FINAL REPORT

Estimating Walking and Bicycling at the State Level

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# ESTIMATING WALKING AND BICYCLING AT THE STATE LEVEL 

Final Report

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by

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## TABLE OF CONTENTS

EXECUTIVE SUMMARY ..... VIII
1.0 INTRODUCTION ..... 9
2.0 LITERATURE REVIEW ..... 10
2.1 MOTOR VEHICLE MILES TRAVELED ..... 10
2.1.1 VMT Avoided Estimates ..... 11
2.2 PEDESTRIAN AND BICYCLE MILES TRAVELED ..... 12
2.3 PEDESTRIAN AND BICYCLE DEMAND ESTIMATION METHODS ..... 12
2.3.1 NCHRP Report 770 ..... 13
2.4 FACTORS THAT MAY IMPACT BICYCLING AND WALKING ..... 14
2.4.1 Level of Urbanism ..... 16
2.4.1.1 Rural-Urban Commuting Area Codes ..... 16
2.4.1.2 Smart Location Database ..... 17
2.4.1.3 Subcenters ..... 17
3.0 DATA SOURCES ..... 18
3.1 COUNT DATA ..... 18
3.1.1 WSDOT Bicycle and Pedestrian Documentation Project Count Data ..... 18
3.1.2 City of Seattle Count Data ..... 18
3.1.3 City of Olympia ..... 19
3.1.4 Methods to Analyze Temporal Variation of Count Data ..... 19
3.1.5 Computing Annual Average Daily Traffic at Permanent Count Sites ..... 19
3.1.6 Estimating Annual Average Daily Traffic at Short-Duration Count Sites ..... 20
3.1.7 Computing Adjustment Factors ..... 20
3.1.8 Computing AADB and AADP Using Adjustment Factors ..... 22
3.1.9 Calculating BMT and PMT ..... 23
3.1.10 Analysis of Existing Count Data ..... 24
3.1.10.1 Limitations ..... 24
3.1.10.2 Adjustment Factors ..... 24
3.1.10.3 Hourly Variation ..... 27
3.1.10.4 Daily Variation ..... 29
3.1.10.5 Monthly Variation ..... 31
3.2 TRANSPORTATION NETWORK DATA ..... 32
3.3 SOCIODEMOGRAPHIC DATA ..... 32
3.4 OTHER DATA SOURCES ..... 32
3.4.1 Safe Routes to School .....  32
3.4.2 GPS Data ..... 34
3.4.3 Adventure Cycling ..... 36
3.5 WASHINGTON STATE BICYCLE MAP ..... 37
3.6 ORGANIZED GROUP RIDES ..... 37
3.7 SUMMARY OF DATA SOURCES ..... 38
4.0 METHODS ..... 40
4.1 TRAVEL SURVEY DATA METHOD ..... 40
4.2 SAMPLE-BASED METHOD ..... 40
4.2.1 Stratified Sample ..... 41
4.2.1.1 Level of Urbanism ..... 41
4.2.1.2 Facility Types ..... 45
4.2.1.3 Region ..... 46
4.2.2 Method Outline ..... 49
4.3 AGGREGATE DEMAND MODEL ..... 50
5.0 RESULTS ..... 53
5.1 NATIONAL SURVEY DATA METHOD ESTIMATES ..... 53
5.2 SAMPLE-BASED METHOD ESTIMATES ..... 54
5.3 AGGREGATE DEMAND MODEL ..... 56
5.4 EXAMPLE COUNTY RESULTS ..... 58
5.5 LOWER AND UPPER BOUND ..... 59
5.6 COMPARISON ACROSS STUDIES ..... 59
6.0 DISCUSSION ..... 63
6.1 BICYCLE ..... 63
6.2 PEDESTRIAN ..... 64
7.0 CONCLUSION ..... 65
8.0 REFERENCES ..... 67

## LIST OF TABLES

Table 2.1: Spatial Variables Found to be Significantly Correlated with Pedestrian Activity ..... 15
Table 2.2: Spatial Variables Found to be Significantly Correlated with Bicycle Activity16
Table 3.1: Monthly as for 2012-2013 Seattle Commute Patterns ..... 25
Table 3.2: Daily/Hourly Adjustment Factors for 2012-2013 Seattle Commute Patterns ..... 25
Table 3.4: Adventure Cycling Route Mileage Estimates ..... 37
Table 3.5: Top-10 Attended Organized Group Rides in Washington ..... 38
Table 5.1: Statewide Estimates Using National Survey Method (in Millions of Miles).. ..... 54
Table 5.2: Summary of Centerline Miles by Group ..... 55
Table 5.3: Estimates Using Count-Based Method (Millions of Miles) ..... 56
Table 5.4: Aggregate Model for Bicycle and Pedestrian Models ..... 58
Table 5.5: Annual PMT and BMT for King County within the Puget Lowlands (Millions of Miles) ..... 58
Table 7.1: Summary of Methods and Recommendations ..... 65
LIST OF FIGURES
Figure 3.1: Estimated AADB at 50 Sites in Seattle in 2012 ..... 26
Figure 3.2: Estimated AADB at 19 Sites in Olympia, WA,, in 2012 ..... 27
Figure 3.3: Seattle Fremont Bridge Hourly Patterns in 2013 ..... 28
Figure 3.4: Olympia June 2012 Hourly Weekday Patterns at 19 Locations ..... 28
Figure 3.5: Olympia June 2012 Hourly Weekend Patterns at 19 Locations ..... 29
Figure 3.6: Seattle Fremont Bridge Daily Patterns in 2013 ..... 30
Figure 3.7: Olympia June 2012 Daily Patterns at 19 Locations ..... 31
Figure 3.8: Seattle Fremont Bridge Bicycle Traffic by Month in 2013 ..... 31
Figure 3.9: Students Using Active Transportation ..... 33
Figure 3.10: Percent of Students Using Active Transportation per Region ..... 34
Figure 3.12: Adventure Cycling Routes ..... 36
Figure 4.1: Population Densities (population per square mile) in Washington by Census Tract ..... 43
Figure 4.2: AADP with Population Density ..... 44
Figure 4.3: AADB with Population Density ..... 45
Figure 4.4: Average AADP Trails vs. No Trail ..... 46
Figure 4.5: Average AADB Trails vs. No Trail ..... 46
Figure 4.6: Eco-Regions (WSDOT, 2013) ..... 47
Figure 4.7: Simplified Regions ..... 48
Figure 4.8: Count Locations and Regions ..... 49
Figure 5.1: BMT Methods Comparison (Solid black bars are data from this report) ..... 60
Figure 5.2: PMT Methods Comparison (Solid black bars are data from this report)61
Figure 5.3: BPMT Methods Comparison (Solid black bars are data from this report) ..... 62

## EXECUTIVE SUMMARY

A key measure of motor vehicle travel activity is vehicle miles traveled. No similar metric exists for bicycling and walking. Consistent with objectives identified in the Washington State Department of Transportation (WSDOT)’s 2014-2017 Strategic Plan and the State of Washington Bicycle Facilities and Pedestrian Walkways Plan, this project is a step toward establishing a performance metric by which statewide progress with respect to bicycling and walking can be evaluated.

This report presents three methods that could be used to create a statewide bicycle miles traveled (BMT) and pedestrian miles traveled (PMT), and investigates implementing these methods. The methods investigated for Washington State included a survey-based method, a sample-based method, and an aggregate demand model. The first approach employs travel survey data. The second approach is sample-based using pedestrian and bicycle count data sampled from 24 location types based on two levels of urbanity, four regions and three facility types. The third approach is an aggregate demand model approach using demographic data combined with count data.

Due to data limitations, none of these methods could be properly implemented on the statewide level. Despite the data limits, the methods were implemented for one county (King County) in order to compare findings. The travel survey method estimated the lowest BMT and PMT, and the sample-based estimated the highest. The travel survey method is useful for a statewide measure, but it does not provide the detail needed for facility-level estimates. For bicyclists, the sample-based method is appropriate if volumes are desired at the facility level. For pedestrians, the aggregate model might be more appropriate because of the more dispersed nature of pedestrian travel. Each method has strengths and weaknesses, and each helps us understand bicycle and pedestrian travel in different ways.

For this reason, the project team recommends improving both statewide travel survey data and pedestrian and cyclist traffic count data which feed these methods. Travel survey data should be collected statewide with oversampling for non-motorized travelers. Pedestrian and cyclist traffic counts should be expanded to include a continuous counting program in addition to the short-duration count program. After the continuous count program is in place, short-duration counts should be chosen randomly within the sampling frame. For example, the sampling frame could consist of all road and path segments in the state divided by region (Coast Range, Puget Lowland, Cascades, Eastern Washington); by urbanity (rural, urban); by facility type (highways/arterials, local/collector roads, paths); and by whether the location is on a bridge or not. To increase sites sampled, the short-duration count program could also be rotated, with each location being counted every three years instead of every year. Better data will allow the state to quantify bicycling and walking at both the state level and facility level to inform decision-making, facility design and planning, and safety analysis.

### 1.0 INTRODUCTION

Estimates of vehicle miles traveled (VMT) drive policy and planning decisions for surface transportation. No similar metric is computed for cycling and walking. What approaches could be used to compute such a metric on the state level? To answer this question, this report explores three approaches, identifies the advantages and disadvantages of each, and applies them to Washington State. Consistent with objectives identified in the Washington State Department of Transportation’s (WSDOT) 2014-2017 Strategic Plan and the State of Washington Bicycle Facilities and Pedestrian Walkways Plan, this project is a step toward establishing a performance metric by which statewide progress with respect to bicycling and walking can be evaluated.

Much research has been done to study levels of cycling and walking using travel survey, geographic positioning system (GPS) data, and count data. However these studies often confine themselves to the local or regional level. This is the first effort we are aware of on the state level.

The three approaches that were investigated are 1) an approach based on travel survey data, 2) a sample-based approach using pedestrian and bicycle count data, and 3) an aggregate demand model approach using demographic data combined with count data. To better evaluate and compare these methods, they were applied to an example state. The state of Washington was chosen due to its collection of standardized bicycle and pedestrian count data in over 30 cities around the state.

This report begins with a discussion of the existing research and describes the data available in Washington State. Next, details of the methods used are given and the results of each method are reported. The report concludes with a discussion of the advantages and disadvantages of each method, recommends when and where they might best be applied, and suggests future ideas for this line of research and additional data needs.

### 2.0 LITERATURE REVIEW

There are many possible methods to estimate cycling and walking at the state level. However, to our knowledge, no such estimate has yet been conducted for any U.S. state. Therefore in this review of relevant literature, we select literature which relates to one of five topics: pedestrian and bicycle demand estimation methods; motor vehicle miles traveled estimation; bicycle and pedestrian miles traveled estimation; factors related to pedestrian and bicycle traffic levels; and methods for measuring level of urbanism.

Accordingly, the review is organized into five sections. The first summarizes some of the literature on computing VMT, since this may be relevant to computing pedestrian and bicycle miles traveled (PMT and BMT). The second section describes methods that have been used specifically for computing PMT and BMT in a region. The third describes methods used for estimating bicycling and walking demand, including the findings from the recently released National Cooperative Highway Research Program (NCHRP) Report 770. The fourth section documents factors that have been found by previous researchers to impact levels of cycling and walking. The fifth section discusses one specific factor that is often considered a predictor of cycling and walking, level of urbanism.

### 2.1 MOTOR VEHICLE MILES TRAVELED

To collect motor vehicle traffic data, a combination of continuous and short-duration counts is used. Continuous-count data are collected using permanent counters, which are usually embedded in the roadway. Typically, continuous-count sites have been strategically selected by transportation agencies in important travel corridors. The Federal Highway Administration (FHWA) presents a methodology for selecting continuous-count sites based on the objectives of the monitoring program.
"The number and location of the counters, type of equipment used, array, sensor technology, and the analysis procedures used to manipulate data supplied by these counters are functions of these objectives. As a result, it is of the utmost importance for each organization responsible for the implementation of the continuous count program to establish, refine, and document the objectives of the program. Only by thoroughly defining the objectives and designing the program to meet those objectives will it be possible to develop an effective and cost-efficient program." (Federal Highway Administration, 2013).

Short-duration counts are needed to collect data over the entirety of the street network. To achieve this, the FHWA guidelines recommend dividing the street network into homogeneous traffic volume segments. As a general rule, the traffic volume on each segment should vary by less than 10 percent. A schedule must then be created to ensure that each segment is counted at least once every six years. Roads in rapidly changing areas should be counted more often. The length of short-duration counts can last up to a seven-day period, but should not be for less than 48 hours.

Kumapley and Fricker conducted a review of a number of methods of estimating VMT (Kumapley and Fricker, 1996). The methods they reviewed included using fuel sales, odometer
recordings, surveys, transit models, and traffic count data from the Highway Performance Monitoring System (HPMS) (Federal Highway Administration, 2013). Kumapley and Fricker report a method of estimating VMT based on national survey data by multiplying the number of licensed drivers for each gender and age cohort by estimated average miles traveled for that type of survey respondent. They caution that this method is highly affected by survey bias (Kumapley and Fricker, 1996).

Using fuel-sale data is one of the oldest methods for estimating VMT, and it has been used since the 1950s. This method is susceptible to a high amount of error as it relies on estimating the fuel efficiency and driving patterns of all vehicles on the nation's roads. As a result it should only be used for preliminary estimates of VMT. Odometer recordings can also be used to estimate VMT. However, it is highly resource-intensive and seldom used. Additionally, odometer readings are subject to a number of sources of error, making it difficult to measure the accuracy of this method.

The HPMS method, the most widely accepted of all methods, uses a formula to convert annual average daily traffic (AADT) data into a VMT estimate. Roads are first classified into one of seven functional classes, ranging from local streets to interstates. They are then further classified as urban or rural, creating a total of 14 functional systems. AADT is estimated for each road segment and AADT values are multiplied by the length of the segment to calculate daily vehicle miles traveled (DVMT). Expansion factors are then used to calculate VMT over a desired geographic area and timeframe. While the HPMS method is the most widely accepted method, it is not free from shortcomings. Bias in the selection of count sites and incomplete traffic data can lead to error in the estimates.

### 2.1.1 VMT Avoided Estimates

Many have made estimates of avoided VMT, including studies specific to the state of Washington (Frank et al., 2011; Moudon and Stewart, 2013). Some of these estimates have computed bicycle or pedestrian miles traveled as a step in the calculation process. An early example of this was a study of the environmental benefits of cycling and walking, which quantified the bicycle and pedestrian miles traveled (Federal Highway Administration, 1993). This study used data from national travel surveys, including the National Personal Transportation Study, to estimate the number of cyclists and pedestrians making trips of five types: commuting, personal, commercial, recreational, and child-related. The typical number of miles traveled for each trip type and days per year of walking and cycling were estimated from various sources. The resulting computation estimated 5,800 million to 21,300 million bicycle miles traveled and 20,500 million to 44,100 million miles walked in the United States in 1991.

A more recent computation was conducted as part of the Non-motorized Transportation Pilot Project (NTPP) (Federal Highway Administration 2012). This report documents a method developed by the Volpe Center referred to as the "NTPP Model" which uses NHTS mode share data and uses changes in count data over time to estimate changes in bicycling and walking mode share, but only computes averted VMT not bicycle and pedestrian miles traveled. The report documents the lack of accepted methods for these computations.

### 2.2 PEDESTRIAN AND BICYCLE MILES TRAVELED

Estimates of pedestrian and bicycle miles traveled, using count data from a spatially representative sample, have been made at the city or county levels, but not at the state level (Davis and Wicklatz, 2001; Molino et al., 2009; Dowds and Sullivan, 2012). Researchers at the University of Minnesota, working for Minnesota DOT, used a sample-based estimation method to compute BMT for three counties in the Twin Cities area (Davis and Wicklatz, 2001). The researchers created their sampling methods by adapting the guidelines found in the FHWA's Guide to Urban Traffic Volume Counting (GUTVC) to bicycling. Data were collected using manual counts of video recordings of the selected sites. Overall, the project found that samplebased methods for determining VMT can be modified to calculate defensible BMT estimates. Looking forward, the researchers concluded that it is possible, but likely expensive, to use their methods to compute statewide BMT estimates.

Researchers at the University of Vermont created BMT and PMT estimates for Chittenden County, VT (Dowds and Sullivan, 2012). Their study produced eight estimates of annual bicycle and pedestrian miles traveled for the county. The different estimates were calculated using two different sets of adjustment factors and four types of classification systems for links in the bicycle pedestrian network. The adjustment factors were determined by using infrared-sensitive lens counters at three sites that produced full-year continuous data. They concluded that while their estimates varied from 74 million to 296 million BMT and PMT per year, this range was still higher than the 32 million BMT and PMT computed based on the NHTS data.

Other efforts are currently underway to estimate bicycle and pedestrian miles traveled in Minnesota (Lindsey et al., 2013; Minnesota Department of Transportation, 2013) and on the nation’s trails through the work of the Rails to Trails Conservancy's Trail Monitoring and Assessment Platform (Hadden-Loh, 2015).

### 2.3 PEDESTRIAN AND BICYCLE DEMAND ESTIMATION METHODS

A common approach to estimating non-motorized travel is to use survey data. Barnes and Krizek (2005) combined census data with data from the National Household Travel Survey (NHTS) to produce estimates of bicycling at different geographic levels. This method of estimation, often referred to as sketch planning, usually relies on readily available data, making it simple to conduct. While census data only capture bicycling for the purpose of commuting, the researchers used commuting bicyclists as an indicator for the total amount of bicycling in an area.

A number of approaches were discussed in the NCHRP 552, "Guidelines for Analysis of Investments in Bicycle Facilities." In addition to discussing methods for estimating non-motorized travel, the report also included original research. Researchers investigated the effects of proximity to bicycle facilities on mode choice. The study found that individuals living close to on-street bicycle facilities were more likely to bicycle on a given day than individuals living further away. However, proximity to off-road bicycle facilities did not impact the likelihood of bicycling (Krizek et al., 2005).

Building on the NCHRP report, researchers used its guidelines to develop an online tool to estimate the costs, benefits, and demand for new bicycle facilities. Demand was calculated using basic
information about the area (demographics, densities, and bicycling rates) in conjunction with the research from the report on proximity to bicycle facilities.

Aggregate demand models have also been used to estimate levels of non-motorized travel. This type of model explains non-motorized travel through spatially varying explanatory variables such as income, gender, and the level of bicycling facilities. Inevitably, aggregate demand models omit numerous variables that influence non-motorized travel, limiting their effectiveness. Additionally, aggregate demand models tend to be very location-specific, making it difficult to apply these models to other geographic areas (Landis, 1996; Lindsey et al., 2007; Jones et al., 2010; MirandaMoreno and Fernandes, 2011; Pulugurtha and Sambhara, 2011; Hankey et al., 2012; Schneider et al., 2012; Wang et al., 2013).

In recent years, more and more Metropolitan Planning Organizations have included non-motorized travel in their regional transportation models. However, the non-motorized components of these models often suffer from data collection and measurement problems. Validation of the accuracy of these methods is also rare, and the volume estimates for locations where no data are available are likely to be highly inaccurate (Barnes and Krizek, 2005; Liu et al., 2012; Singleton and Clifton, 2013).

### 2.3.1 NCHRP Report 770

NCHRP Report 770 is a guidebook which presents several tools for estimating bicycling and walking (Kuzmyak et al., 2014). The NCHRP Project 08-78 research team developed three methods and evaluated three existing methods for estimating biking and walking.

The first tools that the team developed are Tour Generation and Mode-Split Models. This method was developed in conjunction with the Puget Sound Regional Council (PSRC), which was using similar methods in the Seattle region. This approach uses tours as opposed to one-way trips, and looks at five trip purposes in order to estimate biking and walking.

The project team also developed a GIS-based Walk Accessibility Model, which uses mapping techniques to estimate walk trip generation and mode split. The method "uses geospatial overlay and network path-building procedures readily available in GIS to calculate measures of accessibility to or from any point by any mode and by type of attraction" (Kuzmyak et. al., 2014). Currently, this model does not include bicycle demand forecasting, but with sufficient data it will be possible in the near future.

The third tool developed by NCHRP is looking at enhancements to trip-based models. The researchers worked with PSRC data in Seattle "to create a template for systematically enhancing a conventional TAZ/trip-based regional model to improve its sensitivity to land use and nonmotorized travel" (Kuzmyak et al., 2014). This method improves Seattle’s current process with the introduction of a "pre-mode-split" step, "which first divides trips into intra- versus interzonal groups and then performs a mode-split specific step to those groups."

The tools that NCHRP evaluated and included in their guidebook include: Walk Trip Generation and Flow Models, a Portland Pedestrian Model, and Facility Demand models.

### 2.4 FACTORS THAT MAY IMPACT BICYCLING AND WALKING

Many studies have investigated the spatial factors that correlate with areas of high walking and bicycling. A recent thorough literature review on the topic was conducted as part of Transit Cooperative Research Program Report 95, Chapter 16 (Pratt et al., 2012). Understanding what the important factors are in predicting bicycling and walking is important to creating a method for estimating pedestrian and bicycle miles traveled because it allows the sampling framework for the estimate to be based on what actually is correlated with walking and bicycling. Without this knowledge it might be easy to simply sample by road type or other easily accessible roadway attributes.

Tables 2.1 and 2.2 summarize the variables analyzed and found to be significantly correlated with walking and bicycling either positively or negatively in various studies (Dill and Voros, 2007; McCahil and Garrick, 2008; Pulugurtha and Repaka, 2008; Jones et al., 2010; Griswold et al., 2011; Miranda-Moreno et al., 2011; Hankey et al., 2012; Schneider et al., 2012).

In these studies some variables were often associated with non-motorized travel. For both bicycling and walking, some of the most common variables are related to density of employment, population, and proximity to a major attractor such as a downtown area. Another category of variables is related to the facility type of the road or path and the connectivity of the road network. For pedestrians, proximity to transit was a factor. Especially for cycling, slope of the roadway was found to be significant. All of these main variable categories should be included in the consideration of how to create a count program.

All of these studies were examining non-motorized travel on the city or regional level, not on the state level. On the state level, additional factors may become important, such as climate and topography. Washington has many different geographic zones, from mountain areas near the coast and in the Cascade Range to flat and rolling plains in the east, not to mention the fertile farms and urban areas surrounding the Puget Sound. Climate in the state of Washington varies in terms of precipitation from the wet west to the dry east, and in terms of temperatures from the ocean and sound-moderated temperatures of the west to the more extreme cool and warm variations of the inland east. The impacts of climate on cycling and walking have been studied by many and the importance of grade on cycling is documented (Rodríguez and Joo, 2004; Griswold et al., 2011). Both geography and climate are likely to impact cycling and, to a lesser extent, walking.

Table 2.1: Spatial Variables Found to be Significantly Correlated with Pedestrian Activity

| Category | Variable | Relationship with Pedestrian Activity | Source(s) |
| :---: | :---: | :---: | :---: |
| Employment | Employment density within $1 / 2$ mile | + | Jones, Ryan, et al. 2010 |
| Employment | Employment within $1 / 4$ mile | + | Schneider, Henry et al. 2012 |
| Employment | Employment within $1 / 4$ mile | + | Pulugurtha, Repaka 2008 |
| Population density | Population density within $1 / 4$ mile | + | Jones, Ryan, et al. 2010 |
| Population density | Population density within 400 M | + | Miranda-Moreno, Morency et al. 2011 |
| Population density | Households within $1 / 4$ mile | + | Schneider, Henry et al. 2012 |
| Population density | Population within $1 / 2$ mile | + | Pulugurtha, Repaka 2008 |
| Crime | Crime rate | + | Hankey, Lindsey et al. 2012 |
| Demographics | \% Non-white | + | Hankey, Lindsey et al. 2012 |
| Demographics | \% with 4-year degree | + | Hankey, Lindsey et al. 2012 |
| Distance | Distance to downtown | - | Miranda-Moreno, Morency et al. 2011 |
| Distance | Distance from CBD | - | Hankey, Lindsey et al. 2012 |
| Distance | Distance from water | - | Hankey, Lindsey et al. 2012 |
| Land use | Presence of nearby retail | + | Jones, Ryan, et al. 2010 |
| Land use | Commercial space within 50 M | + | Miranda-Moreno, Morency et al. 2011 |
| Land use | Open space within 150 M | - | Miranda-Moreno, Morency et al. 2011 |
| Land use | Number of schools within 400 M | + | Miranda-Moreno, Morency et al. 2011 |
| Land use | Land use mix | - | Hankey, Lindsey et al. 2012 |
| Land use | Urban residential area $1 / 4$ to 1 mile | + | Pulugurtha, Repaka 2008 |
| Land use | Mixed land use within $1 / 4$ mile | - | Pulugurtha, Repaka 2008 |
| Land use | Single-family residential $1 / 4$ mile | - | Pulugurtha, Repaka 2008 |
| Transit | Presence of subway station | + | Miranda-Moreno, Morency et al. 2011 |
| Transit | Number of bus stops | + | Miranda-Moreno, Morency et al. 2011 |
| Transit | Transit stops within $1 / 2$ mile | + | Pulugurtha, Repaka 2008 |
| Facility type | \% of major arterials within 400 M | - | Miranda-Moreno, Morency et al. 2011 |
| Facility type | Street segments within 400 M | + | Miranda-Moreno, Morency et al. 2011 |
| Facility type | Four-way intersection | + | Miranda-Moreno, Morency et al. 2011 |
| Facility type | Traffic signal present | + | Schneider, Henry et al. 2012 |
| Facility type | Arterial street | + | Hankey, Lindsey et al. 2012 |
| Facility type | Collector street | + | Hankey, Lindsey et al. 2012 |
| Facility type | Principal arterial street | - | Hankey, Lindsey et al. 2012 |
| Parking | High parking meter activity zone | + | Schneider, Henry et al. 2012 |
| Grade | Slope of any intersection approach | - | Schneider, Henry et al. 2012 |
| Speed | Speed limit $1 / 2$ to 1 mile | - | Pulugurtha, Repaka 2008 |

Table 2.2: Spatial Variables Found to be Significantly Correlated with Bicycle Activity

| Category | Variable | Relation <br> ship <br> with <br> Bicycle <br> Activity | Source(s) |
| :--- | :--- | :---: | :--- |
| Employment | Employment density within $1 / 4$ mile | + | Jones, Ryan, et al. 2010 |
| Employment | Employment density in census tract | + | McCahill, Garrick 2008 |
| Population density | Population density in census tract | + | McCahill, Garrick 2008 |
| Demographics | \% non-white | + | Hankey, Lindsey et al. 2012 |
| Demographics | \% with 4-year degree | + | Hankey, Lindsey et al. 2012 |
| Demographics | Median HH income | - | Hankey, Lindsey et al. 2012 |
| Demographics | \% age 18-55 | + | Dill, Voros 2007 |
| Distance | Distance from CBD | - | Hankey, Lindsey et al. 2012 |
| Distance | Distance from university (UCB) | - | Griswold, Medury et al. 2011 |
| Distance | Proximity to regional trail | + | Dill, Voros 2007 |
| Distance | Distance to downtown | - | Hankey, Lindsey et al. 2012 |
| Land use | Land use mix |  | Griswold, Medury et al. 2011 |
| Land use | Number of commercial properties within | + | Hankey, Lindsey et al. 2012 |
| Facility type | Road is an arterial | + | Jones, Ryan, et al. 2010 |
| Facility type | Footage of Class I bicycle path within $1 / 4$ mile | + | Griswold, Medury et al. 2011 |
| Grade | Slope of terrain within $1 ⁄ 2$ mile | - | Griswold, Medury et al. 2011 |
| Connectivity | Connected node ratio within $1 / 2$ mile | + | Dill, Voros 2007 |
| Connectivity | Street connectivity |  |  |

### 2.4.1 Level of Urbanism

Many factors listed in Tables 2.1 and 2.2 related to levels of urbanism, including population density, employment, distance to city center, and transit use. For this reason, the research team investigated how levels of urbanism might be measured.

### 2.4.1.1 Rural-Urban Commuting Area Codes

The U.S. Department of Agriculture's Economic Research Service and University of Washington's Rural Health Research Center developed a 10-tiered system for classifying census tracts by level of urbanization. The system, known as Rural-Urban Commuting Area Codes, is based on population density, urbanization, and commute patterns. There are 10 levels of urbanization defined in this system as listed below (USDA, 2014). "Primary flow" refers to the "single largest, commuting share" of the traffic flow. Flows can be described as being to or within an urban core or cluster (UC).

Primary Rural-Urban Commuting Area Codes, 2010 (USDA, 2014)

1. Metropolitan area core: primary flow within an urbanized area (UA)
2. Metropolitan area high commuting: primary flow 30 percent or more to a UA
3. Metropolitan area low commuting: primary flow 10 percent to 30 percent to a UA
4. Micropolitan area core: primary flow within an urban cluster of 10,000 to 49,999 (large UC)
5. Micropolitan high commuting: primary flow 30 percent or more to a large UC
6. Micropolitan low commuting: primary flow 10 percent to 30 percent to a large UC
7. Small town core: primary flow within an urban cluster of 2,500 to 9,999 (small UC)
8. Small town high commuting: primary flow 30 percent or more to a small UC
9. Small town low commuting: primary flow 10 percent to 30 percent to a small UC
10. Rural areas: primary flow to a tract outside a UA or UC

### 2.4.1.2 Smart Location Database

The Smart Location Database provides attributes to quantify variables such as "residential and employment density, land use diversity, design of the built environment, access to destinations, and distance to transit" by census block group (CBG) (Ramsey \& Bell, 2014). The authors classified urban/suburban/rural based on activity density in the census block group for the purposes of computing a Destination Accessibility measure. Activity density represents the total jobs and dwelling units per "unprotected acre" for each CBG.

CBGs where total activity density was less than 0.5 activity units per unprotected acre were deemed rural; activity densities higher than 6 units per unprotected acre were classified as urban; and all other CBGs were classified as suburban. "These designations were developed through visual inspection of areas well known to the study team. They only influenced the tabulation of intrazonal travel times and were not used in any other part of the analysis" (Ramsey \& Bell, 2014).

Unfortunately, they do not provide this urban/suburban/rural attribute in the output data. It would also be infeasible to do visual inspections of the entire state of Washington. However, they do provide many other key metrics such as population and employment densities that could be used to estimate urbanity.

### 2.4.1.3 Subcenters

Guiliano and Small define subcenters as "a continuous set of zones, each with density above some cutoff (D), that together have at least (E) total employment and for which all of the immediately adjacent zones outside the subcenter have density below (D)" (1991). A subcenter is defined with a density cutoff of 10 employees per acre, and a minimum total employment of 10,000 . Cutoffs can be raised or lowered depending on the population of the area. In this method lies the difficulty of determining a cutoff density specific to the state of Washington.

### 3.0 DATA SOURCES

Three main types of data were used for this analysis: bicycle and pedestrian count data, transportation network data, and sociodemographic data. The details of each are included in the sections below.

### 3.1 COUNT DATA

Multiple data types were identified for this report: manually collected two-hour counts, shortterm bicycle counts collected by tube counters, and permanent continuous counters which count 365 days per year. These were collected from a statewide aggregated source and from two cities: Seattle and Olympia. Each data set is described separately in this section. The bulk of the analysis is based on the permanent count data to understand travel patterns with time, and the two-hour counts to understand the spatial distribution of bicycling and walking. The analysis focused on data from 2013 for consistency.

### 3.1.1 WSDOT Bicycle and Pedestrian Documentation Project Count Data

Since 2009, WSDOT has organized an annual statewide bicycle and pedestrian counting program, known as the state's Bicycle and Pedestrian Documentation Project. The 2013 WSDOT's Bicycle and Pedestrian Documentation Project data was the primary bicycle and pedestrian count data source used for spatial analysis. It consisted of 386 two-hour manual counts at 211 different intersections throughout 39 jurisdictions in the state of Washington. Each count included the number of bicyclists and pedestrians that passed through the intersection and the direction that each was heading when they left the intersection.

### 3.1.2 City of Seattle Count Data

The city of Seattle has conducted manual bicycle counts since 1992. This includes a more recent extended count program in conjunction with WSDOT and supplementing the statewide program. Manual counts have been conducted quarterly at roughly 50 locations around the city since 2011 (Seattle Department of Transportation 2013). The quarterly counts are conducted in January, May, July, and September as recommended by the National Bicycle and Pedestrian Documentation Project, at the following times: 5-7 p.m. and 10 a.m. to noon on weekdays, and noon to 2 p.m. on Saturdays. These data are available on the city's website.

Additionally, in October 2012 the city installed its first continuous bicycle count station on the Fremont Bridge in Seattle. This counter provides bidirectional bicycle counts in hourly increments 365 days a year. This analysis used data from the 2013 calendar year.

A second such permanent counter was later installed on an access path on the east end of the Spokane Street Bridge (Seattle Department of Transportation, 2013). Additional counters have
since been installed around the city, but such data were not available in time to be used in this study.

### 3.1.3 City of Olympia

Since 2008, the city of Olympia has counted bicyclists using portable pneumatic tube counters on paths and roadways for seven-day continuous periods at each location (Lindsey, 2013). In 2008 the city counted at nine locations, and increased this to 17 locations in subsequent years and 19 locations in 2012. The city conducts counts three times per year in March, June, and October. The equipment used is commonly used to count motor vehicles, and the manufacturer (TimeMark ${ }^{\mathrm{TM}}$ ) claims that it can also be used to count bicycles, but independent verification has not confirmed this. The city reports counts in terms of average daily count per location by month and year.

### 3.1.4 Methods to Analyze Temporal Variation of Count Data

Counts from the WSDOT's Bicycle and Pedestrian Documentation Project, the city of Olympia, and the city of Seattle were processed and analyzed. This section describes the methods used to analyze the data. Since one of the primary data sources is manual two-hour count data, some method for estimating the average day based on two or more peak hours of count data was needed.

Seasonal, daily and hourly adjustment factors were computed using the one year of available data from Seattle’s Fremont Bridge continuous bicycle counter. This is the only permanent nonmotorized traffic counter with a full year of available data that we are aware of in the state. While applying such factors to all sites in the city of Seattle and beyond is not appropriate, these factors were used as a placeholder until better data become available.

One full week of continuous hourly bicycle count data was available at 19 locations around the city of Olympia. The annual average daily bicyclists was estimated at each location for 2012 using the monthly adjustment factors computed from the Seattle data to demonstrate how this can be done. Hourly and daily patterns were plotted as a function of percent of annual average daily traffic. Volumes at all locations were less than 200 bicyclists per day, but the city did not provide an error adjustment factor to account for any over- or undercounting, so this may not correctly represent the volumes at these locations in Olympia.

The following section details the computations used in this process.

### 3.1.5 Computing Annual Average Daily Traffic at Permanent Count Sites

The data were provided by the Seattle Department of Transportation in hourly increments from October 2, 2012, to September 30, 2013. The counter records bicycle crossings on the bridge in both directions. No continuous record of pedestrian counts was available.

Annual average daily bicyclists (AADB) was computed using the AASHTO method (AASHTO, 1992) for computing annual average daily traffic (AADT). The AASHTO procedure of determining AADT using continuous counts is as follows:

1. Calculate the average for each day of the week for each month to derive each monthly average day of the week.
2. Average each monthly average day of the week across all months to derive the annual average day of the week.
3. The AADT is the mean of all of the annual average days of the week.

The formula for the AASHTO method for determining AADT is:

$$
\begin{equation*}
A A D T=\frac{1}{7} \sum_{i=1}^{7}\left[\frac{1}{12} \sum_{j=1}^{12}\left(\frac{1}{n} \sum_{k=1}^{n} D T_{i j k}\right)\right] \tag{3-1}
\end{equation*}
$$

where
$D T=$ 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 occurrence of a day of week $i$ in month $j$
$n=$ the number of occurrences of day $i$ of the week during month $j$

### 3.1.6 Estimating Annual Average Daily Traffic at Short-Duration Count Sites

For the rest of the count sites across the state the AADB/AADP was not known and had to be estimated. Estimates were made by adjusting the short-duration counts collected by either the monthly or daily/hourly adjustment factors.

### 3.1.7 Computing Adjustment Factors

Monthly and daily/hourly adjustment factors were computed using the one year of available data from Seattle's Fremont Bridge continuous bicycle counter, the only permanent bicycle or pedestrian counter with a full year of data identified in the state.

Monthly Average Daily Traffic (MADT) was calculated for each month by averaging the average daily count for each day of the week in that month as detailed in Equation 3-2 below.

$$
\begin{equation*}
M A D T_{j}=\frac{1}{7} \sum_{i=1}^{7}\left[\frac{1}{n} \sum_{k=1}^{n} D T_{i j k}\right] \tag{3-2}
\end{equation*}
$$

where
$M A D T_{j}=$ Monthly Average Daily bicycle or pedestrian Traffic
The average daily bicycle or pedestrian traffic (ADT) for each day of the week was computed separately for each month as:

$$
\begin{equation*}
A D T_{i j}=\frac{1}{n} \sum_{k=1}^{n} D T_{i j k} \tag{3-3}
\end{equation*}
$$

where
$A D T_{i j}=$ Average daily bicycle or pedestrian traffic for day $i$ of the week in month $j$.
Hourly averages were computed for hours in which short-duration counts were made, specifically for each month of the year:

- Tuesdays, Wednesdays, and Thursdays (TWR) from 7-8 a.m.
- TWR from 8-9 a.m.
- TWR from 10-11 a.m.
- TWR from 11 a.m. to 12 p.m.
- TWR from 4-5 p.m.
- TWR from 5-6 p.m.
- TWR from 6-7 p.m.
- Saturdays from 10-11 p.m.
- Saturdays from 11 a.m. to 12 p.m.

$$
\begin{equation*}
H T_{h j}=\frac{1}{m} \sum_{l=1}^{m} H T_{h j l} \tag{3-4}
\end{equation*}
$$

where
$H T_{h j}=$ hourly count for month $j$ and hour-day combination $h$
$h=$ one of the nine hour-day combinations listed above during which manual counts were conducted
$m=$ the number of occurrences of one of the nine hour-day combinations listed above during month $j$
$l=$ index to identify the occurrence of hour-day combination $h$ in month $j$
The monthly factors were then calculated by dividing AADB or AADP by MADT.

$$
\begin{equation*}
M_{j}=\frac{A A D B}{M A D T_{j}} \tag{3-5}
\end{equation*}
$$

where
$M_{j}=$ monthly adjustment factor
Next, daily factors, $D_{i j}$, for each month were calculated. This was done by dividing MADT by the average number of crossings on a given day of the week in that month as shown in Equation 6. For example, the daily factor for a Monday in January was derived by dividing the MADT for January by the average number of crossings on a Monday in January. This produced a total of 84 daily factors (12 months x 7 days).

$$
\begin{equation*}
D_{i j}=\frac{M A D T_{j}}{A D T_{i j}} \tag{3-6}
\end{equation*}
$$

where
$D_{i j}=$ daily expansion factor for day $i$ of the week in month $j$
Finally, hourly factors by month were created for the hours that the Seattle Department of Transportation and WSDOT conduct bike count collections. The following steps were used to create the hourly factors, using continuous-count data from a permanently installed automated counting device:

1. Calculate the average number of cyclists for each hour of the day by day of the week and month.
2. Calculate adjustment factors for Saturday. This was accomplished by dividing the MADT for each month by the corresponding hourly average traffic for that month. For example, the expansion factor for a Saturday at 10-11 a.m. in January is equal to January AADT divided by the average traffic for a Saturday at 10-11 a.m. in January. This process was repeated for 11 a.m. to noon, and then for each month.
3. Calculate weekday adjustment factors. For the weekday factors, hourly averages for Tuesday, Wednesday, and Thursday were averaged to create a weekday average. MADT is then divided by the weekday average of the desired hour in the corresponding month to produce the expansion factor.

$$
\begin{equation*}
H_{h j}=\frac{M A D T_{j}}{H T_{h j}} \tag{3-7}
\end{equation*}
$$

where:
$H_{h j}=$ hourly/daily adjustment factor for hour-day combination $h$ in month $j$
Note that as defined above the daily adjustment factor $\left(D_{i j}\right)$ and the hourly/daily factor $\left(H_{h j}\right)$ should not both be applied. If a full 24 hours of short-duration count data are available, the daily adjustment factor should be applied in combination with the monthly factor $M_{j}$. If only one or two hours of count data are available, the hourly/daily factor should be applied in combination with the monthly factor.

### 3.1.8 Computing AADB and AADP Using Adjustment Factors

To compute AADB or AADP using one full continuous week of count data, multiply the average daily count by the monthly factor as shown in Equation 3-8.

$$
\begin{equation*}
A A D B \text { or } A A D P=M_{j} \times \frac{1}{7} \sum_{i=1}^{7} D T_{i j} \tag{3-8}
\end{equation*}
$$

where
$D T_{i j}=$ the observed non-motorized traffic volume during a 24-hour period, midnight to midnight, on day of the week $i$ in month $j$.

To compute AADB or AADP using 24 hours of count data, multiply the full 24 -hour count by the monthly factor and the daily factors as shown in Equation 3-9.

$$
\begin{equation*}
A A D B \text { or } A A D P=D T_{i j} \times M_{j} \times D_{i j} \tag{3-9}
\end{equation*}
$$

To compute AADB or AADP using one hour of manual count data (during one of the nine standard count times listed), multiply the bicyclists and/or pedestrians observed during the onehour time period by the monthly factor and the hourly factor, as expressed in Equation 3-10.

$$
\begin{equation*}
A A D B \text { or } A A D P=H T_{h j} \times M_{j} \times H_{h j} \tag{3-10}
\end{equation*}
$$

where
$H T_{h j}=$ the observed non-motorized traffic volume during a one-hour period
If more than one hour or day of count data is available, estimate AADB for each period and average the resulting estimates.

### 3.1.9 Calculating BMT and PMT

Before using the count data, they had to be cleaned. First, all duplicate entries were removed. Next, mislabeled sites were renamed to reflect the previously existing and correct name. In a small number of instances it was clear that in a few sites with multiple counts, the counters were not consistent with which direction was which. In these cases, the data were changed to make all the counts for a particular site consistent with each other. This was done by choosing the direction to use for our data based on the best available location information and changing noncomplying records to be in accord with that direction.

To calculate the one-way AADB or AADP for each direction of each count site, the corresponding monthly and hourly factors were applied to the count data. When both AM and PM peak data were available for a given location, they were averaged. Next, the two-way AADB or AADP was calculated. If a directional count and its opposite directional count (i.e., north and south or east and west) had the same facility type (i.e., highway/arterial, local/collector, or trail) then the AADB or AADP for the two segments were added to each other to produce the two-way AADB or AADP. If the facility type of the opposing segments did not match, then the one-way AADB or AADP was multiplied by two to produce the two-way AADB or AADP.

Each two-way AADB or AADP was then sorted into its respective sampling group. The two-way AADB or AADP estimates were then averaged for each sampling group. To calculate PMT and BMT, the average AADB or AADP of each sampling group is multiplied by the number of centerline miles in the respective group

This method can also be stated mathematically as follows for bicyclists and pedestrians.

$$
\begin{gather*}
B M T=365 \times \sum_{p=1}^{24}\left(\frac{L_{p}}{m_{p}} \sum_{q=1}^{m} A A D B_{p q}\right)  \tag{3-11}\\
P M T=365 \times \sum_{p=1}^{24}\left(\frac{L_{p}}{m_{p}} \sum_{q=1}^{m} A A D P_{p q}\right) \tag{3-12}
\end{gather*}
$$

where
$B M T=$ Bicycle miles traveled in the state
$P M T=$ Pedestrian miles traveled in the state
$A A D B=$ Estimated annual average daily bicyclists at a given count site $q$ in group $p$
$A A D P=$ Estimated annual average daily pedestrians at a given count site $q$ in group $p$
$L_{p}=$ the total centerline miles for each group $p$
$m_{p}=$ the number of count sites in group $p$
$p=$ a counting variable indicating one of the 24 groups into which the roads, paths and count sites of the state have been divided by region, urbanity and facility type as described above $q=$ a counting variable indicating one of the counting sites in group $p$

### 3.1.10Analysis of Existing Count Data

Counts from the city of Seattle were used to estimate monthly and daily/hourly seasonal adjustment factors as described in the previous section. These seasonal and daily/hourly adjustment factors were then applied to the short-duration counts in both the Seattle and statewide count program to illustrate how estimates of the annual average daily bicyclists and pedestrians (AADB/AADP) could be made.

### 3.1.10.1 Limitations

It is not appropriate to apply these factors to all the locations in the city of Seattle because many locations are likely to have patterns that differ from the highly commute-related patterns observed on the Fremont Bridge. It is even less appropriate to apply these factors to locations around the state which experience different climate, school schedules and work patterns than those in the Seattle area. It is also not appropriate without further information to apply factors computed for bicyclists to pedestrian traffic which is known to often exhibit different behavior at the same locations (Nordback et al., 2013).
However, no other factors were found that would be more appropriate. For this reason, please consider this calculation not as an accurate estimation, but as a placeholder to demonstrate how the appropriate factors would be used in the future when more data are available and appropriate climate-specific factors can be computed.

### 3.1.10.2 Adjustment Factors

Using the methods for computing adjustment factors detailed in the previous section, the following factors were computed using the Seattle Fremont Bridge data (October 2012 to September 2013). The Annual Average Daily Bicyclists (AADB) for this time period is 2,461 computed using the AASHTO method detailed in the Research Approach section of this report. No other permanent count locations were identified with which to compute such factors, and no permanent pedestrian count data were available. Table 3.1 lists the monthly factors and Table 3.2 lists the daily/hourly factors developed using the Fremont Bridge data using the methods detailed in the Methods section of this report.

Table 3.1: Monthly as for 2012-2013 Seattle Commute Patterns

| Month | Monthly AADB | Factor |
| :--- | :---: | :---: |
| January | 1,448 | 1.7 |
| February | 1,787 | 1.4 |
| March | 2,132 | 1.2 |
| April | 2,400 | 1.0 |
| May | 3,502 | 0.7 |
| June | 3,237 | 0.8 |
| July | 3,806 | 0.6 |
| August | 3,373 | 0.7 |
| September | 2,691 | 0.9 |
| October | 2,254 | 1.1 |
| November | 1,688 | 1.5 |
| December | 1,173 | 2.1 |

Table 3.2: Daily/Hourly Adjustment Factors for 2012-2013 Seattle Commute Patterns

|  |  |  |  |  |  |  |  | 7-8 AM <br> Week- <br> day | 8-9 AM <br> Week- <br> day |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathbf{1 0 - 1 1}$ <br> AM <br> Week- <br> day | 11- <br> Noon <br> Week- <br> day | 4-5 PM <br> Week- <br> day | 5-6 PM <br> Week- <br> day | 6-7 PM <br> Week- <br> day | Noon-1 <br> PM <br> Satur- <br> day | 1-2 PM <br> Satur- <br> day |  |  |  |
| January | 9.0 | 6.1 | 26.5 | 32.3 | 11.0 | 5.5 | 8.1 | 28.3 | 21.0 |
| February | 8.8 | 6.0 | 28.4 | 33.4 | 11.2 | 5.4 | 7.8 | 17.1 | 16.3 |
| March | 9.9 | 7.1 | 29.4 | 39.3 | 13.2 | 6.3 | 8.6 | 13.9 | 12.5 |
| April | 8.2 | 6.2 | 25.7 | 31.4 | 10.0 | 5.3 | 6.7 | 26.9 | 33.1 |
| May | 8.7 | 6.7 | 29.9 | 41.0 | 12.1 | 5.6 | 7.5 | 21.4 | 17.5 |
| June | 9.3 | 7.1 | 27.8 | 34.8 | 11.4 | 5.7 | 7.3 | 16.2 | 14.4 |
| July | 10.3 | 7.5 | 25.7 | 33.9 | 12.0 | 6.2 | 7.9 | 19.2 | 18.0 |
| August | 9.8 | 6.8 | 24.6 | 33.4 | 11.7 | 5.7 | 7.1 | 22.1 | 19.8 |
| September | 8.7 | 5.8 | 23.7 | 31.6 | 10.8 | 4.9 | 6.2 | 27.6 | 24.5 |
| October | 14.5 | 15.2 | 17.4 | 17.0 | 14.4 | 15.3 | 22.0 | 25.1 | 22.8 |
| November | 8.1 | 5.8 | 24.0 | 31.0 | 9.4 | 5.5 | 8.4 | 17.0 | 19.9 |
| December | 8.6 | 5.6 | 24.2 | 33.6 | 10.1 | 5.3 | 8.3 | 24.7 | 25.1 |

For locations other than the Fremont Bridge, the AADB was estimated by applying the monthly and daily/hourly factors listed above to the short-duration counts available. For Seattle, both factors were needed since the short-duration counts were composed of manual two-hour counts. Since these counts were taken at multiple time periods throughout the year, they could be averaged. At most locations in Seattle, peak hour (5-7 p.m.), off-peak and weekend two-hour counts were collected during four times per year (January, May, July, and September as recommended by the National Bicycle and Pedestrian Documentation Project) at each of the 50 locations included in the count program. The factors were applied to each count and averaged for each month and then averaged for the year. The average estimated AADB is shown by month and by location in Figure 3.1, with the thick black line indicating the average AADB estimate over the
year. Estimates range from just 35 bicyclists per day at the intersection of Martin Luther King Way and South Othello Street to 1,905 bicyclists per day at the intersection of Fremont Avenue and $34^{\text {th }}$ Street. Figure 3.1 illustrates how AADB estimates based on only a few hours of data can be highly variable.


Figure 3.1: Estimated AADB at 50 Sites in Seattle in 2012
The Olympia bicycle volume data consisted of at least one week of continuous counts per location. By multiplying by the monthly adjustment factor computed from the Seattle continuous-count data, estimates of AADB were obtained for each of the 10 sites counted in July 2012. While applying Seattle factors to Olympia data is not the best practice, this illustrates how the method could be used if Olympia-specific factors were available. The resulting AADB estimates are shown in Figure 3.2. All of the Olympia sites have relatively low AADB estimates, with less than 200 bicyclists per day.


Figure 3.2: Estimated AADB at 19 Sites in Olympia, WA,, in 2012
To understand hourly, daily and monthly traffic patterns, the bicycle volumes per hour and per day were plotted as a percent of the AADB. These patterns are discussed in the following three subsections.

### 3.1.10.3 Hourly Variation

To understand how bicyclist traffic varies over the hours of the day, data from Seattle and Olympia were plotted as a percent of AADB. No such data were available for pedestrians.

For the Fremont Bridge, the patterns were grouped by work days vs. weekend and summer vs. winter. Federal holidays were removed from the workdays. Because May through September have higher-than-average bicycle volumes at this site, these "summer" months were plotted separately. For convenience, "winter" months were defined as October through April. The resulting patterns are shown in Figure 3.3, which shows that workdays exhibit a strong commuter pattern with peaks from 8-9 a.m. and 56 p.m., while weekends have lower volumes which peak at midday between 1-4 p.m.


Figure 3.3: Seattle Fremont Bridge Hourly Patterns in 2013
Data from the city of Olympia were also available to examine hourly patterns at the 19 locations where one week of bicycle counts were collected using pneumatic tube counters. Figure 3.4 shows the patterns for weekdays (Monday through Friday) at all 19 locations counted in June 2012. Most locations seem to show a morning (7-8 a.m.) and evening ( $5-6$ p.m.) commute pattern, though at least one location has larger midday use and some locations have somewhat steady use throughout the day. This would indicate mixed uses from recreational to utilitarian.


Figure 3.4: Olympia June 2012 Hourly Weekday Patterns at 19 Locations

Figure 3.5 shows the patterns at the same locations on the weekends. As is common, there is much greater variability on the weekends.


Figure 3.5: Olympia June 2012 Hourly Weekend Patterns at 19 Locations

### 3.1.10.4 Daily Variation

Daily patterns over the week were examined in the two cities for which such data were available: Seattle and Olympia.

In Seattle, average percent AADB by day of the week at the Fremont Bridge were plotted for 2013 (Figure 3.6). Because May through September have higher-thanaverage bicycle volumes at this site, these months were categorized as "summer" and plotted separately. The daily pattern over the week seems similar for both seasons with lower counts on weekends than weekdays.


Figure 3.6: Seattle Fremont Bridge Daily Patterns in 2013
Data from the city of Olympia were also available to examine hourly patterns at the 19 locations where one week of bicycle counts were collected using pneumatic tube counters. Figure 3.7 shows the patterns for days of the week at all 19 locations counted in June 2012. The patterns vary considerably by location with the locations having lower counts on weekends on average. Because each line represents only one week of data and volumes are relatively low (less than 200 bicyclists per day), there is high variability between sites.


Figure 3.7: Olympia June 2012 Daily Patterns at 19 Locations

### 3.1.10.5 Monthly Variation

Monthly variation was only available at one site, the Seattle Fremont Bridge (Figure 3.8). April through September have higher than average counts with peak average daily volumes in July.


Figure 3.8: Seattle Fremont Bridge Bicycle Traffic by Month in 2013

### 3.2 TRANSPORTATION NETWORK DATA

For the statewide estimates, centerline miles were calculated using three street network geographic information system (GIS) shape files provided by the Washington State Department of Transportation (WSDOT). Road segments were considered urban if they were contained in an urbanized area or urban cluster, as defined by the 2010 U.S. Census. All other roads were categorized as rural.

For the example roadway and trail GIS shape files were provided by King County and the Puget Sound Regional Council, respectively.

### 3.3 SOCIODEMOGRAPHIC DATA

Sociodemographic data for this report are from the 2008-2012 five-year American Community Survey. Newer data from 2013 were not available at the time of the analysis. All of the data were collected at the census-tract level. Additionally, this analysis also used data from the 2009 National Household Travel Survey.

### 3.4 OTHER DATA SOURCES

### 3.4.1 Safe Routes to School

Safe Routes to School programs across the U.S. encourage students to walk and bike to school in order to promote healthy lifestyles and healthy communities. They conduct studies and work with schools to plan ways to make streets around schools safer for children. This helps to reduce traffic congestion and air pollution around schools, and gets kids thinking about making healthy lifestyle decisions from an early age.

Figure 3.9 displays the percentage of students at various schools using active transportation across the state of Washington. Data for this map came from WSDOT's Safe Routes to School Program research, which had children in Washington schools raise their hands if they use any form of active transportation to get to school. Figure 3.10 shows some correlation of schools with a high percentage of active transportation by region. Rates of active transportation to schools are generally much lower in the Cascades region than in other regions. The Eastern Region has the highest rates of active transportation, with over 20 percent of schools in the 30-percent-or-above range.


Figure 3.9: Students Using Active Transportation


Figure 3.10: Percent of Students Using Active Transportation per Region

### 3.4.2 GPS Data

Recreational riders, as well as some commuters, use applications like Strava, Ride with GPS, Map My Ride, and other smart phone apps in order to track where they have been, how long they have ridden, and how far they have gone. With GPS technologies now included in most smart phones, and the increasing availability of bike computers that monitor anything from speed to heart rate, the amount of big data available from these users is growing quickly.

Strava, an application popular among recreational riders, will provide its data for a price. For example, the Oregon Department of Transportation (ODOT) has acquired Strava data and estimates that there were 400,000 Strava trips recorded in 2013, totaling 5 million bicycle miles traveled (ODOT, 2014). Strava does, however, provide publicly online heat maps. Figure 3.11 displays heat maps for the state of Washington and the city of Spokane. This is an especially attractive opportunity for understanding bicycle use in rural areas where recreational riding is common and it is impractical to ask volunteers to count.


Figure 3.11: Strava Global Heatmap (Strava, 2014)
Because of the large numbers of trips captured by GPS data, it is an important factor to consider for future studies of BMT. As access to GPS devices increases, the amount of data readily available will grow rapidly, giving researchers much more to work with when estimating these measures. This data can be useful not only in estimating miles traveled, but also for planning purposes. It allows planners to see cyclist behaviors, such as when cyclists have to take less direct routes to their destinations so that they can feel safe. It also can be a helpful measure to understand bicyclists' level of stress and level of comfort to help plan safer, more complete streets. However, without corresponding count data, GPS tracking data should not be used to compute BMT. Only if GPS data can be demonstrated to correlate reliably to observed counts, can it be used to estimate volumes between counts sites where count data are not available.

### 3.4.3 Adventure Cycling

The Adventure Cycling Association is a nonprofit organization that promotes bicycling as a means of transportation across the country. They map out routes across the continental U.S. for both the Adventure Cycling Route Network as well as the US Bicycle Route System for people to follow on long-distance bike trips. Figure 3.12 displays the Adventure Cycling routes for the State of Washington.


Figure 3.11: Adventure Cycling Routes
These routes could be especially important in counting rural bicycle miles traveled because of their popularity. In Table 3.4, we determined how many physical maps were sold in a given year and multiplied that number by the total mileage of the Adventure Cycling routes in the state. Of course, this is not an estimate of BMT, because some people may order maps and never ride, only ride part of route, and one map may serve many riders. However, the computation in Table 3.4 is provided to inform our estimate of miles traveled in rural areas.

GPS point data for the routes can also be purchased online as a supplement to the paper maps. During the time of study, smartphone and GPS battery-life made sole reliance on electronic devices for navigation on multi-day bicycle tours in remote areas challenging; although some riders use solar chargers and hub generators to power devices when power sources are not
available. The Adventure Cycling Association also guides tours using its routes. So, a count of tour attendees could also inform our estimates.

Long-distance cycling on Adventure Cycling routes would only account for a small percent of total state BMT. However, since the routes are long, the potential for route users to contribute to total state BMT is high. If use of these routes increases, they could significantly impact statewide BMT, especially in rural areas. This is an area to watch. Fortunately, such route use would be captured by a rigorous count program and could also be captured in GPS data, although it would not be included in most travel surveys.

Table 3.3: Adventure Cycling Route Mileage Estimates

| Adventure Cycling |  | Map Sales by Year |  |  |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: |
| Route Name | Section <br> Number | $\mathbf{2 0 1 1}$ | $\mathbf{2 0 1 2}$ | $\mathbf{2 0 1 3}$ | Total Route Mileage | Miles Biked 2013 <br> (Map Sales * Route <br> Mileage) |
| Pacific Coast | 1 | 728 | 819 | 694 | 317 | 220,000 |
| Northern Tier | 1 | 389 | 387 | 364 | 419 | 152,520 |
| Sierra Cascades | $1 \& 2$ | 542 | 561 | 449 | 897 | 402,750 |
| Washington Parks | $1 \& 2$ | 367 | 369 | 438 | 1,046 | 458,150 |
| Lewis and Clark Trail | 7 | 283 | 263 | 252 | 324 | $\mathbf{3 0 0 3}$ |

### 3.5 WASHINGTON STATE BICYCLE MAP

WSDOT also publishes a statewide bicycle map available online. Many of these routes overlap with the Adventure Cycling routes and can be useful when estimating total miles of bicycle infrastructure in the state.

For example, limited counting program efforts and early estimates of BMT should first focus on the routes designated as cycling routes on the map. Simply counting highly frequented routes in large cities such as Seattle will not yield an accurate estimate of BMT. Therefore, counting along these lesser-used trails is extremely important for miles-traveled estimations.

### 3.6 ORGANIZED GROUP RIDES

Another useful source of information are large, organized group bike rides. Every year, thousands of bicyclists participate in rides throughout the state of Washington for charities or their own personal recreation. Table 3.5 displays that just the top 10 attended rides account for millions of miles travelled. Most notably, Seattle to Portland has to be capped every year at 10,000 riders because of its immense popularity.

While this short list falls far from capturing all of the organized rides in the state, it does capture some of the most popular. The total BMT from these rides is roughly 3 million, is a small percent ( $<4 \%$ ) of the total for the state even assuming the lowest estimate. However, these events are not
included in travel survey-based estimates could be easily missed by even a rigorous counting program. So, it is important to remember that such rides generate many miles of cycling, and similar lists of organized runs and walks generate many miles of walking. If BMT estimates are to be used by those interested in understanding levels of physical activity, inclusion of such events may be important.

Table 3.4: Top-10 Attended Organized Group Rides in Washington

| Name | Start Location | Distances | Number of riders | Miles Ridden |
| :---: | :---: | :---: | :---: | :---: |
| Seattle to Portland | Seattle | 203 | 10,000 | 2,030,000 |
| Chilly Hilly | Bainbridge Island | 34 | 3,005 | 102,170 |
| Flying Wheels Summer Century* | Redmond | 40 | 1,570 | 62,800 |
|  |  | 100 | 1,570 | 157,000 |
| Totals |  |  | 3,139 | 219,800 |
| Bike MS* | Mt. Vernon | Day 1 | 1,800 |  |
|  |  | 22 | 34 | 737 |
|  |  | 59 | 34 | 1,977 |
|  |  | 78 | 34 | 2,613 |
|  |  | 97 | 34 | 3,250 |
|  |  | Day 2 | 1,000 |  |
|  |  | 50 | 500 | 25,000 |
|  |  | 75 | 500 | 37,500 |
| Totals |  |  | 1,800 | 71,076 |
| RSVP | Seattle | 187 | 1,400 | 261,800 |
| RSVP 2 | Seattle | 187 | 1,365 | 255,255 |
| Cycle the WAVE | Bellevue | 12 | 134 | 1,608 |
|  |  | 25 | 225 | 5,625 |
|  |  | 42 | 300 | 12,600 |
|  |  | 62 | 225 | 13,950 |
| Totals |  |  | 884 | 33,783 |
| Kitsap Color Classic* | Kitsap | 24 | 404 | 9,696 |
|  |  | 57 | 404 | 23,028 |
| Totals |  |  | 808 | 32,724 |
| Seattle Bike-n-Brews* | Seattle | 25 | 391 | 9,775 |
|  |  | 50 | 391 | 19,550 |
| Totals |  |  | 782 | 29,325 |
| Obliteride | Seattle | 25 | 224 | 5,600 |
|  |  | 50 | 240 | 12,000 |
|  |  | 100 | 159 | 15,900 |
|  |  | 180 | 69 | 12,420 |
| Totals |  |  | 692 | 45,920 |
| Grand Totals |  |  | 23,875 | 3,081,853 |

*For rides where total riders were not given for each distance, ridership was distributed evenly between mileage options

### 3.7 SUMMARY OF DATA SOURCES

In this chapter, the team explored various sources of data: manual count programs conducted by WSDOT and the city of Seattle, temporary automated bicycle counts collected by the city of Olympia, permanent automated bicycle counts on the Fremont Bridge, facility data across the
state's transportation network and sociodemographic data from national sources, safe routes to school on travel to school, GPS bicycle route data from apps, and information on recreational riding from bicycle touring groups and event organizers. Some of these sources are for bicycles only, while others are for both cycling and walking. Not all of these data sources were found to be useful for estimating state-wide bicycle and pedestrian miles traveled.

Of the count data, the continuous counts from the Fremont Bridge were useful in understanding temporal patterns by hour, day-of-week, and season. The short duration manual counts across the state and in Seattle were useful in studying spatial variation in bicycle and pedestrian travel across the state. Road type, land use (urban/rural), and centerline-miles from WSDOT's GIS layers were useful for determining what spatial characteristics are associated with higher or lower bicycle and pedestrian volumes, based on the variables of interest identified in Chapter 2. Similarly, socio-demographic variables from the American Community Survey were helpful to interpret where pedestrian and bicycle volumes were expected to be higher.

Other data sources, such as trip to school reporting from Safe Routes to School, and recreational bicycle trip reporting from Adventure Cycling and event organizers were not used on the state level, because they provided only a partial picture of total bicycle and pedestrian use. The team did not see a way to extend these datasets to a more generalized measure of cycling and walking across the state. For this reason, these data sources will not be discussed further in this report.

### 4.0 METHODS

Given the data available as detailed in Chapter 3, no method is sure to result in actual bicycle and pedestrian miles traveled. For this reason, three methods were investigated in an effort to triangulate toward what might be a likely range of values, or, failing that, to at least identify the problems and data needs associated with each method. Each method is detailed below in order of increasing complexity. The first method uses travel survey data and the second two rely on count data: a sample based method and a statistical modeling method.

### 4.1 TRAVEL SURVEY DATA METHOD

BMT and PMT can be estimated based on the responses to questions in the National Household Travel Survey (NHTS), but this approach requires broad assumptions and has been found by others to underestimate bicycle miles traveled (Dowds and Sullivan 2012). Dowds and Sullivan created their NHTS-based estimate by incorporating "person-trip weights" in an effort to correct for survey bias.

In order to compare the count-based and aggregate demand methods for estimating BMT and PMT, a "back of the envelope" computation was made to understand roughly what order of magnitude for miles of travel one might expect.

Ideally, data from a Washington State travel survey would be used for this estimate, but no such household travel survey exists for the state. In the 2009 NHTS, there were 415 households surveyed in Washington State, which included a total of 891 individuals. Of the individuals, 96 (11\%) reported making at least one bike trip in the past week and 645 individuals (72\%) reported making at least one walking trip in the past week. However, only two and nine individuals biked and walked to work in the past week, respectively. As a result, it was necessary to use nationwide data in order to produce an acceptable sample size of bicyclists and walkers.

Using research from Pucher et al. on the NHTS in combination with U.S. Census data, PMT and BMT estimates can be produced by simply multiplying the average miles of cycling per person over five years of age per year ( 112.4 miles of walking and 24.1 miles of cycling per person per year in 2009) by the appropriate population (Pucher et al. 2011). While these are national numbers, not specific to Washington State, this method will act as a comparison for other methods.

In 2009, 14 state departments of transportation paid for oversampling in their state in the NHTS. In these states, it may be possible to perform the same analysis of bicycle and pedestrian behavior using state-level data, removing the need to rely on national data.

### 4.2 SAMPLE-BASED METHOD

The sample-based method involves sampling bicycling and walking at a representative sample of locations and based on that extrapolates BMT and PMT for the state.

### 4.2.1 Stratified Sample

The sampling frame is composed of every road and path segment in the state. Choosing a representative sample of such a large and diverse population can be simplified by stratifying the sample. In the literature review, the following spatial attributes seem relevant to cycling and walking:

- Level of urbanism (population or employment density, distance to major attractor such as downtown, and connectivity)
- Facility type
- Proximity to transit, for walking
- Slope, for biking
- Geographic and climatic region

Each of these attributes were considered for potential categories with which to divide the sample. Slope was specific to cycling and transit proximity to walking. These were dropped from consideration, because a set of categories appropriate for both modes would simplify data collection.

As part of a stratified sampling approach, all the roads and path segments in the state were divided into categories by region, urbanity and facility type: 24 stratified-sample groups from which count locations can be sampled.

### 4.2.1.1 Level of Urbanism

Based on the literature reviewed, the level of urbanism is an important variable for determining the level of cycling and walking. It is related to other variables identified in the literature, such as population density, employment density, street density, and proximity to transit. In order to identify a metric of urbanism that could readily apply to the study of bicycle and pedestrian volumes, the project team conducted a review of similar measures discussed in the literature review.

For this study, we considered many approaches. No one definition of suburban seemed to emerge from the literature. We considered how population density, a common measure of urbanism, seemed related to the WSDOT Bicycle and Pedestrian Documentation Project data (Figure 4.1). While population density is correlated with AADB and AADP, there is no clear threshold population density above which counts increase dramatically as shown in Figures 4.2 and 4.3; although for the few locations in very high-population areas ( $>10,000$ people per square mile) there is evidence that such a threshold may exist. Unfortunately, we did not have enough count sites at high-density locations to verify this. In addition, there are few locations in the state with such high-population densities as illustrated in Figure 4.1.

Areas in Washington with sufficient density to substantially impact bicycle and pedestrian volumes are few and mostly located in Seattle's downtown area. There was
not a sufficient difference between Seattle's urban area and what we believed to be suburban areas to warrant a separation of the two for this study.

The measures considered were evaluated with respect to their use in creating a simple categorization for the state-level analysis. In the end, locations were described as either urban or rural based on city limits, which roughly corresponded to the roadways designated as urban and rural by WSDOT. The urban vs. rural category is a coarse division compared to other measures of urbanism found in the literature, such as employment and population density or proximity to downtown or a university. It is appropriate on the state level, where urban areas and rural areas are likely to have dramatically different walking and bicycling levels.


Figure 4.1: Population Densities (population per square mile) in Washington by Census Tract

AADP vs. Population Density


Figure 4.2: AADP with Population Density


Figure 4.3: AADB with Population Density

### 4.2.1.2 Facility Types

Each segment of road was classified into one of two categories using the Federal Functional Classification system for roadways. The first category contains interstates, other freeways, other principal arterials, and minor arterials. The second category contains major collectors, minor collectors, and local access roads.

As seen in Figures 4.4 and 4.5, there appears to be substantially higher non-motorized traffic counts on trails than on roads, especially for bicycles. For this reason, the trail facility type is expected to be highly influential when calculating BMT and PMT. Trails and paths used by non-motorized traffic separate from motor vehicles were a third category of facility type: Trail.


Figure 4.4: Average AADP Trails vs. No Trail


Figure 4.5: Average AADB Trails vs. No Trail

### 4.2.1.3 Region

To account for both, geography and climate, the research team sought a regional classification that would account for the main categories of both. The U.S. Environmental Protection Agency (EPA) has created a map of eco-regions, which categorize the regions of the state as shown in Figure 4.6 (WSDOT 2013). While the regions were created based on local vegetation, they also represent the major regions of climate and geologic variation throughout the state. For the purposes of the study of cycling and walking, we grouped these regions into four categories listed from west to east (Figure 4.7): Coast Range, Puget Lowlands, Cascades, and Eastern Washington.


Figure 4.6: Eco-Regions (WSDOT, 2013)


Figure 4.7: Simplified Regions
The four regions are a simplified version of WSDOT's Ecoregion map (WSDOT 2013) which was derived from the Level III ecoregions as defined by the EPA (U.S. Environmental Protection Agency 2013). Figure 4.8 displays the four regions, the urban areas in Washington State, and all of the count locations.


Figure 4.8: Count Locations and Regions

### 4.2.2 Method Outline

BMT and PMT could be estimated using count data if all facilities were counted or if counts were representative of the stratified-sample groups. Unfortunately, the current short duration count data were not randomly sampled and may be biased toward locations with higher volumes of cyclists and walkers. Despite this, the count data were used due to lack of alternative data sources.

Below is an outline of this proposed method as applied to the state of Washington:

1. Identify sampling framework: all road and path segments in the state.
2. Determine appropriate groups: Twenty-four groups were chosen based on the following three attributes:
a. By level of urbanism (2 categories): Urban and Rural.
b. By facility type (3 categories): Highway/Arterial, Local/Collector and Trail.
c. By geographic and climatic regions (4 regions): Coast Range, Puget Lowland, Cascades, Eastern Washington.
3. Select sample sites randomly from each group, and collect short-duration counts at each site.
4. Compute seasonal, daily and hourly adjustment factors based on continuous-count data.
5. Apply factors to short-duration counts to estimate annual average daily bicycle and pedestrian traffic (AADB and AADP) at each site.
6. Total the centerline miles in each of the groups.
7. Average the $A A D B$ and AADP estimates for all the sites in each group.
8. Multiply centerline miles in each group by the average AADB and AADP for each group.
9. Sum these estimates and multiply by 365 to estimate the annual BMT and PMT.

Research shows that relatively little reduction in AADB estimation error occurs for short duration counts longer than seven days and, for this reason, often recommends seven-day short duration counts (Nordback, et al 2013, Hankey, et al 2014, Nosal, et al 2014). A recent study shows that short duration counts of as little as two hours can still result in less than 20 percent average absolute error in estimating seasonal average day traffic if disaggregate factoring is used and the correct factor group is applied (Budowski et al 2017).

### 4.3 AGGREGATE DEMAND MODEL

This method also uses the AADB and AADP estimations calculated from manual and automated count data. Each AADB and AADP estimation was then associated with the following variables:

- Facility type, which has three categories:
o Local and collector roads
o Arterial roads and highways
o Trail
- Bridge, a dummy variable that indicates if the bicyclist or pedestrian is crossing a bridge
- Population density - density of population in the census tract
- Percent of the population aged 18 to 54
- Percent of the population with a four-year degree or more

With the exception of the bridge variable, these variables were chosen because previous research described in the literature review have found them to be correlated with levels of bicycling and walking, and because they all had readily available data sources. Trail was added to the categorization of facility types used in the count-based method, because counts on trails were found to be significantly higher than counts on other facilities. The bridge variable was added after an inspection of the data revealed many of the sites with the highest bicycle volumes occurred on a bridge.

These models can then be used to calculate BMT and PMT at the statewide level using the following procedure:

1. Associate road and trail segments throughout the state with the corresponding census tract and American Community Survey (ACS) data.
2. Apply the model to each segment to estimate AADB and AADP for the segment.
3. Multiply AADB and AADP by the length of the segment.
4. Sum all of the segments throughout the state.
5. Multiply by 365 to get estimates for annual PMT and BMT.

For the purposes of estimating PMT, the bridge variable should be removed from the model. The bridge variable was included to illustrate the magnitude of its impact on bicycle traffic, and its lack of significance on pedestrian traffic.

### 5.0 RESULTS

Estimates of BMT and PMT were made on two spatial levels, the state level for one example state, Washington State, and the county level for one example county, King County in Washington State. The count-based method and the aggregate demand model method could not be used on the state level due to lack of count data in rural areas of the state. For this reason, these methods were instead applied on the county level for comparison purposes.

### 5.1 NATIONAL SURVEY DATA METHOD ESTIMATES

As a rough estimate for the purposes of comparison, the estimates shown in Table 5.1 were derived from research conducted by Pucher et al. (2011). Pucher et al. calculated per capita bicycle and pedestrian miles traveled estimates for the entire United States. The estimates used the 2009 National Household Travel Survey. The analysis was restricted to survey respondents over the age of 5 .

Walking and bicycling trips to access public transportation are included in the survey, but walking and bicycling trips to access motor vehicles are not included if driving a motor vehicle is the primary mode of transport. Walking and bicycling trips for recreation, such as taking a walk, are included even if no destination is reached, but counted as two "trips," one for the outbound portion and the other for the inbound portion of the walk or bike ride. Also, short walking trips within one address are not included.

Data from the 2010 U.S. Census was then used to estimate BMT and PMT for the entire state of Washington in both 2010 and 2013. Pucher et al.’s (2011) per capita estimates were multiplied by Washington State's census data of the population over the age of 5. The 2013 estimate uses the U.S. Census Bureau's 2013 population estimate for Washington State.

The 95 percent confidence interval (CI) represents only error from the National Household Travel Survey as reported by Pucher et al. (2011). The actual error is much higher for the following reasons, not included in the confidence interval computation:

- NHTS does not include short trips with an address, such as walks to the mailbox, within a shopping mall, or to a parked car.
- Nonsampling errors associated with the NHTS, such as misunderstanding respondents and sampling bias due to households without landline telephones, are not included (FHWA 2011).
- Applying national data to the state of Washington is a simplification that is most likely to underestimate cycling and walking, since walking and cycling commute mode shares are higher in Washington than in other states (bicycle mode share was 0.9 percent in Washington State vs 0.6 percent nationally and pedestrian mode share was 3.5 percent in Washington State vs. 2.8 percent nationally based on the American Community Survey 2008-2012, McKenzie 2014, and U.S. Census Bureau 2014).


## Table 5.1: Statewide Estimates Using National Survey Method (in Millions of Miles)

| Year | PMT (95\% CI)* | BMT (95\% CI)* |
| :---: | :---: | :---: |
| 2010 | $710(680$ to 740$)$ | $150(140$ to 170$)$ |
| 2013 | $730(700$ to 770$)$ | $160(150$ to 180$)$ |

* The confidence interval (CI) only accounts for error from the National Household Travel Survey as reported by Pucher et al., (2011). Actual error is likely to be much higher.


### 5.2 SAMPLE-BASED METHOD ESTIMATES

Before estimating PMT and BMT, the centerline miles in each of the 24 groups identified based on region, urbanity and facility type had to be calculated. The results are summarized in Table 5.2. Note that the local category includes local roads and collectors, and the arterial category includes highways and major and minor arterials.

Centerline miles were calculated using three street network layers provided by WSDOT. For the most part, roads on all three layers were represented by a single polyline. However, highways and certain major arterials were represented by two lines, one for each direction of the roadway.

To avoid double counting highways for the purpose of determining centerline miles, all segments classified with a direction of decreasing (in relation to mileposts) were removed. Additionally, ramps, HOV lanes, and other lanes that would result in double counting were also removed. Roads classified as couplets, spurs, and alternate route highways were included in the calculation of centerline miles.

The total number of centerline miles ( 156,109 miles) as determined using this methodology is significantly higher than the FHWA's estimate of 83,527 miles for the state (FHWA, 2008). The centerline miles for interstates, arterials, and collectors are all similar to the FHWA estimates. Thus, the difference between the two estimates is attributable to the centerline mileage for local streets.

Trail mileage was obtained from the Rails to Trails Conservancy's GIS of trails in the state of Washington.

Table 5.2: Summary of Centerline Miles by Group

| Region | Level of Urbanism | Road/Path Type | Total Miles |
| :---: | :---: | :---: | :---: |
| Coast Range | Urban | Arterial | 409 |
|  |  | Local | 739 |
|  |  | Trail | 6 |
|  | Rural | Arterial | 128 |
|  |  | Local | 13,062 |
|  |  | Trail | 69 |
| Puget Lowlands | Urban | Arterial | 4,042 |
|  |  | Local | 20,730 |
|  |  | Trail | 344 |
|  | Rural | Arterial | 183 |
|  |  | Local | 15,380 |
|  |  | Trail | 163 |
| Eastern Washington | Urban | Arterial | 2,574 |
|  |  | Local | 7,140 |
|  |  | Trail | 108 |
|  | Rural | Arterial | 1,448 |
|  |  | Local | 54,407 |
|  |  | Trail | 376 |
| Cascades | Urban | Arterial | 219 |
|  |  | Local | 352 |
|  |  | Trail | 4 |
|  | Rural | Arterial | 576 |
|  |  | Local | 33,526 |
|  |  | Trail | 124 |
| Total Centerline Miles in Washington State |  |  | 156,109 |

Using the available data, annual PMT and BMT were estimated for the groups for which data were available. In some cases, counts were taken in parking lots. These counts were included in the local roads category.

The results are shown in Table 5.3. It is important to note that these estimates may be biased, because site selection was not random. Site selection may have been biased toward locations with more cycling and walking. This bias can be corrected in the future by randomly sampling count locations from the stratified sampling framework listed in Section 4.2.1.

Table 5.3: Estimates Using Count-Based Method (Millions of Miles)

|  | PMT | BMT |
| :--- | :---: | :---: |
| Puget | $3,500(2,700$ to 4,300) | $1,200(900$ to 1,500) |
| Eastern | $1,400(800$ to 2,000) | $340(200$ to 480) |
| TOTAL (two regions only) | $4,900(3,500$ to 6,300$)$ | $1,540(1,100$ to 1,980$)$ |

In order to estimate the error, confidence intervals were computed around the average count estimate for each of the 24 categories. The 95 percent confidence interval was constructed for the mean AADB or AADP for each sampling group using the following formula:

$$
\overline{A A D B \text { or } A A D P} \pm 1.96\left(\frac{\sigma}{\sqrt{n}}\right)
$$

where
$\sigma=$ standard deviation
$n=$ number of count sites

### 5.3 AGGREGATE DEMAND MODEL

In order to create an aggregate demand model of bicycle and pedestrian count volumes, each count site was associated with the demographic data from the census tract the count site lies within. In six of the cases, the count site fell on the boundary between two census tracts. For these cases, the data from the two bordering census tracts were averaged (weighted by the population of the census tracts).

Median household income was initially included in the analysis because others had found this variable to be a good predictor of bicycle travel. However, it was later excluded from this analysis due to its correlation (Pearson correlation coefficient of 0.64 ) with the percent of the population with a four-year degree. Additionally, separate studies of bicycling and pedestrian rates found the percent of the population with a four-year degree to be significant (Hankey et al. 2012).

Region was removed as a variable in this analysis since there was only count data available within two of the four regions in Washington State. Furthermore, population density accounts for some of the major differences between regions.

The distribution of values for both the AADB and AADP were positively skewed. As a result, the logarithm of each independent variable plus one (i.e., $\log (A A D B+1)$ ) was taken to produce a normal distribution. One was added to the values to prevent values of zero from being undefined. A multiple linear regression was then performed with the associated variables as the independent variables for both AADB and AADP.

The model was estimated using ordinary least squares regression using SPSS. The basic form of the model is:

$$
\begin{equation*}
Y=\alpha+\beta_{1} \mathbf{x}_{1}+\beta_{2} \mathbf{x}_{2} \ldots \beta_{n \times n} \tag{5-1}
\end{equation*}
$$

where
$\mathrm{Y}=$ the dependent variable, in this case the log of AADB or AADP plus one
$\alpha=\mathrm{a}$ constant
$\beta=$ the coefficients for each term
$n=$ the number of independent variables to be included in the model
$x=$ the independent variables
The equation for the bicycle model is:

$$
\begin{equation*}
\log (\text { AADB }+1)=0.620+\left(1.766 \times 10^{-5}\right) x_{1}+0.010 \times 2+0.009 \times 3+0.212 x_{4}+0.625 \times 5+0.635 \times 6 \tag{5-2}
\end{equation*}
$$

The equation for the pedestrian volume model is:

$$
\begin{equation*}
\log (\text { AADP }+1)=1.342+\left(3.784 \times 10^{-5}\right) x_{1}+0.012 x_{2}+0.001 x_{3}+0.095 x_{4}+0.187 \mathrm{x}_{5}+0.117 \mathrm{x}_{6} \tag{5-3}
\end{equation*}
$$

where
$x_{1}=$ Population density (people/square mile)
$x_{2}=$ Percent of the population between 18 and 54
$x_{3}=$ Percent of the population with a four-year degree
$x_{4}=$ Arterial ( 1 if count site is located on an arterial, 0 otherwise)
$x_{5}=$ Bridge ( 1 if count site is located on a bridge, 0 otherwise
$x_{6}=$ Trail (1 if count site is located on a trail, 0 otherwise)
After removing household income and region, the remaining explanatory variables were found to be significant at the 0.1 level for AADB. Additionally, $34 \%$ of the variation in AADB was explained by the model. All seven of the tested variables (including the constant term which represents local/collector streets not located on a bridge) were found to be significant at 0.1 level for AADB.

For pedestrians, 16 percent of the variation in AADP was explained by the model. The percentage of the population with a college degree and the bridge and trail indicator variables were not significant at the 0.1 level.

Each model was also run with the lower bound $\beta$ of a 95 percent confidence interval for each independent variable to produce a minimum estimations from BMT and PMT. This process was repeated with upper bound $\beta$ 's to calculate maximum BMT and PMT.

A next step of this analysis may investigate using a negative binomial model as recommended by Wang et al. (2013). This approach makes sense since counts are discrete variables and are often found to be overdispersed.

It should be noted that this model has been built based on data from the state of Washington and may not be applicable elsewhere.

Table 5.4: Aggregate Model for Bicycle and Pedestrian Models

| Independent Variables | Unstandardized Coefficients |  | Standardized Coefficients | T | Sig. |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | B | Std. Error | Beta |  |  |

Bicycle Model: $\log ($ AADB+1) is dependent variable

| (Constant) | .620 | .119 |  | 5.215 | .000 |
| :--- | ---: | ---: | ---: | ---: | ---: |
| Population Density | $1.766 \mathrm{E}-05$ | .000 | .145 | 3.759 | .000 |
| \% of Pop 18-54 | .010 | .002 | .179 | 4.665 | .000 |
| College Degree | .009 | .001 | .255 | 7.977 | .000 |
| Arterial | .212 | .044 | .161 | 4.761 | .000 |
| Bridge | .625 | .125 | .159 | 4.978 | .000 |
| Trail | .635 | .063 | .343 | 10.023 | .000 |

Pedestrian Model: $\log ($ AADP+1) is dependent variable

| (Constant) | 1.342 | .142 |  | 9.481 | .000 |
| :--- | ---: | ---: | ---: | ---: | ---: |
| Population Density | $3.784 \mathrm{E}-05$ | .000 | .251 | 5.959 | .000 |
| \% of Pop 18-54 | .012 | .003 | .191 | 4.546 | .000 |
| College Degree | .001 | .001 | .015 | .399 | .690 |
| Arterial | .095 | .053 | .070 | 1.790 | .074 |
| Bridge | .187 | .147 | .047 | 1.272 | .204 |
| Trail | .117 | .074 | .063 | 1.585 | .113 |

### 5.4 EXAMPLE COUNTY RESULTS

In order to directly compare the three methods, they were tested on the area of King County that lies within the Puget Lowland region of Washington State. This area was chosen since it had the necessary data to employ all three methods. Table 5.5 displays the results.

Table 5.5: Annual PMT and BMT for King County within the Puget Lowlands (Millions of Miles)

| Method | PMT (95\% CI) | BMT (95\% CI) |
| :--- | :---: | :---: |
| National Survey Data | $200(190$ to 210) | $45(40$ to 50) |
| Sample-Based Method (All Puget Sites) | $1,800(1,200$ to 2,400) | $510(370$ to 650) |
| Sample-Based Method (King County Sites Only) | $2,400(1,400$ to 3,300) | $690(460$ to 930) |
| Aggregate Demand Model | $560(100$ to 3,000) | $220(50$ to 910) |

### 5.5 LOWER AND UPPER BOUND

In order to understand what range of values to expect for BMT and PMT, upper and lower bounds were estimated based on the analysis. The lower bound estimate was based on the lower bound National Household Travel Survey (NHTS) estimate for 2013 (Table 5.1): 700 million PMT and 150 million BMT. Per individual, this would be 0.3 miles walked per person per day and 0.06 miles bicycled per person per day.

The upper bound estimate was based on the estimates from the sample-based method in which cycling and walking rates (miles per person per year) for King County were applied to the population in the rest of the state: 8,000 million PMT and 2,400 million BMT. This may be an upper bound, because cycling and walking rates for King County may be higher than those for the rest of the state. Per individual in the state, this translates to roughly 3.2 miles walked per person per day and 0.9 miles bicycled per person per day.

### 5.6 COMPARISON ACROSS STUDIES

In order to determine that the estimated BMT and PMT values were reasonable, BMT and PMT per person per day was comparable to those of other studies. Figures 5.1, 5.2, and 5.3 show BMT, PMT, and bicycle and pedestrian miles traveled (BPMT) estimates per person per day for other studies in white and from this study in black. Other studies compared include survey-based estimates from Wisconsin (McAndrews et al 2013) and the Puget Sound Region in Washington State (PSRC 2007), and sample-based estimates from the Minneapolis/St. Paul area in Minnesota (Davis and Wicklatz 2001) and Chittenden County in Vermont (Dowds and Sullivan 2012). The upper and lower bound estimates were near the high and low end of all other studies, indicating that these may be appropriate upper and lower bound estimates for cycling and walking in Washington State.

The King County counts were slightly higher than comparable studies. However, because none of our estimates were dramatically higher or lower than comparable studies, we can conclude that our methods for estimating BMT and PMT are within the realm of reason. Unfortunately, the realm of reason is wide.

Estimates made based on travel survey data seem to result in much lower estimates of cycling and walking per person than estimates made from count data. There are two reasons for this. Recreational Trips. Travel surveys focus on transportation trips and often exclude or neglect recreational travel such as exercise. Count data, on the other hand, include all types of trips, so estimates using these data should be higher than those using count data. Count Location Bias. The count locations were not chosen randomly, but chosen by local count coordinators. For this reason, they may not be representative of the road type or region in which they were collected, but may be biased toward higher volume.

Within the two types of estimates (survey method and sample-based method), there is some variation. The aggregate model is based on count data, but predicts much lower volume per person. This may indicate that this modeling reduces some of the error compared to the samplebased method. It is also interesting to note in Figure 5.2 that the Twin Cities estimate (Davis and

Wicklatz, 2001) of BMT is the only sample-based estimate that is similar in magnitude to the survey-based methods. This may be because this study was more successful in obtaining a representative sample of count sites.

Figures 5.1 to 5.3 show estimates for King County with and without "trails" as a separate facility classification from local roads. In general, including trails as a separate category resulted in lower estimates of BMT and PMT since trails generally have higher volumes in the count data analyzed.

BMT Methods Comparison Across Studies


Figure 5.1: BMT Methods Comparison (Solid black bars are data from this report)

## PMT Methods Comparison Across Studies



Figure 5.2: PMT Methods Comparison (Solid black bars are data from this report)

## BPMT Methods Comparison Across Studies

BPMT/Person/Day


Figure 5.3: BPMT Methods Comparison (Solid black bars are data from this report)

### 6.0 DISCUSSION

Gauging accuracy is difficult, because the actual values of BMT and PMT are unknown. Given the existing data for the state of Washington, none of the three methods investigated are able to yield an accurate estimate of BMT or PMT. However, estimates are likely to be in the range of 700 to 8,000 million PMT and 150 to 2,400 million BMT. In comparison, motor vehicle travel in the state of Washington was estimated to be 31,650 million VMT on state highways in 2013 (WSDOT, 2014). Table 6.1 offers a summary of the three approaches and their results.

As shown in Table 5.5, which compares the three methods for King County, the sample-based method yields the highest estimates, as would be expected if location selection were biased toward relatively high count volumes. It should be noted that the estimates for King County from both count-based methods are on the same order of magnitude and are about one order of magnitude higher than that estimated by the national travel survey method. This finding is similar to those of Dowds and Sullivan for Chittenden County, VT, who found travel surveybased estimates to be substantially lower than estimates based on counts (Dowds and Sullivan 2012).

The data sources for each method would need to be improved in order to obtain a more reliable estimate of bicycle and pedestrian miles traveled. Additional data sources, such as GPS data discussed in Section 3.4.2, could also enhance the two count-based methods discussed by filling in gaps in knowledge, but such data also need to be improved before they can be used reliably.

Because bicycle and pedestrian travel behavior is different, the following discussion will focus on each mode separately.

### 6.1 BICYCLE

During the investigation, the importance of bridges and trails to increased bicycle volumes was observed in the count data. Both facility types typically carried more cyclists than other nearby facilities. In the case of bridges, this is likely due to the funneling effect of bridges that offer a way to cross a physical barrier. In the case of trails, it could be that trails offer a preferred facility for cyclists, who will go out of their way to access the trails (Broach et al. 2012).

In terms of accuracy, the counting method with sample-based estimation offers the best approach, because it is based on direct observations of human behavior instead of self-reported behavior. It could be combined with some other data sources, such as a representative GPS triptracking log. This could help identify which links of the network are used by cyclists in numbers. Unfortunately, representative counting programs and representative GPS trip-tracking data are rare and difficult to obtain. The potential bias of current count programs that may oversample where bicycle and pedestrian volumes are highest suggests that extrapolating from these data could likely result in overestimates.

### 6.2 PEDESTRIAN

Pedestrian travel is on an even smaller scale (shorter trips) than bicycle travel and, as a result, even less like motor vehicle travel. It is also less constrained by physical infrastructure than bicycle travel. For example, a pedestrian may cut across a property, step over a concrete barrier, walk through a small opening in a fence and climb stairs, while vehicles are constrained to the roadway. For this reason, different approaches for estimating pedestrian volumes and activity might be more appropriate for PMT.

For pedestrian miles of travel, the survey-based method might be more appropriate since it is more difficult to capture pedestrian trips by counting and because the pedestrian network is more fine grained and harder to quantify.

As observed by Schneider et al. (2013), since it is not possible to sample counts on all locations given the density of the pedestrian transportation network, the aggregate demand model provides a way to estimate counts at locations where no counts were collected. If the model has high explanatory power, one might even choose to reduce the number of count stations after a level of comfort was established with the method. However, much additional analysis would be needed before such a model could be established on the state level. Efforts to enable and automate aggregate demand model estimates, such as the Non-motorized Travel Analysis Toolkit, may prove helpful for future efforts (Raw, 2015). For the time being, additional counts would benefit both the sample-based and aggregate demand models.

Table 6.1 Summary of Methods, Data, and Results

| Approach | Data Source | Results <br> PMT | Results <br> BMT |
| :--- | :--- | :--- | :--- |
| Statewide <br> survey | National Household Travel Survey (NHTS) | $700-770$ <br> million miles <br> (entire state) | $150-180$ <br> million miles <br> (entire state) |


| Samplebased | Washington State bicycle and pedestrian documentation project data and Seattle's Fremont Bridge permanent bicycle counter data | 3,000-6,000 <br> million miles <br> in Puget and <br> Eastern <br> regions only | 1,000-2,000 million miles in Puget and Eastern regions only |
| :---: | :---: | :---: | :---: |
| Aggregate <br> Demand <br> Method | Washington State bicycle and pedestrian documentation project data and Seattle's Fremont Bridge permanent bicycle counter data | 100-3,000 <br> million miles <br> in King <br> County only | 50-1,000 <br> million miles <br> in King <br> County only |

### 7.0 CONCLUSION

Overall, while the count data are not representative of the state at large, the data do include a much more far-ranging sample of the state than data from a single municipality, county or region. Due to a lack of representative data, it is not possible to confidently estimate bicycle miles traveled or pedestrian miles traveled for the state of Washington. Instead of providing one basic method that should be applied, we have investigated three potential methods. Some are based on traditional transportation approaches while others stretch the limits of current practice.

Limitations of these methods include

- Selection of count locations may be biased toward locations where cyclists and pedestrian volumes are known to be high. This means estimates based on these data may be biased toward higher volumes.
- Because travel survey data do not include very short trips and often omit recreational trips, estimates based on these data may be biased toward lower volumes.

For each approach, we have outlined a potential method, listed existing data sources, and discussed the advantages and disadvantages for estimating statewide BMT and PMT. These are summarized in Table 7.1. The purpose of these computations are to demonstrate the method, not to be used as a baseline for actual BMT and PMT.

Table 7.1: Summary of Methods and Recommendations
$\left.\begin{array}{llll}\hline \text { Approach } & \text { Pros } & \text { Cons } & \begin{array}{l}\text { Recommended Data } \\ \text { Improvements }\end{array} \\ \hline \begin{array}{l}\text { Statewide } \\ \text { survey }\end{array} & \begin{array}{l}\text { Expanding existing } \\ \text { dataset is easier than } \\ \text { creating new dataset. } \\ \text { Computationally easy. }\end{array} & \begin{array}{l}\text { Data are not at the } \\ \text { facility level. }\end{array} & \begin{array}{l}\text { Fund an oversampling of the } \\ \text { next NHTS or a statewide } \\ \text { travel survey that includes } \\ \text { sufficient walking and } \\ \text { cycling trips. }\end{array} \\ \text { Sample- } & \begin{array}{l}\text { Data are at the facility } \\ \text { level. }\end{array} & \begin{array}{l}\text { Data may be biased } \\ \text { based }\end{array} & \begin{array}{l}\text { Expand count program to } \\ \text { locations. } \\ \text { Pedestrian locations } \\ \text { allow for a statewide } \\ \text { representative sample. }\end{array} \\ \text { challenging to }\end{array}\right]$

Recommendations for expanding the WSDOT count program specifically have been made in a previous report to WSDOT (Nordback and Sellinger, 2014). Generally, permanent count sites should be located in each climatic/geographic regions of a state, in both urban and rural areas, and on both on-street and path locations, as well as bridges. Ideally, there would be at least seven permanent counters per factor group ${ }^{1}$, based on previous research in Colorado (Nordback et al, 2013). In addition, the previous report to WSDOT recommended at least 150 short duration counts per sampling group, each collected for one week (not in winter) using automated equipment. Where permanent counters are available, the same short duration site need not be counted each year but can be part of a cyclic count program that counts every other year or every third year, for example. For the sample-based approach to be representative (remove bias), sites should be selected randomly from each sampling groups. As discussed in Section 4.2.1, there are 24 sampling groups identified in this study based on the four geographic/climatic regions of the state, two levels of urbanity, and three facility types.

Of the three methods examined, travel survey-based methods are best for statewide estimates of both cycling and walking. Sample-based sampling methods are best for facility-level bicycle volume estimates. Aggregate demand modeling approaches are best for bicycle and pedestrian estimation at the census-tract level. Each method provides valuable information. Which method is appropriate depends on the purpose of the estimate.

Regardless of the method used, the data used to produce estimates should be improved to increase accuracy and reduce bias. Also, regardless of the method and data used, bias should be understood. Until more representative count data are available, count-based methods (either sample-based or aggregate demand) are likely to overestimate volumes. Even if sample size increases, travel surveys will likely continue to underestimate cycling and walking unless recreational trips and short trips can be better integrated into the survey. GPS data offer a potential for filling in where these other data sets are blind (large rural areas), but should be combined with count data to produce reliable estimates of BMT and PMT.

While the three methods of calculating BMT and PMT investigated have the potential to yield rough estimates, much more data are necessary in order to accurately estimate these measures statewide. WSDOT is working to broaden its count program to include counts from all geographic regions of the state and expand permanent as well as short-duration counting programs. Efforts to improve travel survey data collection and GPS trip tracking are also needed.

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[^0]:    ${ }^{1}$ A factor group is a way to group permanent counters based on similar traveler behavior. For walking and cycling previous studies have identified three or four factor groups per region (Turner and Lasley, 2012; Miranda-Moreno et al. 2013, Nordback et al 2013). For example, one group may have a typical commute travel pattern, while another a recreational pattern.

