the key dependent variables are cycling demand and cycling collision rate. The key independent variables fall into four major categories: whole-network measures, network quality measures, socio-economic characteristics of the neighborhood, and built environment characteristics.

Table 2. Cycling Models: Study Variable Category, Description, and Source

Category	Variable Name	Description	Source
Dependent Variable			
Cycling Demand	AADB	Average Annual Daily Bicycle Volume	Estimated from short duration and automated counts
Cycling Collision Rate	CollRate	Number of Collisions/Average Annual Bicycle Volume	City of San Diego and SDSU
Independent Variables			
Whole-Network	BetCen	Betweenness Centrality	Calculated in GIS
Network Quality	LTS	Level of Traffic Stress (LTS)	Calculated in GIS
	Speed	Posted Vehicle Speed	SANDAG
	DistFwy	Straight-line Distance between Count Segment and Freeway	Calculated in GIS
Built Environment	PopDen	Population Density	Census Bureau American Community Survey
	JobDen	Job Density	Census Bureau American Community Survey
Socio-Economic	HHI	Median Household Income	Census Bureau American Community Survey

Figure 5 shows the conceptual framework underlying the cycling demand model and expected relationships between these variables.

Table 3. Study Variable Descriptive Statistics (N=1,474)

Variable Name	Min	Max	Mean	St Dev
AADB	0	623	45.67	72.39
CollRate	0	.00933	.00038	.00082
BetCen	0	1.0	.1998	.2144
LTS	1	4	2.79	1.45
Speed	0	50	27.32	8.61
DistFwy	0	12,376	2,124	2,319
PopDen	0	73.63	11.50	11.75
JobDen	0	971.38	31.25	74.60
HHI	0	245,089	59,941	25,005

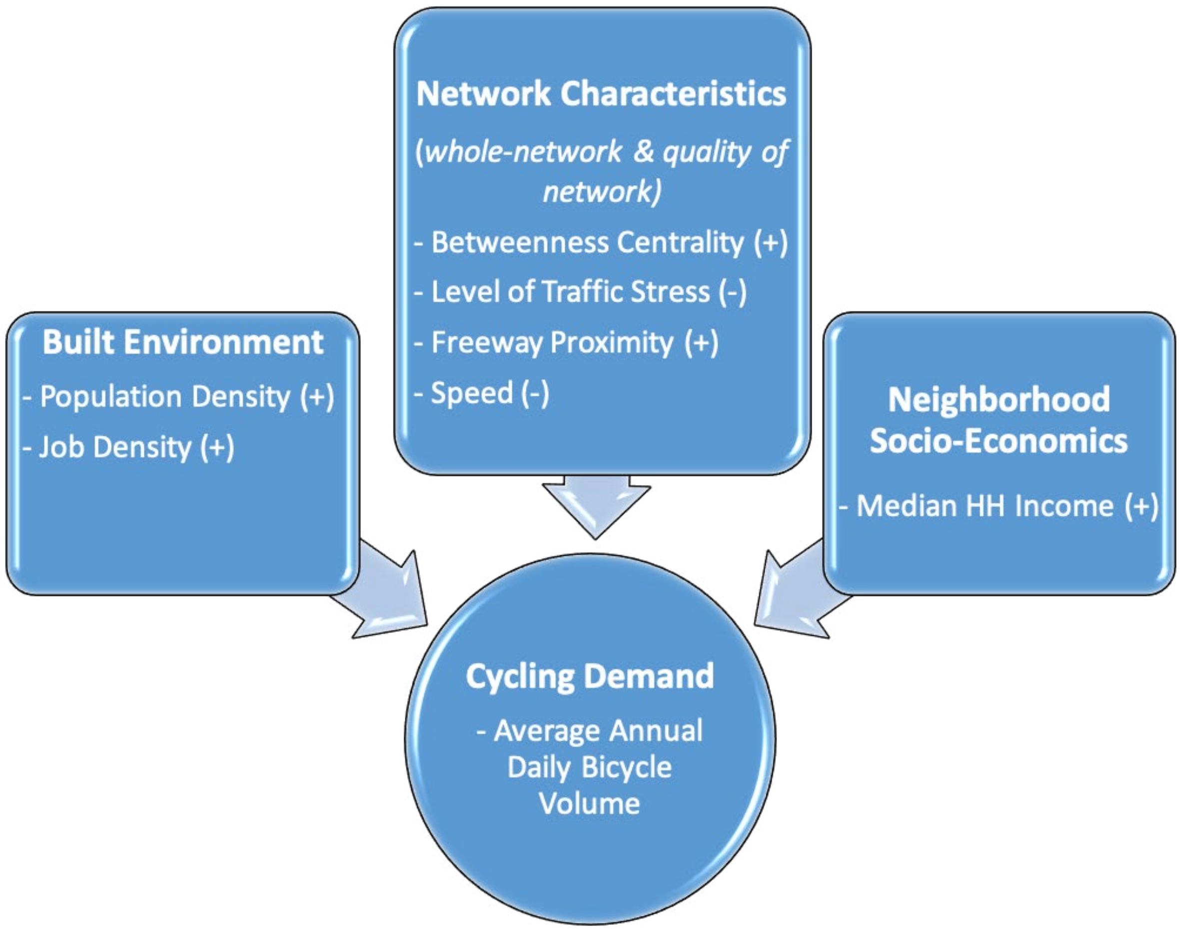

Figure 5. Conceptual Framework, Model Variables, and Hypothesized Relationships

The development of each of these variables is discussed in the following sections.

Average Annual Daily Bicycle Volumes

AADB was developed using automated counts from 34 permanent counter sites in San Diego County in combination with almost 1,500 short duration counts collected over a period from 2008 to 2018. The short duration counts were largely collected by the City of San Diego in conjunction with updating their community plans. Specific data collection periods include

June 2008; June 2009; May 2011; October 2013; April, May, and September–December 2015; November–December 2016; and June 2018. The majority of the counts were collected in 2015. Each peak period intersection turn movement count was translated into peak period segment counts for each of the respective intersection approaches. Figure 6 shows the locations of the peak hour bicycle segment counts across the City of San Diego, as well as count segments distinguished by the year when data collection occurred.

The short duration count periods varied from two to six hours. Some count periods had different start and end times, resulting in a total of 11 different periods as shown in Table 4.

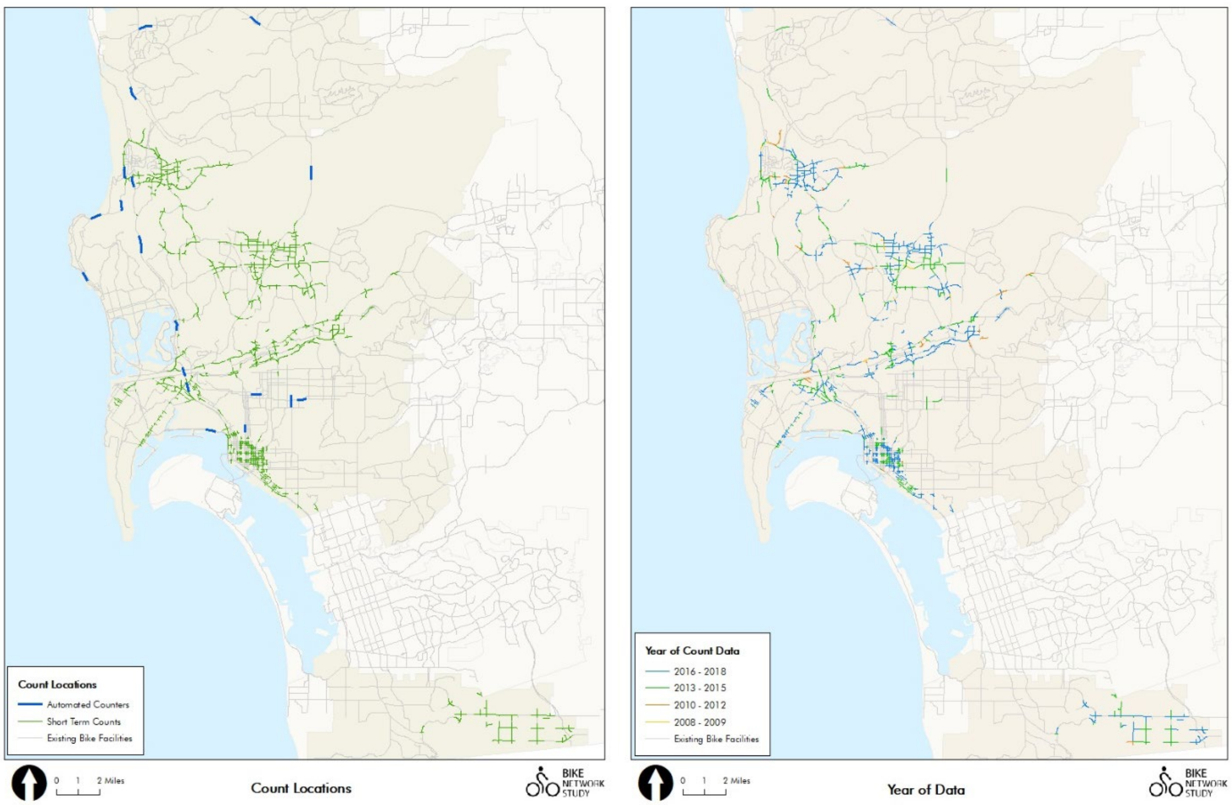

Figure 6. Count Locations and Year of Data Collection

Table 4. Count Periods for City of San Diego Short Duration Bike Counts

Count Period	Hours
2A	7–8 am, 4–5 pm
2B	7–8 am, 5–6 pm
2C	8–9 am, 4–5 pm
2D	8–9 am, 5–6 pm
3A	7–8 am, 12–1 pm, 5–6 pm
3B	8–9 am, 12–1 pm, 5–6 pm
4A	7–9 am, 4–6 pm
5A	7–9 am, 12–1 pm, 4-6 pm
6A	7–9 am, 11 am–1 pm, 4–6 pm
6B	7–9 am, 2–6 pm
6C	6–9 am, 3–6 pm

The following process was used to expand these short duration counts to an Average Annual Daily Bike (AADB) count for each segment. The 34 permanent bike counters were grouped into three categories based on their average Weekend/Weekday Index (WWI), where counters with a WWI greater than or equal to 0.8 were assigned to *Weekday Commute (WD-C)*, counters with a WWI between 0.8 and 1.2 were assigned to *Weekly Multipurpose (W-MP)*, and counters with a WWI greater than 1.2 were assigned to *Weekend Multipurpose (WE-MP)*.[28] Of the total of 34 counters, two were classified as *Weekday Commute*, 12 were *Weekly Multipurpose*, and 20 were *Weekend Multipurpose.* Hourly factors for these three categories of counters were then calculated using data from the permanent bike counters collected in 2015. Data from 2015 were used because this year had the most complete data, and the majority of the short duration counts were completed in 2015. The short duration counts were expanded to 24-hour (daily) counts by first summing the appropriate hourly factors associated with the hours when the short duration counts were collected and then dividing the short duration count by the summation of the appropriate hourly factor. Table 5 shows the hourly factors for each of the three categories of automated counters.

Table 5. Average Hourly Expansion Factors for WD-C, W-MP, and WE-MP

Hour	Avg Hourly Factor Weekday Commute (WD-C)	Avg Hourly Factor Weekly Multi-Purpose (W-MP)	Avg Hourly Factor Weekend Multi-Purpose (WE-MP)
6:00	0.049	0.039	0.026
7:00	0.068	0.070	0.054
8:00	0.085	0.082	0.085
11:00	0.060	0.067	0.103
12:00	0.064	0.065	0.087
14:00	0.056	0.062	0.067
15:00	0.072	0.065	0.067
16:00	0.082	0.075	0.068
17:00	0.074	0.076	0.064

Once the short duration counts were expanded to daily volumes, the next step was to expand the daily counts to Average Annual Daily Bike volume (AADB). Day-of-Week-of-Month factors were calculated from continuous bike count data collected over 2015 and were applied to the AADB for each of the 365 days in one year. To calculate the Average Annual Bike volumes (AAB), the AADB was multiplied by 365.

An Example:

Twenty-eight bikes were seen during a 4-hour count that was performed on Road Segment #181046 during the hours 7–9 am and 4–6 pm on April 29, 2015. The road segment where the count took place was categorized as Weekly Multipurpose. Using the hourly factors in the table above and a Day-of-Week-of-Month factor of 1.15, the AADB is calculated below.

AADB = (4 hour Count / (Sum of hourly factors for the 4 hours of the count)) /

Day-of-Week-of-Month factor for a Wednesday in April.

Figure 7 shows the study segments across the City of San Diego with the level of estimated average daily bicycle volume distinguished by three categories: high, medium, and low.

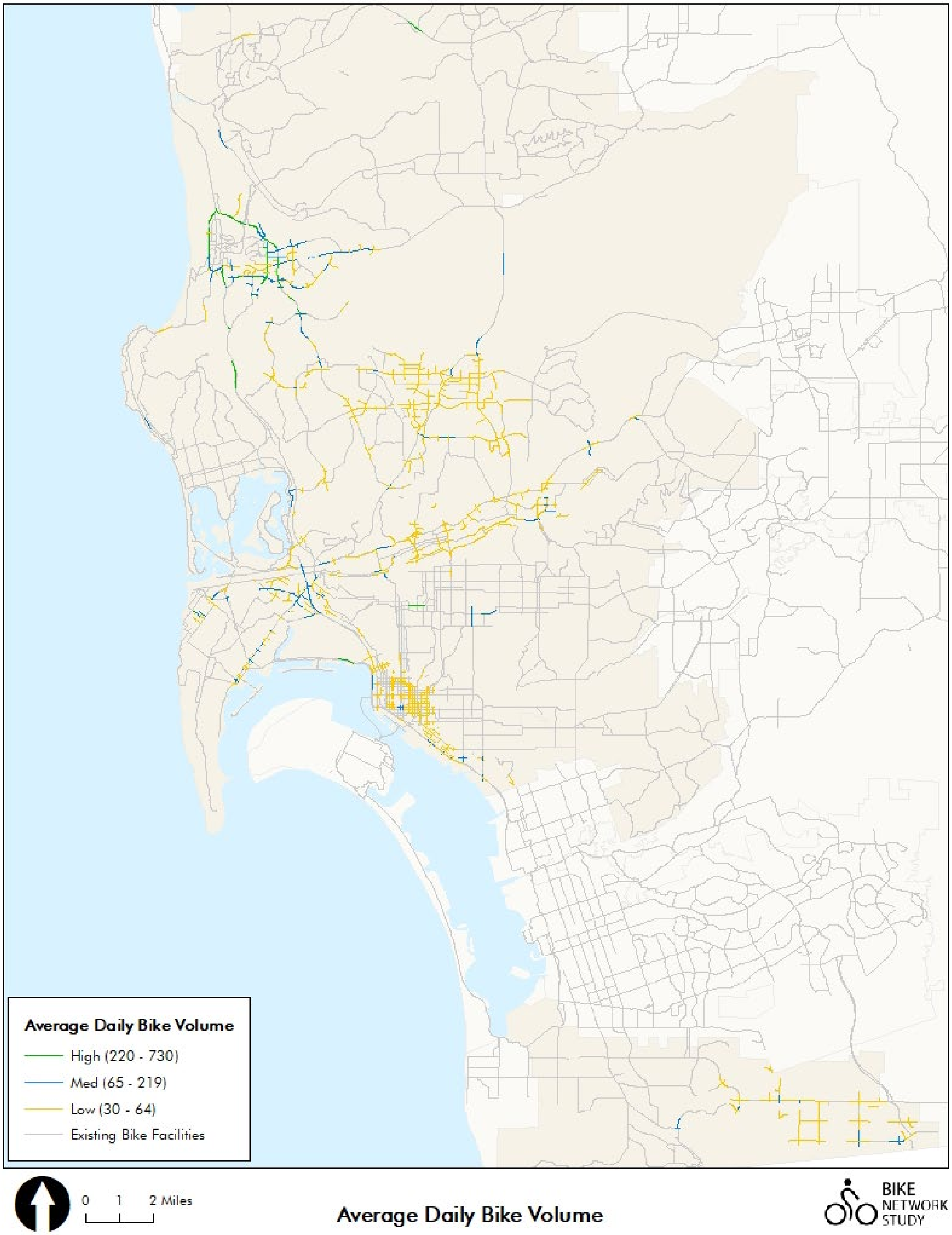

Figure 7. Average Daily Bicycle Volume

Whole-Network Measures

Characteristics of the bicycle network were measured in terms of "whole-network" indicators and bicycle network quality. Some of the recently evaluated whole-network measures included network size, connectivity, density, fragmentation and directness, with density tending to show the strongest relationship with cycling volume.[29] In this study, betweenness centrality was used to depict the key whole-network measure. San Diego maintains a high-quality roadway shapefile with all links, including very low capacity roadways like alleys. Freeway and other non-bikeable links were removed from this shapefile, and separate network measures were calculated using the bikeable roadway network. Figure 8 shows the development of betweenness centrality used in this study. The procedure generally follows the steps outlined below:

- Identify each count segment along the bikeable roads shapefile;
- Buffer each count segment with a half-mile street network buffer;
- Extract all intersection nodes within half-mile street network buffer;
- Calculate shortest path to/from all nodes; and
- Divide number of paths crossing count segment by all paths.

In the example shown in Figure 8, 32 of the 110 shortest paths generated within this half-mile area utilize the segment where the count is located, resulting in a betweenness centrality ratio of 0.29. Betweenness centrality will range from 0 to 1.0, with higher values indicating that the segment is more “central” or important to connectivity and lower values indicating that the segment is not important to achieving connectivity within the area. Figure 9 shows the distribution of betweenness centrality across the almost 1,500 count segments, with the centrality categorized as high, medium, or low.

Network Quality

The quality of the cycling environment is measured using the bicycle LTS methodology as developed by Mekuria et al.[30] of the Mineta Transportation Institute. LTS classifies street network segments into categories (LTS 1 through 4) according to the level of stress caused to cyclists, with LTS 1 meaning very little stress and LTS 4 meaning high levels of stress. Inputs for calculating LTS include consideration a cyclist’s physical separation from moving vehicles, vehicular traffic speeds along the roadway segment, the number of travel lanes, and factors related to intersection approaches with dedicated right-turn lanes and unsignalized crossings. Whereas the whole-network measures are derived from the shape of an entire network across a study area, and relationships between these segments, the network quality measures are strictly focused on the characteristics of unique segments, without consideration of what is surrounding these individual segments

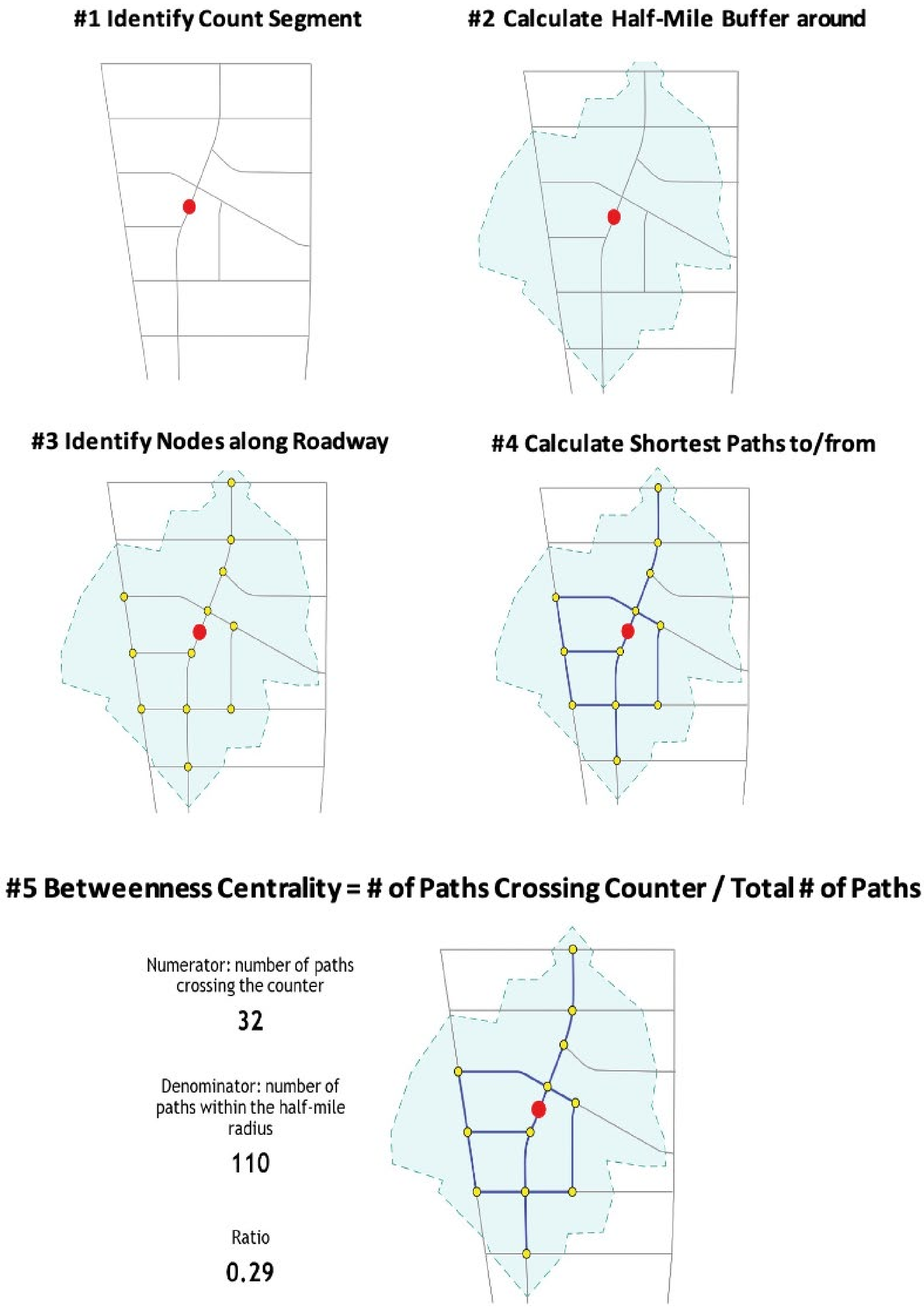

Figure 8. Calculating Betweenness Centrality

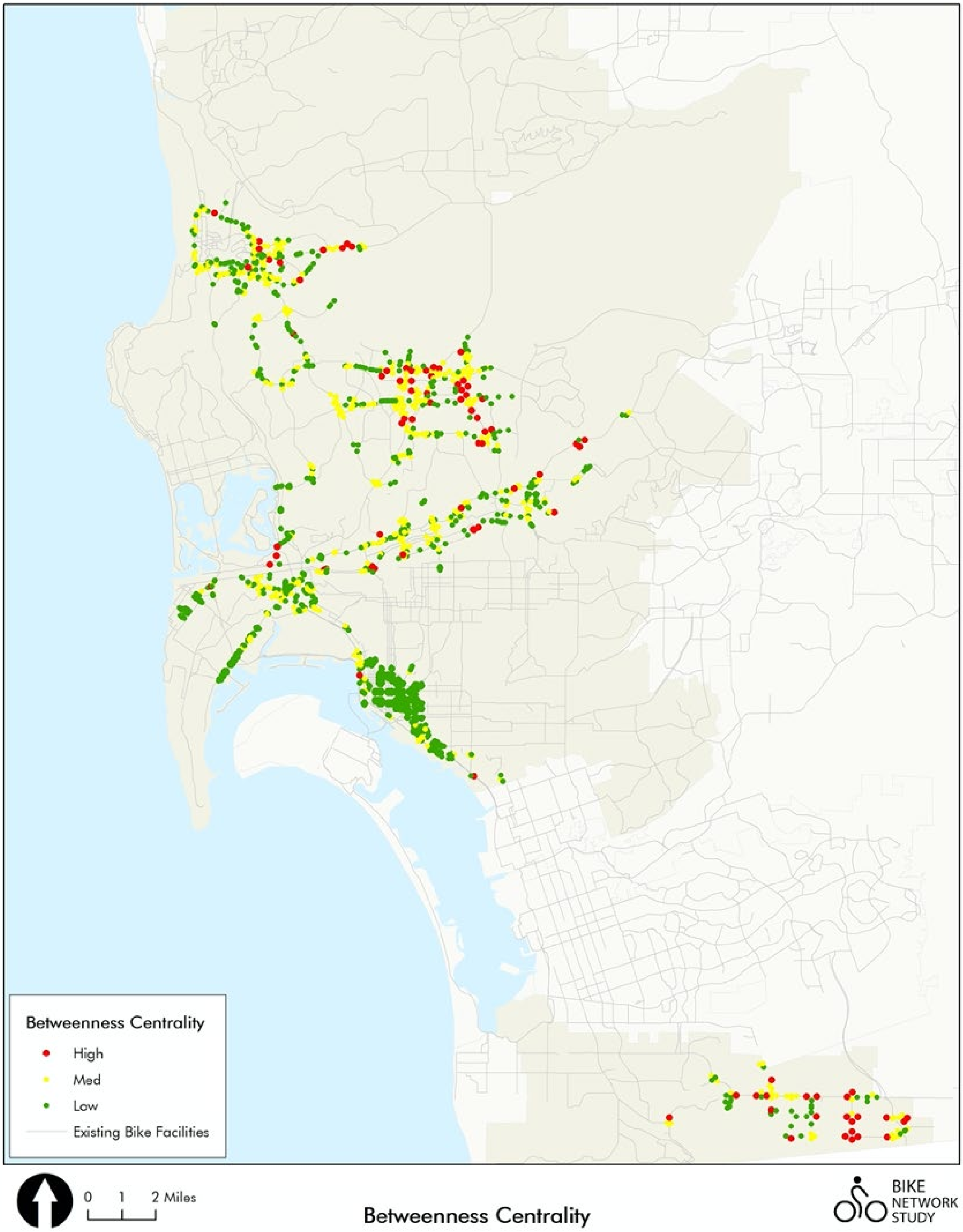

Figure 9. Betweenness Centrality

LTS has gained traction in U.S. bicycle planning practice, as it is fairly easy to calculate and provides an objective measure of the cycling environment along a roadway, and from which improvement recommendations can be offered in plan documents. The LTS network segment categorization has been related to categories of cyclists based on their cycling experience. More experienced cyclists would tolerate higher levels of stress, such as would be found in environments categorized as LTS 3 and 4, while less experienced cyclists would only be comfortable in environments categorized as LTS 1 and 2. Figure 10 shows a visual depiction of four categories of cyclists generally thought to correspond to the four levels of LTS. The first category, the “Non-Cyclists,” are people who, for a variety of reasons, would almost never get on a bicycle. About 32% of the population identifies with this category and would only be amenable to LTS 1 environments. In the second category, the “Interested But Concerned,” are people who would like to ride their bike but are cautious. This category of cyclist prefers LTS 1 and 2 facilities that cause low levels of traffic stress. Approximately 60% of the population falls into this category, making it the largest category of cyclists. The third category is referred to as “Causal and Somewhat Confident” category, which characterizes approximately seven percent of the population, and would be amenable to LTS 3 environments. The final category is referred to as the “Strong & Fearless” or the “Experienced & Confident.” These are the cyclists who are willing to ride their bicycles regardless of the facility type, and they make up about one percent of the population. The last category of cyclists would tolerate LTS 4 environments.

As shown in Table 6 and Figure 11, roadways in the City of San Diego predominantly exhibit characteristics of LTS 1 environments. Roadways with an LTS 1 or 2 environment are generally residential streets and collectors, and these are considered high quality cycling environments. These types of roadways are generally characterized as having one lane in each direction while providing adequate width for cyclists and vehicles, with a low posted speed. A number of roadways in the city reflect LTS 4. In these cases, speed limits, vehicular volumes, and roadway widths create environments that are not comfortable enough for the typical cyclist. Table 6 and Figures 11 and 12 show the miles of roadway in the City of San Diego by LTS category. The majority of roadway miles in the City of San Diego, or roughly 82% of all roadways in San Diego, fall into the LTS 1 category. A small number fall into the LTS 2 and 3 categories, and about 16% of roadways fall into the LTS 4 category. Figure 12 displays the distribution of LTS across the City of San Diego roadways. The LTS in red is largely found along major roadways that provide high levels of connectivity across the city but are also high volume, high speed facilities that are undesirable for cyclists.

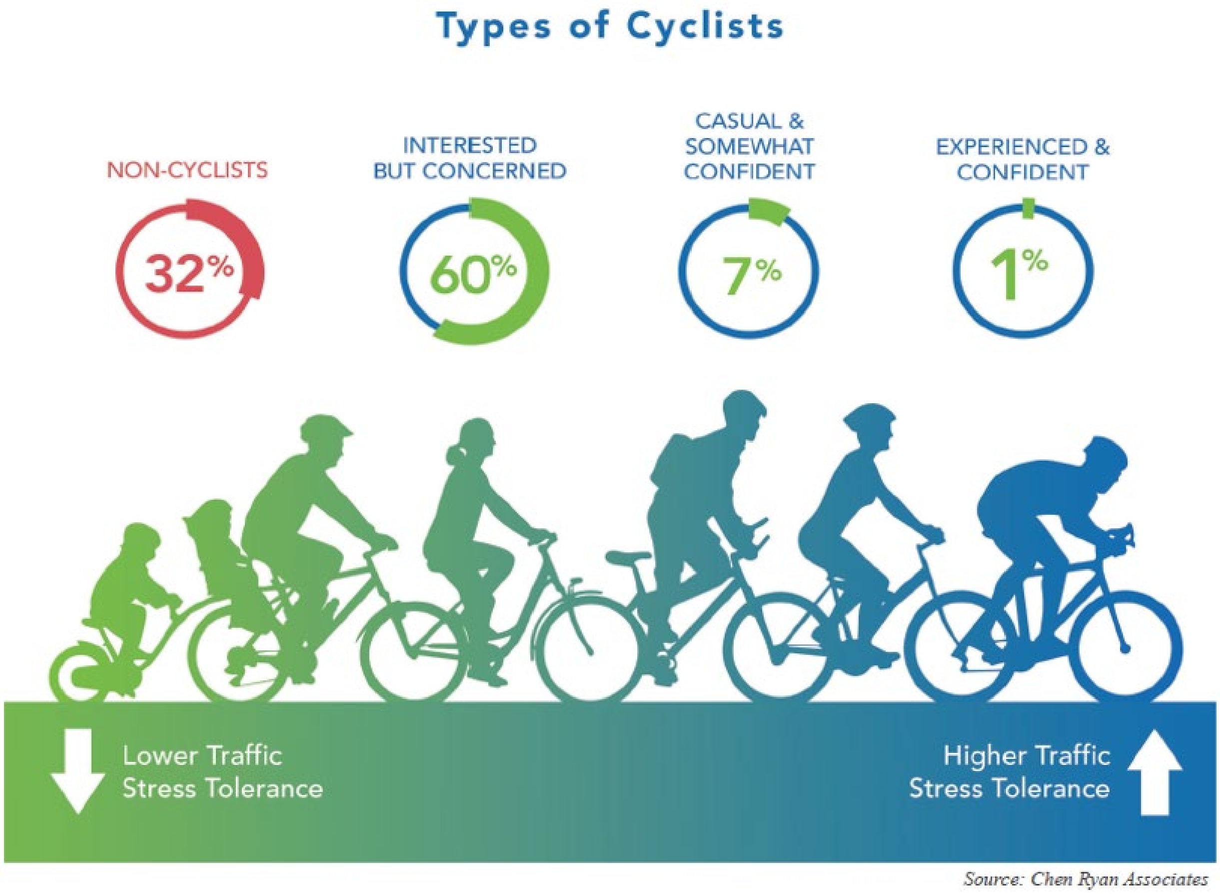

Figure 10. Four Types of Cyclists and Level of Traffic Stress

Table 6. Miles of Bikeable Roadway Network by LTS

LTS Category	Miles	Percent of Total
LTS 1	3,130	81.8%
LTS 2	18	0.5%
LTS 3	58	1.5%
LTS 4	620	16.2%
Total	**3,826**	**100.0%**

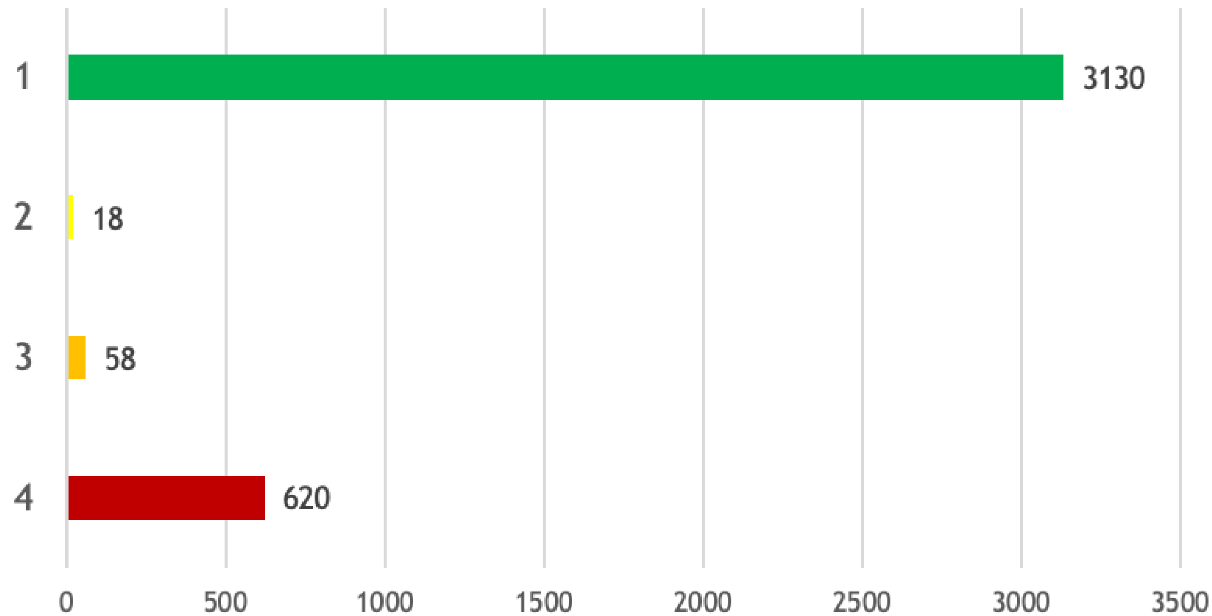

Figure 11. Miles of Bikeable Roadway Network by LTS Category

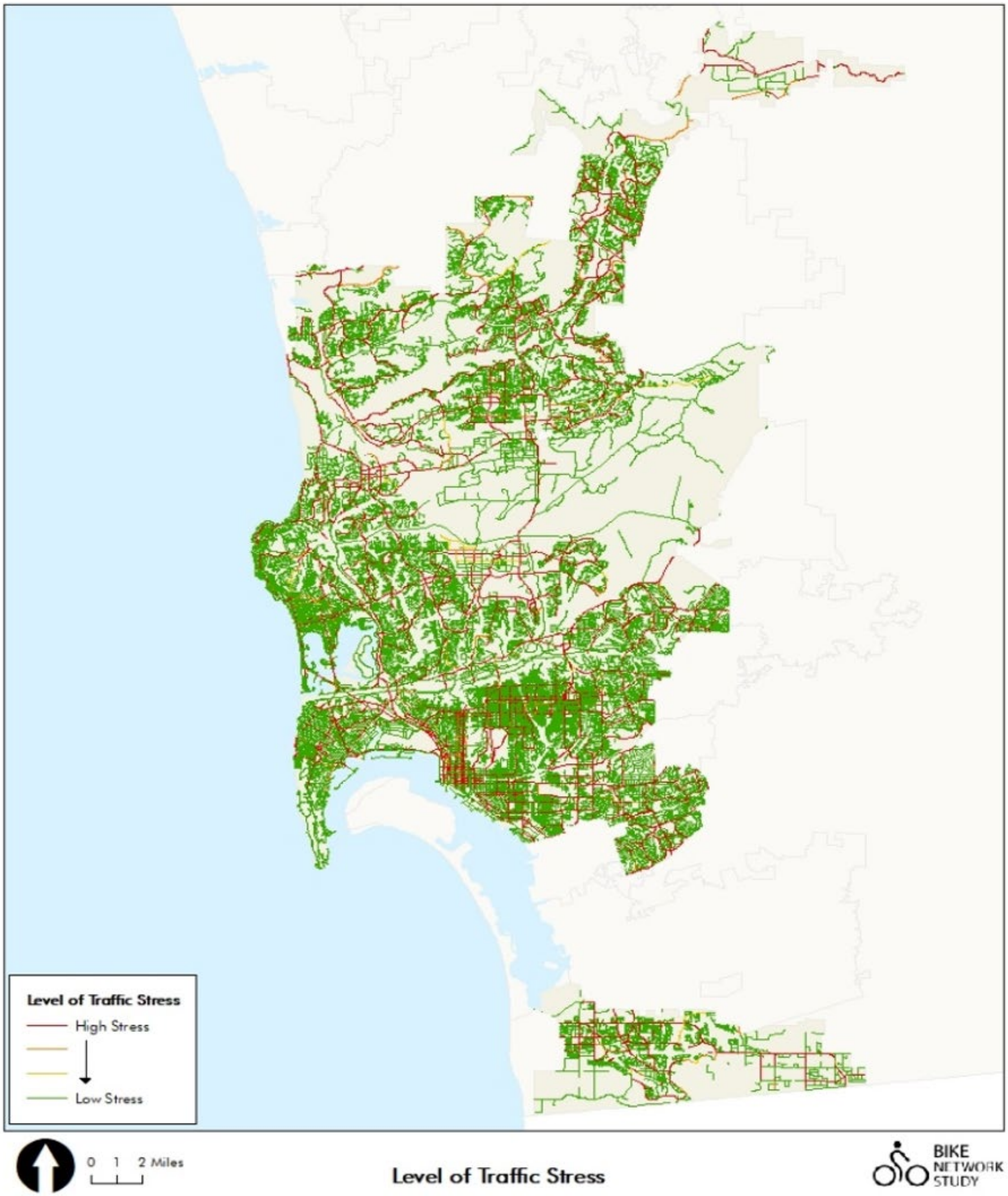

Figure 12. Level of Traffic Stress

Safety Measures

Bicycle collision rates were calculated by dividing total collisions within 500 feet of a count segment by the average annual bike volume along the count segment. Figure 13 shows the distribution of total collisions across the City of San Diego, as well as collision rates along the study segments. Collision data was obtained from the City of San Diego for the years 2012 to 2016.

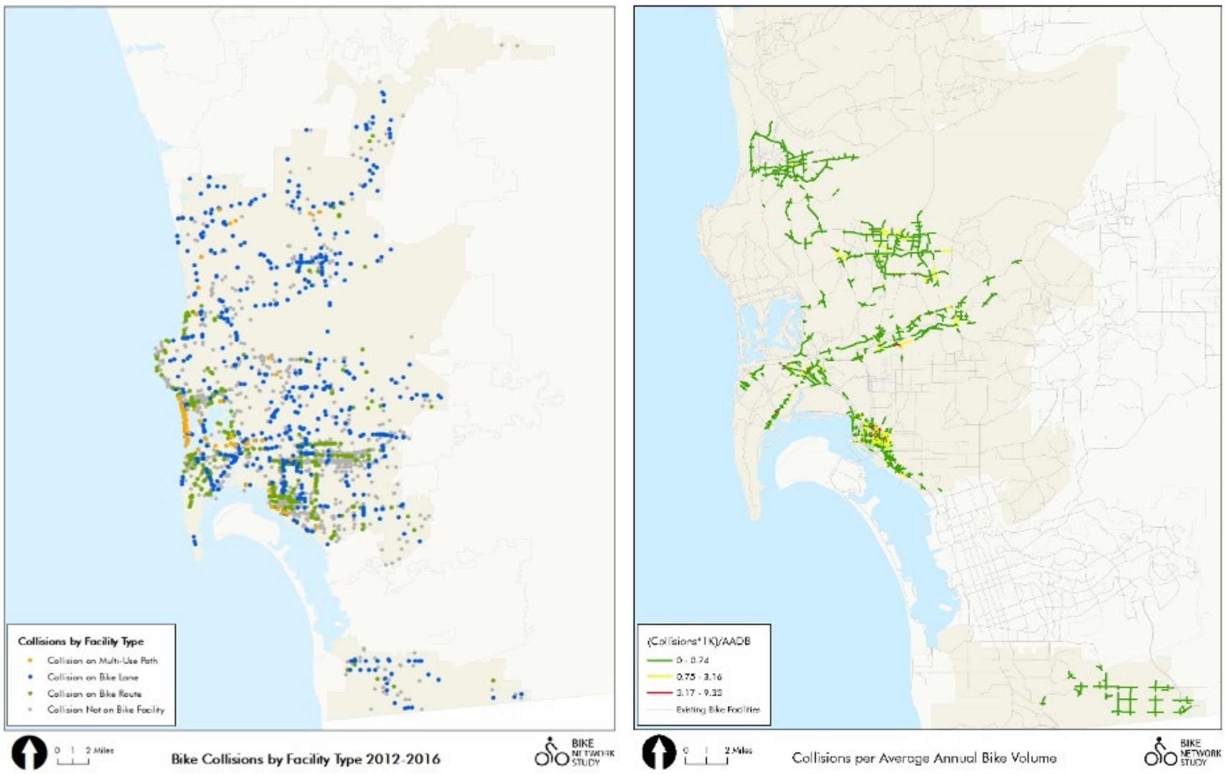

Figure 13. Bike Collisions by Facility Type 2012–2016 and Collisions per AADB

Built Environment and Socio-Economic Characteristics

Data from 2015 describing population density and job density are used to reflect built environment characteristics. Higher density is expected to vary directly with bicycle volumes, and this relationship has been established in previous literature.[31]

Median household income has also been generally shown to be significantly related to travel, with higher incomes associated with higher levels of travel. The relationship between cycling levels and income, however, is inconsistent.[32] Cycling is sometimes associated with high income neighborhoods where community members have ample leisure time to spend on exercise and recreation. For the purposes of this study, each of the count segments was buffered by a 500-foot area, and the densities and median income inside these areas were calculated. Areal apportioning was applied in this process. Figures 14 to 16 show the population density, job density, and median household income, respectively in relation to average annual daily bicycle volumes.

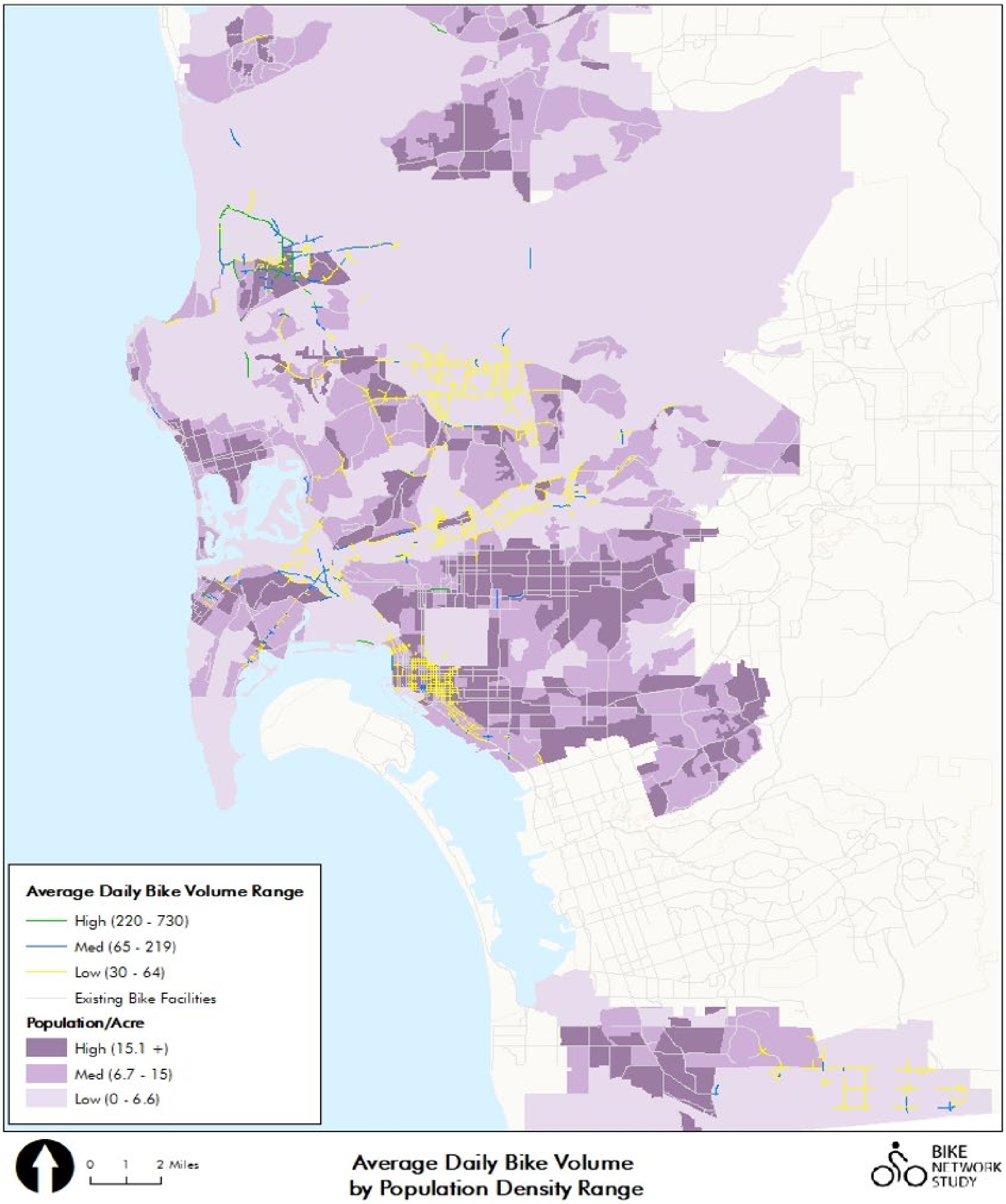

Figure 14. Average Daily Bike Volume and 2015 Population Density

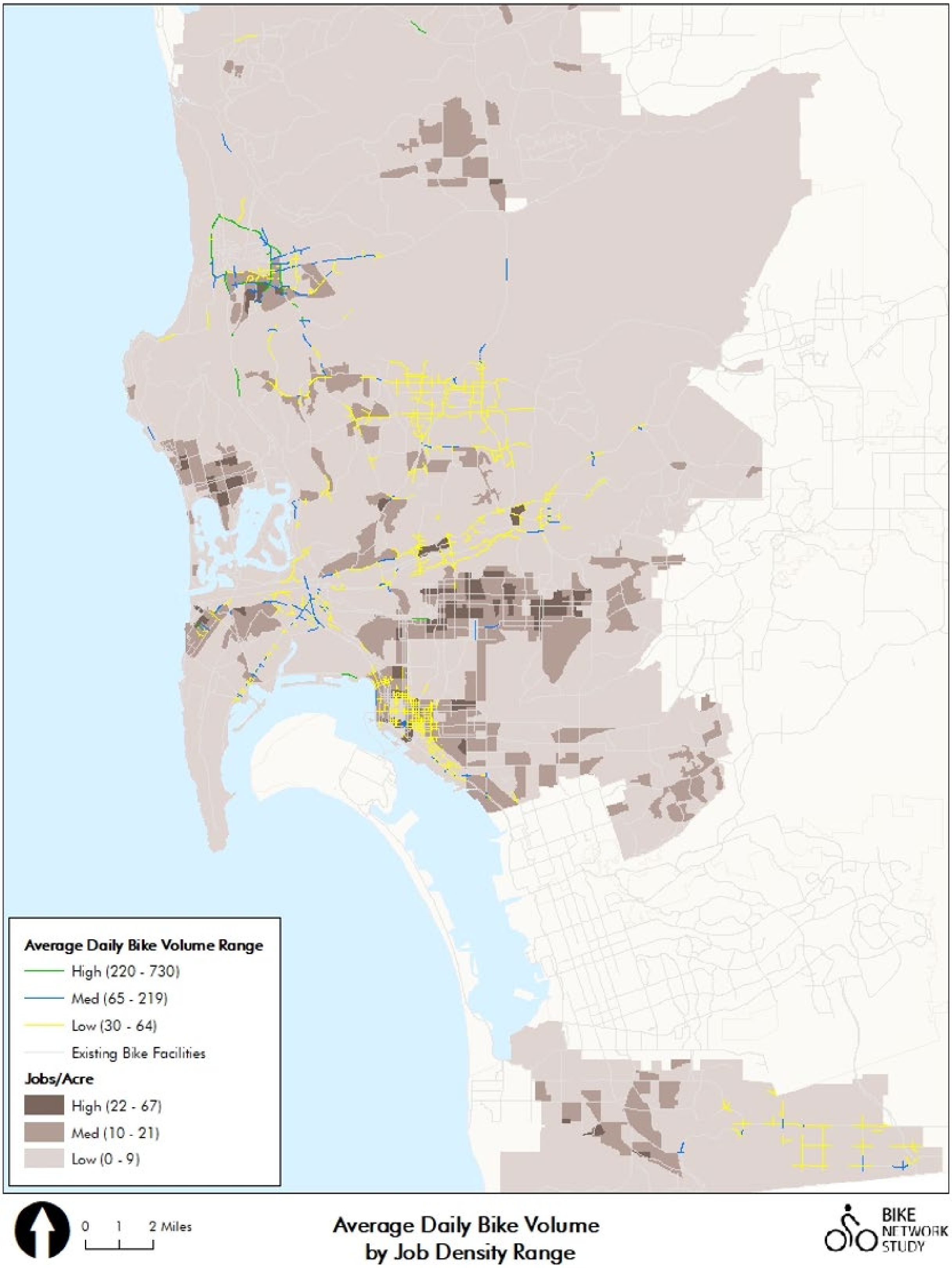

Figure 15. Average Daily Bike Volume and 2015 Job Density

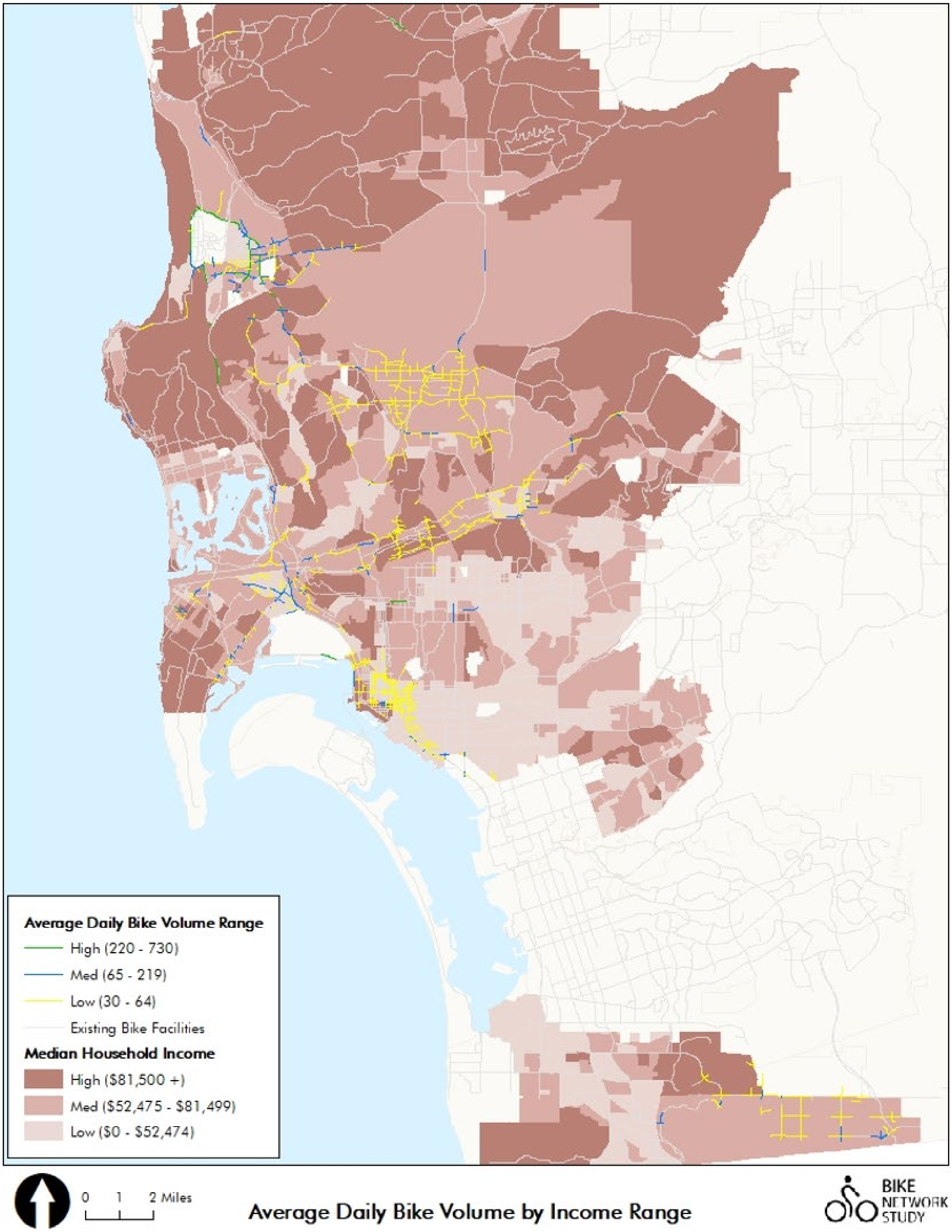

Figure 16. Average Daily Bike Volume and 2015 Median Household Income

Cycling Propensity Models

In the absence of widespread cycling demand data, the City of San Diego employs a cycling propensity model consisting of over 25 inputs that are weighted and scored.[33] The propensity model has not been assessed for how well it correlates with actual demand. A key purpose of this research is to understand the correlation between the propensity model and actual average annual daily bicycle volume.

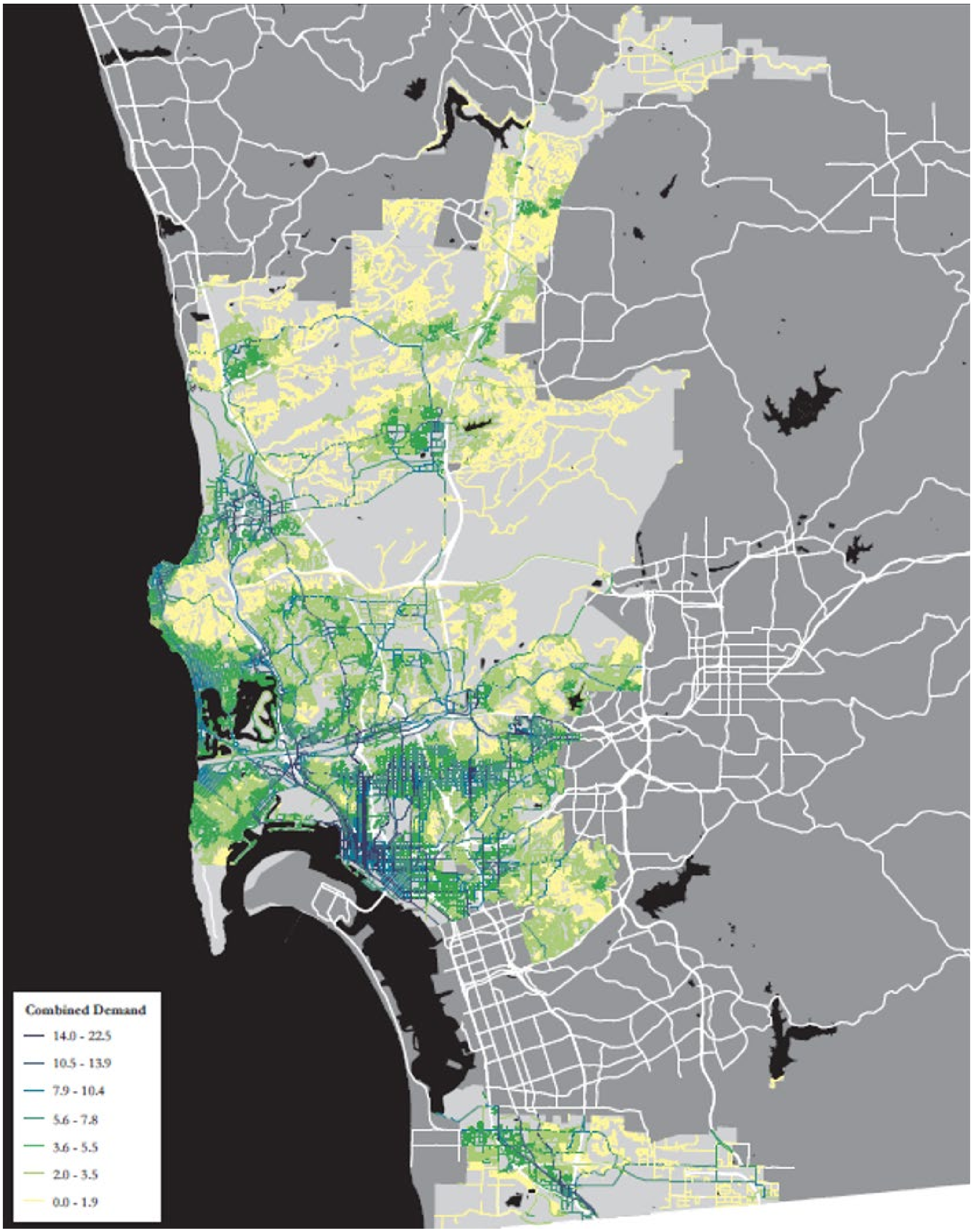

Figure 17. City of San Diego Cycling Propensity Model

IV. ANALYTICAL APPROACH

CYCLING DEMAND MODEL DEVELOPMENT

AABD is the key dependent variable and is estimated using four sets of independent variables: whole-network indicators, network quality indicators, socio-economic variables, and built environment measures. The unit of analysis for all of these variables is a roadway segment along the bikeable roadway network within the City of San Diego, or a buffered area around these roadway segments. Betweenness centrality was defined within a half-mile area of the study roadway segments, while density and income variables were calculated using a 500-foot street network buffer around the study segments. Model estimation techniques from recent literature guided the analytical methods used here. Linear regression analysis was employed to estimate the cycling demand model. The AABD was transformed to its natural log to ensure a normal distribution. The frequency distributions of the key study variables are shown in Figure 18.

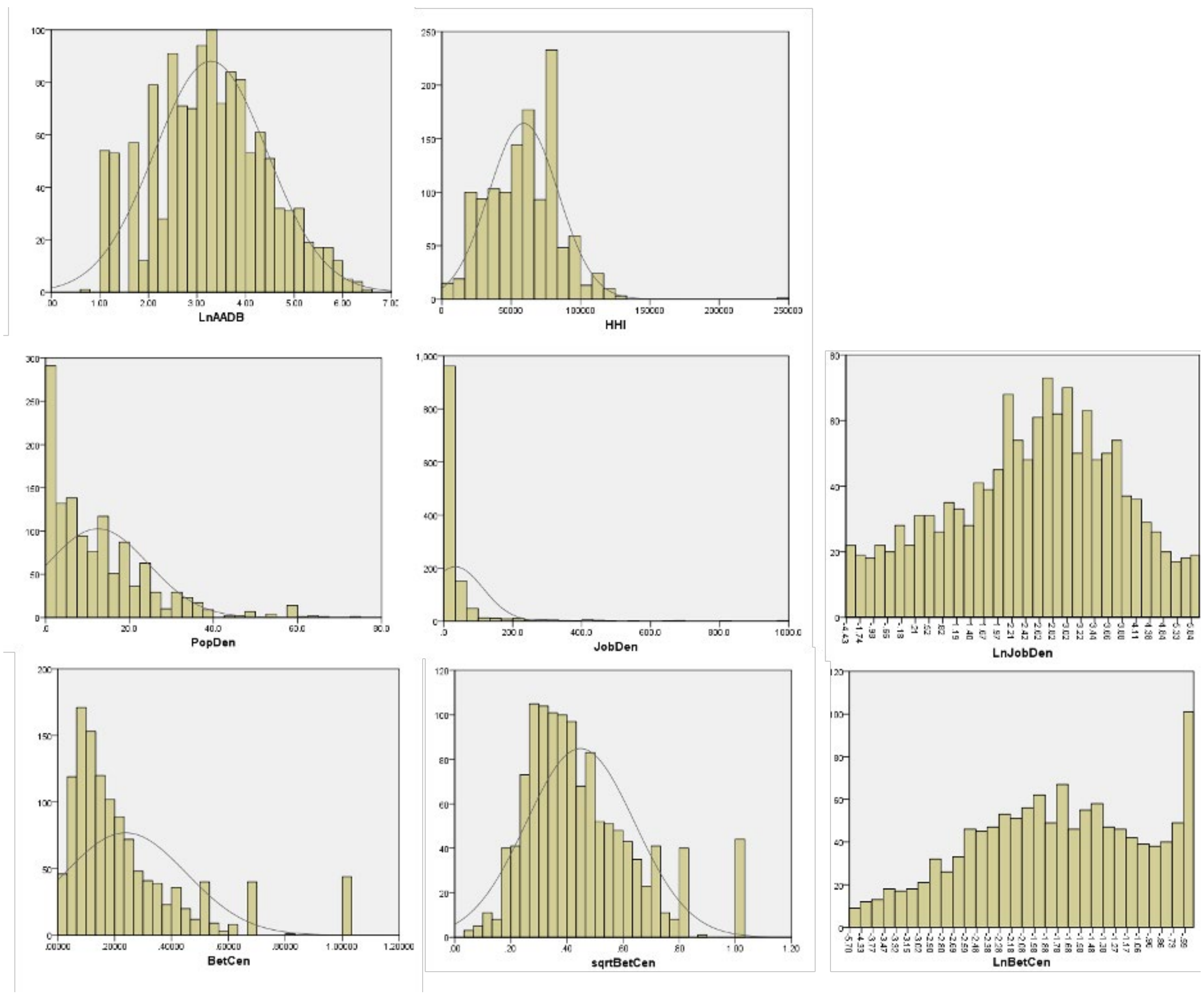

Figure 18. Frequency Distribution of Key Study Variables

The cycling demand model development includes bivariate Pearson correlations, partial correlations, ANOVA, and multiple linear regression.

CYCLING SAFETY MODEL DEVELOPMENT

The improved cyclist exposure data allow for a more rigorous safety analysis than simply assessing collision counts. The cycling collision rate variable was modeled based upon independent variables related to the network, built environment, and neighborhood socio-economics. Linear regression analysis was employed to estimate the cycling safety model. The distribution of collision rates is shown in Figure 19.

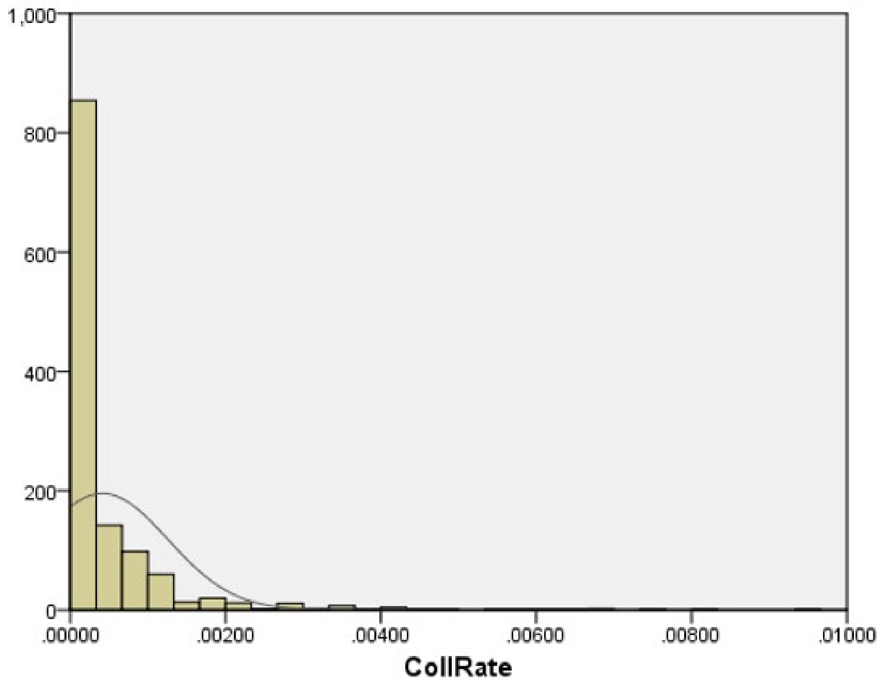

Figure 19. Frequency Distribution of Collision Rate

COMPARING AABD AND CYCLING PROPENSITY

Pearson correlations are employed to assess the relationship between AADB and cycling propensity to determine the validity of propensity modeling, which has been widely used in long range bicycle planning practice in the San Diego region. It will assist planners to understand the degree to which cycling propensity models are related to actual bicycle volume. The frequency distribution of cycling propensity scores for the City of San Diego bikeable network is presented in Figure 20.

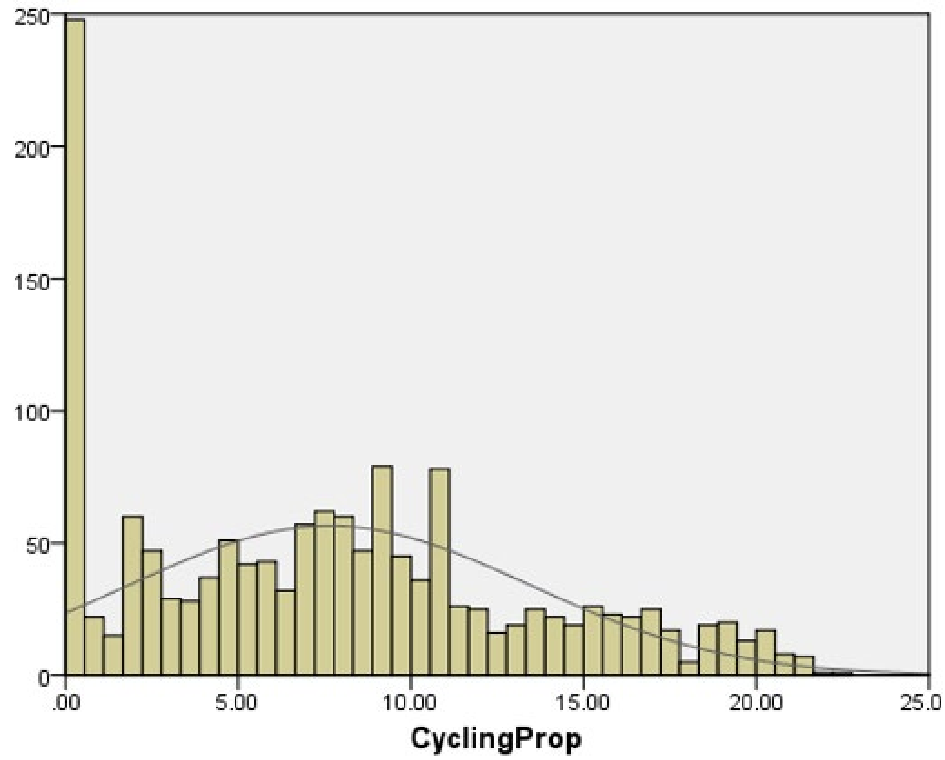

Figure 20. Frequency Distribution of Cycling Propensity

V. ANALYSIS AND RESULTS

CYCLING DEMAND MODELING RESULTS

Pearson Correlations

Pearson correlations were used to examine the degree of association between the study variables. The two conditions for examining the Pearson correlation are met: namely, continuous variables that are normally distributed. LTS was not included since it is a nominal variable. Table 7 shows the Pearson correlation coefficients and the level of significance.

Table 7. Bivariate Correlations (Pearson Correlation)

		LnAADB	SqrtBetCen	PopDen	JobDen	HHI
LnAADB	Pearson Correlation	--	.098**	-.051	-.050	-.028
	Sig. (2-tailed)	--	.001	.095	.101	.354
SqrtBetCen	Pearson Correlation	--	--	-.374**	-.129**	.237**
	Sig. (2-tailed)	--	--	.000	.000	.000
PopDen	Pearson Correlation	--	--	--	.080**	-.236**
	Sig. (2-tailed)	--	--	--	.005	.000
JobDen	Pearson Correlation	--	--	--	--	-.177**
	Sig. (2-tailed)	--	--	--	--	.000
HHI	Pearson Correlation	--	--	--	--	--
	Sig. (2-tailed)	--	--	--	--	--

** Correlation is significant at the .01 level.

Bicycle volume is positively and significantly related to betweenness centrality. This is the expected relationship: as the centrality of a segment within the network increases, the segment would be more highly utilized by cyclists. Several of the independent variables also have significant relationships at the 0.01 level with other independent variables, indicating the potential for multicollinearity.

Betweenness centrality is inversely and significantly related to population density and job density, and it is positively and significantly related to household income. It is reasonable that network centrality and population or job density are inversely related. Network centrality is higher as the network becomes sparser; as roadway networks become sparser, land use density would typically be lower. Network centrality in many ways measures the degree or presence of bottlenecks, or the lack of alternative routes.

Partial Correlations

Tables 8 through 10 show partial correlations, controlling for household income, population density, and job density, respectively.

Table 8. Partial Correlations (controlling for HHI)

		LnAADB	SqrtBetCen	PopDen	JobDen	HHI
LnAADB	Pearson Correlation	--	.109	-.058	-.056	--
	Sig. (2-tailed)	--	.000	.055	.066	--
SqrtBetCen	Pearson Correlation	--	--	-.349	-.083	--
	Sig. (2-tailed)	--	--	.000	.006	--
PopDen	Pearson Correlation	--	--	--	.034	--
	Sig. (2-tailed)	--	--	--	.261	--
JobDen	Pearson Correlation	--	--	--	--	--
	Sig. (2-tailed)	--	--	--	--	--

Note: Shading indicates significant correlation.

Even when controlling for income, as shown in Table 8, bicycle volumes and betweenness centrality are significantly and positively related and the density variables are not significantly related to bike volumes.

Table 9. Partial Correlations (controlling for PopDen)

		LnAADB	SqrtBetCen	PopDen	JobDen	HHI
LnAADB	Pearson Correlation	--	.085	--	-.046	-.040
	Sig. (2-tailed)	--	.005	--	.128	.185
SqrtBetCen	Pearson Correlation	--	--	--	-.108	.198
	Sig. (2-tailed)	--	--	--	.000	.000
HHI	Pearson Correlation	--	--	--	-.173	--
	Sig. (2-tailed)	--	--	--	.000	--
JobDen	Pearson Correlation	--	--	--	--	--
	Sig. (2-tailed)	--	--	--	--	--

Note: Shading indicates significant correlation.

When controlling for the population density, as shown in Table 9, betweenness centrality is significantly and positively related to bike volumes, and income is not significantly related.

When controlling for the job density, as shown in Table 10, betweenness centrality is significantly and positively related to bike volumes, as is population density, and income is not significantly related.

Table 10. Partial Correlations (controlling for JobDen)

		LnAADB	SqrtBetCen	PopDen	JobDen	HHI
LnAADB	Pearson Correlation	--	.092	-.380	--	-.038
	Sig. (2-tailed)	--	.002	.000	--	.211
SqrtBetCen	Pearson Correlation	--	--	-.380	--	.245
	Sig. (2-tailed)	--	--	.000	--	.000
HHI	Pearson Correlation	--	--	-.209	--	--
	Sig. (2-tailed)	--	--	.000	--	--
JobDen	Pearson Correlation	--	--	--	--	--
	Sig. (2-tailed)	--	--	--	--	--

Note: Shading indicates significant correlation.

Regression Analysis

Models 1A, 1B, 2A, and 2B in Table 11 present the results of the multivariate regression conducted to estimate the natural log of bicycle volumes. Model 1A and 1B assess differences in model results with betweenness centrality transformed by the natural log (Model 1A) and by the square root (Model 1B). Neither Model 1A or 1B includes the LTS measure. Models 2A and 2B include the same variables as Model 1A and 1B and also include LTS.

Table 11. Linear Regression with Dependent Variable LnAADB

	Model 1A		Model 1B		Model 2A		Model 2B	
Independent Variables	**Coef**	**Sig**	**Coef**	**Sig**	**Coef**	**Sig**	**Coef**	**Sig**
LnBetCen	.187	.000*	--	--	.129	.005	--	--
SqrtBetCen	--	--	.465	.001*	--	--	.291	.037
LTS	--	--	--	--	.192	.000*	.196	.000*
PopDen	.001	.806	-.002	.528	-.001	.694	-.004	.207
LnJobDen	-.124	.000*	-.118	.000*	-.129	.000*	-.117	.000*
HHInc	-2.715E-6	.075	-2.243E-6	.110	-2.835E-6	.056	-2.505E-6	.066
Constant	4.063		3.524		3.448		3.064	
Adj R-Squared	.046		.035		.099		.091	
F-Statistic	13.291	.000	11.648	.000	23.570	.000	24.908	.000

All four models show relatively low R-squared values between 0.035 and 0.099, meaning that only between 3.5% to 10% of the variation in average annual daily bicycle volumes is explained by these models. The F-statistics are significant for all four models. In both models without LTS, the betweenness centrality measure contributes significantly to estimating bike volumes. When LTS is added to the models, betweenness centrality is no longer significant. The direction of the LTS coefficient is unexpected, showing that as LTS increases (cycling becomes more stressful), bike volumes increase. This result was also found in the Pearson coefficients.

There may be several reasons for this unexpected finding. It is possible that LTS is not accurately reflecting stress levels experienced in the cycling environment, as Harvey et al.[34] mention. It is also possible that cycling in San Diego is irrational in the sense that it places people in direct risk of harm, and only cyclists willing to use stressful routes will ride a bike, or that individuals willing to ride a bike in this context are insensitive to roadway environments and select their route based upon other factors.

Another consistent finding across all four models is the inverse relationship between bicycle volumes and job density. As job density increases, bike volume decreases. This is also a somewhat unexpected finding and indicates that cycling is occurring away from job centers—which may be consistent with more suburbanized, recreational cycling. Neither household income nor population density is significant in the four models.

CYCLING COLLISION RATE MODEL

An important planning benefit and application of average annual bicycle volume is the calculation of collision rates. Collision rates, as opposed to collision counts, is a better indication of cycling risk along the network.

Table 12 shows the Pearson correlation coefficients and the level of significance.

Table 12. Bivariate Correlations (Pearson Correlation)

		Coll Rate	Dist Fwy	Detractor	Speed	Pop Den	Job Den	HHI
CollRate	Pearson Correlation	--	**-.066***	.023	**-.175****	**.273****	**.065***	**-.141****
	Sig. (2-tailed)	--	**.012**	.378	**.000**	**.000**	**.013**	**.000**
DistFwy	Pearson Correlation	--	--	.046	.046	.045	**-.054***	**.171****
	Sig. (2-tailed)	--	--	.076	.076	.086	**.037**	**.000**
Detractors[1]	Pearson Correlation	--	--	--	**.353****	.019	.013	-.014
	Sig. (2-tailed)	--	--	--	**.000**	.456	.611	.593
Speed	Pearson Correlation	--	--	--	--	**-.184****	**-.132****	**.097****
	Sig. (2-tailed)	--	--	--	--	**.000**	**.000**	**.000**
PopDen	Pearson Correlation	--	--	--	--	--	**.093****	**-.235****
	Sig. (2-tailed)	--	--	--	--	--	**.000**	**.000**
JobDen	Pearson Correlation	--	--	--	--	--	--	**-.168****
	Sig. (2-tailed)	--	--	--	--	--	--	**.000**
HHI	Pearson Correlation	--	--	--	--	--	--	--
	Sig. (2-tailed)	--	--	--	--	--	--	--

* Correlation is significant at the .05 level.

** Correlation is significant at the .01 level.

[1]Detractors is a network-based composite score combining multiple variables obtained from the City of San Diego's Bicycle Master Plan planning effort.

Distance to freeway, speed, and household income show significant inverse relationships with collision rates. As distance to freeway, speed, and income decrease, collision rates increase. The inverse association with distance to freeway is reasonable: roadways closer to on/off ramps and other freeway infrastructure likely have higher vehicular volumes and speeds, making these locations less safe for cyclists. The inverse correlation with income is unfortunate and indicates that higher rates of collisions are happening in lower income neighborhoods, which is consistent with other published findings. [35] The inverse relation with speed is contrary to expected findings and may be related to the contradictory association found between bike volume and LTS. Collision rates are positively and significantly related to population density and job density, which is reasonably expected.

Table 13 shows two multivariate linear regression models estimating collision rates.

Table 13. Linear Regression with Dependent Variable Collision Rates (CollRate)

	Model 1		Model 2	
Independent Variables	**Coef**	**Sig**	**Coef**	**Sig**
DistFwy	-4.297E-5	.001	-4.817E-5	.000
LnBetCen	--	--	-.114	.006
LTS	.001	.000	.011	.715
Speed	-.023	.000	-.021	.000
PopDen	.017	.000	.015	.000
HHI	-1.020E-6	.421	-8.643E-7	.528
Constant	1.142		.899	
Adj R-Squared	.117		.131	
F-Statistic	26.218	.000	22.151	.000

Both models show relatively low R-squared values: between 0.117 and 0.131, meaning that only between 11% to 13% of the variation in collision rates is explained by these variables. The F-statistics are significant for each model. In both models, distance to freeways and speed are inversely and significantly related to collision rates. In Model 1, LTS has the expected positive relationship with collision rates, while in Model 2, when betweenness centrality is included, LTS is not significant.

COMPARING AABD AND CYCLING PROPENSITY

Cycling propensity, as calculated for the 2013 City of San Diego Bicycle Master Plan, appears to be correlated with Peak Hour Bicycle Volume (PKBikeVol) and with AADB, suggesting that it could be a viable way to estimate demand for cycling, although correlation is fairly low.

Table 14. Correlation between AADB, PkBikeVol, and Cycling Propensity

		CyclingProp
AADB	Pearson Correlation	.067*
	Sig. (2-tailed)	.010
PkBikeVol	Pearson Correlation	.062*
	Sig. (2-tailed)	.017

*. Correlation is significant at the 0.05 level (2-tailed).

VI. DISCUSSION

This section summarizes key study results, compares the results to several previous publications, and links the current findings to policy implications. As shown in Figure 4, this study set out to improve upon cycling demand models by incorporating more extensive network measures as independent variables. The study also attempted to improve upon cycling safety models by estimating cycling risk (collisions/bike volumes) rather than the more typical measure of number of collisions.

Table 15 presents comparisons of study design and model strength from recent relevant studies.

Table 15. Comparing Study Design and Results of Current and Previous Studies

Author	Study Area (Study Unit)	Demand Measure	Network Measures	Network Measures Significant?	R-squared
Current Study (Ryan et al.)	City of San Diego (1,474 roadway segments)	Average Annual Daily Bicycle Volume by segment	*Betweenness Centrality*	Yes	0.035 to 0.099
Osama et al (2017)	City of Vancouver (134 TAZs)	Aggregate bike volume per bike network length by TAZ	Connectivity, *Coverage*, Continuity, *Edge Length*, Slope	Yes	0.42 to 0.61
Schoner and Levinson (2014)	74 U.S Cities (cities)	Bicycle Commute Rate per 10,000 commuters by City	*Density, Connectivity, Fragmentation,* and *Directness*	Yes	0.804
Buehler and Pucher (2012)	90 U.S. Cities (cities)	Bicycle Commute Rate per 10,000 commuters by City	*Density*	Yes	0.33 to 0.65

The three studies highlighted in Table 15 show some of the most recent research considering the influence of networks on cycling demand. The unit of analysis is a key difference in study design between the current and previous studies. Two of the studies aggregate data to the city level, while Osama et al. use data aggregated to TAZs. The current study employs the smallest unit of analysis, roadway segments and the area within a 500-foot buffer.

Another important difference is that the current study as well as Osama et al. both use observed bicycle volumes, while the other two studies use self-report census data on bike commute trip-making.

The current study did not include multiple network measures. Including multiple measures whole network measures may be important given the improvement in explanatory power between Schoner and Levinson, where four network measures were included, and Buehler and Pucher, who only included network density. Finally, the overall explanatory power of the current demand model is not as strong as the previous studies reported in Table 15. Taken together, the study results shown in Table 15 underscore the difficulty of predicting bicycle flows along networks, which is a goal of the current study and an important direction for future research. This type of modeling has not explicitly been attempted in previous literature, mainly because bicycle volumes along segments has not been widely available. The weak model strength of the current study shows that estimating flows along network segments is difficult compared to estimating more aggregate, zone-based models of cycling demand.

In terms of objectives, this study succeeds in offering a first ever examination of cycling demand models using bicycle volumes along roadway segments. It successfully integrates a unique “whole-network” measure in the demand estimation. It also presents a statistically significant cycling risk model using an improved measure of cycling safety (collisions per volume). And finally, the study examines how an ad hoc cycling propensity model relates to actual bike volumes along segments, finding the correlation to be fairly low but still significant.

Further research should continue to focus on improving model specification for cycling demand models that use bike flows along segments rather than zonal level cycling demand. These types of models will continue to be more readily deployable given the generally improved count data starting to be collected across several U.S regions. Future research should also focus on improving and validating the multiple ad hoc tools currently employed in bicycle planning practice. The current research attempts to assess and validate one city’s ad hoc planning tools with observed data.

VII. CONCLUSIONS

This research used a unique database of cycling volumes from the San Diego region to estimate a cycling demand and a cycling collision model. Continuous cycling count data collected from 34 automated counters were used to extrapolate over 1,400 short duration counts to average annual daily bicycle volumes (AADB). Network characteristics, built environment, and socio-economic characteristics were the primary independent variables employed in the modeling. A key contribution of this research is to incorporate both a whole-network measure (betweenness centrality) and a network quality measure (LTS) in estimating cycling volumes. Another key contribution is the assessment of the correlation between cycling propensity models used by practicing planners in San Diego and actual AADB.

The correlation analyses show that betweenness centrality is positively and significantly related to average annual daily bicycle volumes, even when controlling for density and income. This is the expected finding, meaning that as the importance of the segment within the overall network increases, the number of cyclists using that segment increases. The regression analysis supports this finding as well. Given the relatively poor quality of cycling infrastructure and low levels of cycling across many regions including San Diego, examining demand is not always useful. Using network characteristics to assess and substantiate the need for cycling infrastructure holds promise for local and regional bicycle planners, and it does relate to the demand for cycling. Roadway segments with high centrality are often bottlenecks within the network—not only for cyclists, but also for drivers. Planners and engineers often make difficult decisions at these bottleneck locations about how to accommodate vehicles and cyclists. This research shows that cyclists are indeed sensitive to the centrality of segments within the network, and priority should be placed on these segments for accommodating cyclists. Based upon the findings of this research, dropping bicycle infrastructure when rights-of-way narrow is very likely detrimental to cycling levels, especially if these segments hold high centrality.

The findings related to network quality are contrary to expectations. The analyses showed that LTS is positively associated with cycling volumes, meaning that when cycling stress along the roadway increases, bicycle volumes increase. This could be caused by inaccurate data used for calculating LTS, since it requires highly detailed inputs about the roadway environment. Alternatively, it could be caused by an “irrational” cyclist phenomenon, where cycling environments are generally so treacherous across San Diego that only people who are fully insensitive to this stress choose to ride a bike.

In terms of cycling collision rates, this research shows that distance to freeway and income are inversely related to collision rates. It is reasonable that proximity to freeways is inversely related to collisions, meaning that as cyclists get closer to freeways, collisions tend to go up. Cycling collision rates are also higher in lower income neighborhoods—a finding which has important equity implications for bicycle planning. As environmental justice has become mandatory in local governments’ general plans, it will be important to assess how low income and high minority populations experience disproportionate impacts from transportation systems, such as higher rates of cycling collisions than neighboring high income neighborhoods.

Finally, in terms of planning tools, this research shows that there is an association between cycling propensity as developed by the City of San Diego for the purposes of long range bicycle planning and actual bicycle volume. A key effort in this research is to validate ad hoc tools that bicycle planners must develop in the absence of more formal tools, such as regional transportation planning models maintained by Metropolitan Planning Organizations (MPOs). This issue underscores two related concerns: first, regional transportation models are incredibly resource intensive and allow almost no treatment of cycling or walking. In an era of mandated complete street planning, the over-investment in large-scale regional models that assess driving but have no ability to assess cycling and walking is concerning. The institutional dedication to modeling large-scale regional travel, of the type we are trying to discourage, is ineffective. Simple measures related to network quality and capacity across modes would suffice to reflect the gross imbalance in our systems and the growing and seemingly irreversible problem of increasing vehicle-miles-travelled (VMT). A second concern is the persistent disconnect between active travel planning as undertaken by local and regional governments and the academic literature. The academy needs to do more to understand local government planning processes and “meet them where they are” in terms of making recommendations for improving planning approaches. Academics needs to do more to make their research relevant to practicing planners. Examining and improving planners’ ad hoc tools, especially in the case of active travel planning where almost no tools exist, is an excellent role for academics to play in improving planning outcomes.

ABBREVIATIONS AND ACRONYMS

AADB	Average Annual Daily Bicycle Volumes
ANOVA	
BetCen	Between Centrality
BLOS	Bicycle Level of Service
CollRate	Number of Collisions/Average Annual Bicycle Volume
CSUUTC	California State University Transportation Center
CyclingProp	Cycling Propensity
DistFwy	Straight-line distance between study area count segment and nearest freeway
HHI	Median Household Income
JobDen	Number of Jobs per Acre
Ln	Natural Logarithm Transformation
LTS	Level of Traffic Stress
MPO	Metropolitan Planning Organization
NHTS	National Household Travel Survey
PKBike Vol	Peak Hour Bicycle Volume
PopDen	Population per Acre
Sqrt	Square Root
VMT	Vehicle-Miles-Travelled
WWI	Weekend/Weekday Index
WD-C	Weekday Commute
W-MP	Weekly Multipurpose
WE-MP	Weekend Multipurpose

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PEER REVIEW

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