Spring 7-25-2013

Bicycle Traffic Count Factoring: An Examination of National, State and Locally Derived Daily Extrapolation Factors

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10.15760/etd.998

Bicycle Traffic Count Factoring: An Examination of National, State and Locally Derived Daily Extrapolation Factors

by

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A thesis submitted in partial fulfillment of the
requirements for the degree of

Master of Urban Studies
in
Urban Studies

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Portland State University
2013

Abstract

Since nearly the beginning of the wide spread adoption of the automobile, motorized traffic data collection has occurred so that decision makers have information to plan the transportation system. Widespread motorized traffic data collection has allowed for estimating traffic volumes using developed extrapolation methods whereby short-term counts in sample locations can be expanded to longer periods. As states and local planning agencies make investments in bicycle infrastructure and count programs develop, similar extrapolation methods will be needed. The only available guidance on extrapolating bicycle counts comes from the National Bicycle and Pedestrian Documentation Project (NBPDP), yet no validation of these factors have been done to assess their usability in specific areas. Using bicycle traffic count data from the Central Lane Metropolitan Planning Organization Count Program in Oregon, this research demonstrates that using study area data to generate time-of-day factors. Factors are generated in two separate ways in order to reduce error from estimating daily bicycle volumes. Factors groups are developed using bicycle facility type where counts are collected. This research also seeks to add to the literature concerning bicycle travel patterns by using study area data to establish a university travel pattern exemplified by a flat hourly distribution from morning to evening.

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1. Introduction

Motorized traffic data collection has been around nearly as long as the widespread adoption of the automobile. Understanding motorized traffic volumes is vital to planning the transportation system. As investments into infrastructure for non-motorized traffic such as bicycles increase, similar dedication to tracking bicycle traffic is necessary. The literature suggests performance measures like bicycle counts be put in place to monitor the impact that investments into bicycle infrastructure are having on overall demand so that planners and policy makers can make more informed decisions (OAG 1994, OAG 1997, Fleisher, and Mahafy 1997). The use of short-term, typically two-hour peak period, manually-gathered bicycle counts is a popular method for collecting data on bicycle demand in many areas around the United States (FHWA 2005; FHWA 2011).

Short-term counts are not necessarily representative of demand beyond the brief count period when they are collected. However, these short term counts are oftentimes used to represent relative levels of traffic in comparison to one another and are also used to estimate demand for longer periods of time, such as daily, monthly or yearly. This is done by using short-term counts to estimate 24-hour counts, which in turn, are used to estimate longer term counts of interest (e.g. week, month, or year). Factors for expanding short-term counts to longer term counts are created by using patterns found in data from long term counts and applying them to data collected over a shorter period.

These longer-term estimates are more meaningful when trying to understand the related economic, health, safety and environmental effects of bicycle usage for research and planning. For instance, the World Health Organization (WHO) uses average daily bicycle travel to assess the health and economic impacts for new infrastructure or as inputs to larger health impact assessments (WHO 2011). A number of studies analyzing safety information utilize some form of daily counts (Wang and Nihan 2004, Sælensminde 2004). Further, travel demand modeling tools require an average daily figure to compare and validate estimated traffic volumes. As these analysis tools progress and bicycle travel is explicitly represented in these models, average daily bicycle counts will be needed for estimation and validation.

The National Bicycle and Pedestrian Documentation Project (NBPDP) have accumulated data from over 600 count locations, gathered by more than 100 organizations. These data have been used to build a spreadsheet tool that extrapolates short-term bicycle counts data such as two-hour manual counts, up to full day, week, monthly, and yearly estimates. The NBPDP is the only recognized standard in both data collection methodology and estimation for daily, weekly, monthly, and yearly counts from short-term data. The Seamless Travel Project (2010) claims the NBPDP data, "should be applicable to a broad range of communities nationwide". Some reports and studies (New Orleans 2009; Buffalo Valley 2012, FABB 2011, Alta/Land People 2010) have implemented the data collection and data extrapolation methodology. The World Health Organization cites the NBPDP as a resource for adjusting short-term counts to longer term levels of bicycling (WHO 2011). Currently no review has been published that examines the reliability of using the NBPDP extrapolation factors to estimate 24-hour bicycle volumes.

This research will examine a number of items related to bicycle traffic factoring including a review of available data sets that describe bicycle traffic time-of-day travel patterns, exploration of bicycle travel patterns, and the formation and application of time-of-day extrapolation factors. The Central Lane Metropolitan Planning Organization (CLMPO) collects data via mobile automatic pneumatic tube counting devices. This data set includes bicycle traffic counts collected over multiple 24-hour periods across several months and locations which allows for the creation and application of a set of local extrapolation factors asd well as comparison of study area factors with factors derived from other sources.

The outcomes of this research will add to what is currently understood about bicycle traffic factoring in a number of ways. Firstly, a summary and comparison of existing data sources from which daily extrapolation factors could be derived will be presented. These existing data sources include both travel survey information and existing bicycle count data collected at the national, state and local level. This summary and comparison will establish the differences in morning and evening peak factors derived from these different data sets.

The second outcome of this research expands on the current literature regarding classification of bicycle traffic patterns. Bicycle traffic count data collected in the study area suggests that the current set of bicycle traffic patterns classifications should not be limited to commute and recreational (and mixes thereof) typologies as described in **Miranda-Moreno 2013** but should include another category that describes bicycle travel related to university campuses. This 'University" bicycle travel pattern is characterized by less distinguishable peaks in either the morning or evening and instead possesses a relatively stable traffic flow throughout the day. A higher numbers of bicyclists on average during weekdays compared to weekends is another element that characterizes 'University' bicycle travel patterns based on the data collected in the study region. The addition of this typology will be helpful to planners and practitioners looking to understand users on particular facilities but may not be as useful in the formation of time-of-day factor groups.

Lastly, the application of time-of-day extrapolation factors from study area bicycle counts and the NBPDP will be completed in order to give potential users of these factors some indication of their potential error. Using extrapolation factors that expand a short-term count to a full day 24-hour count from data collected in the study region, this work will assess the application of these factors in comparison to factors derived from national data sets gathered through the NBPDP. Currently, no published work has been done to assess the reliability of applying the NBPDP factors in specific areas of the U.S., leaving a gap in the understanding of how well these factors perform when employed. Understanding the accuracy of using these different factors will give planners and practitioners looking to expand short-term counts a better understanding regarding the possible levels of error. **Figure 1.1** summarizes this research's primary goals.

Figure 1.1 – Research Goals

Research Goals

1. Summarize and compare daily expansion factors derived from national, state and local data sources.

2. Use data collected in the study region to establish a "University" bicycle traffic travel pattern.

3. Establish the reliability of commonly used national daily expansion factors compared to locally derived daily expansion factors.

The study area for this work is the CLMPO which encompasses the cities of Eugene, Springfield, and Coburg in the Willamette Valley of Oregon (See **Figure 1.2** below) with a population of roughly 242,000 people. The region supports a strong bicycling culture making it an ideal location for this research. The U.S. Census shows that the Eugene-Springfield urbanized area consistently report a higher than the national average percentage of workers commuting to their jobs by bicycle (see **Figure 1.3).** U.S. Census information also (see Table 1.1) shows that Eugene has one of the highest percentages of bicycling to work mode shares in the country compared to other large bike-friendly communities, with 8.0% of workers commuting to work by bicycle (US Census 2010). The Springfield commute to work by bicycle percentage is 2.5% which is higher than the national average but lower than Eugene and the region as a whole. The CLMPO region supports 12 Safe Routes to School Programs with more schools in the region adding programs each year (McRhodes 2012). There are a number of advisory and advocate groups, including the Greater Eugene Area Riders (GEARS) group and Bike Lane Coalition, as well as Bicycle and Pedestrian Advisory Committees maintained by both Eugene and Springfield.

The region is home to the University of Oregon (UO) with a student population of approximately 25,000. The campus has a strong effect on local bicycle traffic demand (CLMPO 2013) with a recent travel survey of students indicating that 26% use a bicycle as their primary means of transportation to school (UO 2013). The UO supports a number of bicycle friendly programs including the UO Bike Program that offers free space, guidance and tools to fix and maintain student bicycles. The UO has plans to initiate a bike share program very soon as well. Also, like many university towns throughout the country, a great deal of the bicycle traffic for the area is generated by the UO, since the campus has policies that restrict automobile travel to the campus.

Figure 1.2 – Map of Study Area

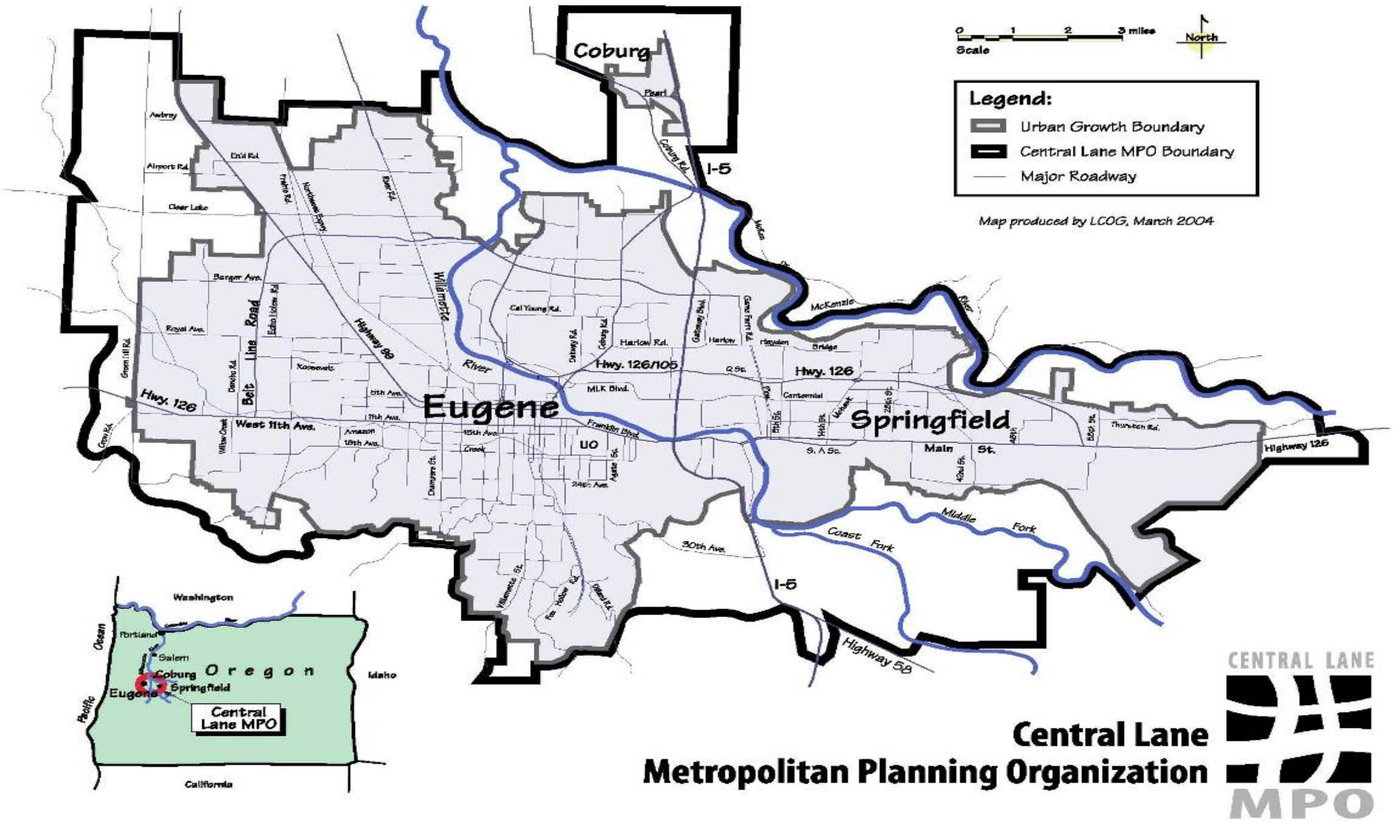


Figure 1.3 - CLMPO Region Commute to Work by Bicycle Mode Share

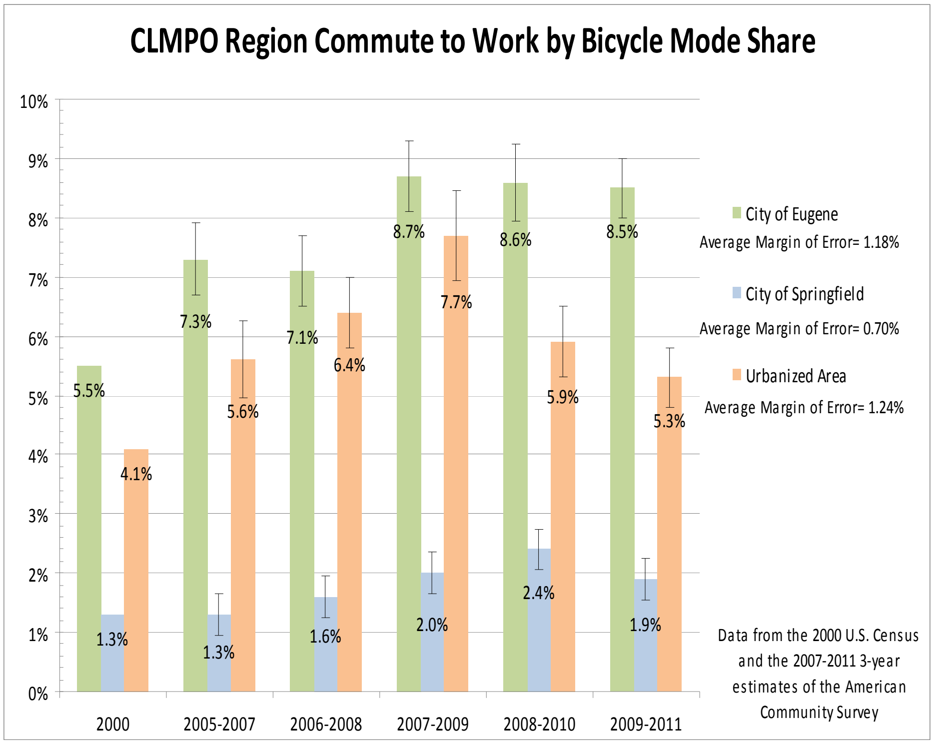


Table 1.1 – U.S. Census Journey to Work by Bicycle Comparison

2010 Census - Journey to Work %			
City	**State**	**Population**	**Percentage of Bicycle Commuters**
Davis	California	65,740	22%
Boulder	Colorado	97,585	10%
Eugene	**Oregon**	**156,299**	**8%**
Berkeley	California	112,824	8%
Cambridge	Massachusetts	105,337	7%
U.S. Average		306,738,433	< 1%

Additionally, the CLMPO region has extensive bicycle infrastructure with more than 120 miles of bike lanes, nearly 8 miles of bicycle boulevards, and a network of over 60 miles of off-street multiuse regional paths. Table 1.2 below details the number of miles of bicycle infrastructure by type and also describes attributes associated with each kind of infrastructure.

Table 1.2 – Bicycle Related Infrastructure Summary

Facility Type	Miles In CLMPO network	Description
Bike Lanes	121	Bike Lanes are marked space along a length of roadway designated for use by bicyclists. Wheelchair users and some motorized scooters are allowed in bike lanes.
Bike Boulevard	7.6	Low-volume and low-speed streets that have been optimized for bicycle travel. Bicycle Boulevard treatments can be applied at several different intensities. The City will determine the exact treatments needed for each corridor during project design, but it is assumed that all Bicycle Boulevards in Eugene will at a minimum have way finding signs, pavement markings, traffic calming (if needed to keep vehicle speeds low), and some type of intersection crossing treatments.
Multi-use Regional Path	63	Multi-use regional paths are paved paths separate from the roadway network that are designed for both walking and bicycling. Where space allows and if sufficient additional maintenance funding can be dedicated, an additional unpaved path may be provided alongside the paved path.
No Facility	-	A roadway that does not have any formal or informal bicycle facilities.

Local planning priorities and policies also continue to support increasing current levels of bicycling. The region's local planning agencies have adopted goals to increase the bicycle mode share beyond its current level and have identified bicycle counts as one of the ways to monitor this progress (City of Eugene 2012, City of Springfield 1998).

The study area is located in the Marin West Coast climate zone with temperatures varying from cool to warm, with dry summers and cool wet winters. Some winter snowfall occurs but is often time irregular and typically does not accumulate in large quantities.

2. Literature Review

The state of the practice for collecting traffic counts and developing factors from those counts for motorized travel is well established but remains in the development stage for bicycle traffic. Bike counts are becoming more common around the U.S. which has facilitated investigation into the development of factors for this mode. An important part of developing traffic expansion factors is definition of factor groups which are associated with the usage patterns at the count site. Some research attempts to use observed bicycle counts and their relationship with surrounding urban form variables to establish a method for using limited count data to estimate demand for larger geographic area. Much of this work is relatively new and so there is less accumulated knowledge on the subject.

An important example of advanced stage of motorized traffic monitoring is the Highway Performance Measuring System (HPMS). The HPMS is a national level highway information system that develops federal guidelines for state and local departments of transportation count collection programs (FHWA 2001). These guidelines are published in the Traffic Monitoring Guide (TGM) published by the Federal Highways Administration (FHWA) and details traffic evaluation protocols including data collection and processing (FHWA 2001). These data collection and processing guidelines inform state and local government transportation agencies on how to estimate total vehicle miles traveled (VMT) for their jurisdictions. The VMT estimates are important in understanding basic details about an area's transportation system and are significant metrics for allocating federal and state transportation funding dollars (MAP-21). A section of this guidance document details the creation and application of expansion factors that expand short-term counts of as little as 12 hours to daily, weekly, monthly, and annual estimates and also describe guidance as to the usage of factors for greater geographic coverage. Types of factors include:

Figure 2.1 – Traffic Factor Types

Factor Types

1. Time-of-day: This factor adjusts a sub-daily count to a total daily count.

2. Day-of-week: This factor adjusts a single daily count to an average weekday count, weekend count, or day of week count.

3. Month/season-of-year: This factor adjusts an average daily count to an average annual count.

Continuous counts (i.e., counts taken over the course of an entire year), which allow for a comprehensive understanding of day of the week, monthly, and other seasonal effects are used to construct the above described expansion factors. These adjustment factors are developed for distinct factor groups, which are groups of continuous counters with similar traffic patterns. The continuous counters in this factor group provide year-round traffic counts and permit short term counts to be annualized in a way to minimize error (TMG (2012). Counting programs are augmented by shorter term data collected systematically across a state and depending on resources, are bolstered by smaller agency data collection efforts at the county and city level.

The TMG tome has a soon to be released (July of 2013) chapter offering guidance on non-motorized traffic data collection and processing. Most of the principles used in motorized traffic counting apply to non-motorized traffic though there are some key differences. One of the major differences is the general state of the practice for non-motorized data collection. Most non-motorized data collection programs are smaller scale and limited in duration, often times just two hours per day. The non-motorized section of the TMG describes the primary differences between motorized and non-motorized count collection programs. An important difference is that non-motorized traffic is typically higher on roadways with fewer automobiles like shared use paths. Most motorized traffic counts are focused on streets with high volumes of automobiles. The last important difference between motorized and non-motorized traffic count programs according to the TMG, is that the technologies for counting bicycles and pedestrians are still emerging and the levels of error associated with these counting devices is not as well known. The forth-coming non-motorized section of the TMG offers guidance about creating factor groups from continuous data whereby patterns of variation are used to create groups of similar count locations that can be used to factor short-duration counts to annual volume estimates. Finally, the chapter on non-motorized traffic counting in the TMG discusses data collection methods and technologies including referencing the National Bicycle and Pedestrian Documentation Project (Jones 2009) discussed in more detail below. More guidance is expected on non-motorized travel factoring through the National Cooperative Highway Research Project 8-78, which will be producing a guide for measuring bicycle and pedestrian use entitled “Estimating Bicycle and Pedestrian Demand for Planning and Project Development” to be completed June 2013 (TR News 2012).

Some progress has been made in the recent past to collect information from around the U.S. on non-motorized traffic. Jones (2009) attempts to establish a consistent national collection methodology and database for bicycle and pedestrian traffic counts. This methodology for count collection has become the current state of the practice and is also referenced in the forth-coming guidelines on non-motorized traffic monitoring (TMG 2012; Hankey et al. 2012). The Federal Highways Administration (FHWA) compiled information on count programs including methodologies and technologies which attempted to understand the state of the practice. A conclusion of this synthesis was that the common practice of extrapolating short-term sample counts has the “potential to produce skewed interpretations of the level of bicycling and or walking occurring in a community”. The report also mentioned that, “the extrapolation of limited count locations to larger geographic areas is a common struggle and no known reliable solution exists” (FHWA 2011). The idea of using nationally derived factors can be questioned by findings in Jones (2009) which demonstrated that non-motorized traffic on trails in Indianapolis differ from patterns of use documented in other regions of the U.S. and concluded that, "unlike vehicle use patterns, there appear to be significant regional differences in seasonal patterns". There has been much less standardization in bicycle traffic factor estimation compared to methods long since developed for motorized traffic. For many years, at both the state and federal level, guidance has been issued for factoring automobile traffic but not for non-motorized transportation.

Even though much more work has been done in developing extrapolation factors for motorized traffic, similar work is beginning to be done for non-motorized traffic. Nordback et al. (2012) quantified the uncertainty when estimating annual average daily bicycle traffic counts from short-term counts. The authors use continuous count data from the equivalent of six permanent counting devices to form two sets of factors (one commute pattern and one non-commute pattern), and then tests the performance through application of those factors to different samples of short-term counts ranging from one hour peak period to four weeks. This research demonstrated that with short term counts of three hours or less, error could range from 25 – 58% absolute percentage difference, but with short term counts of at least a week, error could be minimized to an average of 22% absolute percertage difference. The research also concluded that to form meaningful factors, five to six continuous counters should be used.

Defining meaningful factor groups is an important part of expansion factor development. For motorized traffic factor groups are typically defined by the federal classification of the road way, either a freeway/interstate, major/minor arterial, major or minor collector, or some other lower status facility type. These classifications are related to the total volumes observed on these facilities and make associating the usage patterns clear because of their connection with the observed traffic volumes. Bicycle traffic does not fit as nicely into this framework because of the variation in traffic volumes by facility type from one urban area to another (Barnes and Krizek 2005). Though facility type may not offer a high level definition of the usage patterns for a particular bicycle facility, Miranda-Moreno et al. (2013) offer another method for classifying usage patterns. Using data from five large North American cities including Montreal, Ottawa, Portland, San Francisco, and Vancouver, the authors create factor groups based on observed hourly distributions and total average weekday and weekend volumes. The factor groupings include a Primarily Utilitarian, Mixed-Utilitarian, Mixed-Recreational, and Primarily Recreational. These typologies represent the usage pattern on a continuum from strictly commuter with strong morning and evening and less travel on weekends compared to weekdays, to strictly recreational patterns where no definable morning or evening peaks periods exist but instead have a broad hourly peak from early afternoon to early mid evening hours with more daily travel on weekends compared to weekdays. These patterns are useful in helping to think about how to define factor groups for bicycle count stations, and the work from Miranda-Moreno et al. helps to inform one of the goals of this research which is to define another usage pattern discussed in more detail below.

Other work using bicycle count data include Lindsey et al. (2007) which advance methods using data collected through infrared detectors on urban greenway trails in Indianapolis, Indiana to develop two methods for estimating annual trail traffic. The first method used socio-demographic and urban form information in conjunction with time of year and weather attributes as inputs for a regression model to estimate annual trail traffic. This method provided estimates within 20 – 30% of the observed counts. The second method used a factoring methodology similar to the methodology proposed in this research where an observed sample of traffic is extrapolated to a full day estimate, which is then used to create week, month and annual estimates. This method produced results for monthly estimates ranging in accuracy from -6.2% to -31.6% and -20.2% to -36.4% for annual traffic estimates. (Lindsey et al. 2007).

Similar to one of the methods featured in Lindsey et al. (2007), there are bicycle traffic estimation models that use socio-demographic and urban form information to predict bicycle volumes where count data has been collected. Hankey et al. (2012) developed an estimation model using bicycle counts data collected from 259 locations in Minneapolis, Minnesota using manual data collection methods. Using ordinary least squares and negative binomial regression the authors attempted to estimate 12-hour traffic counts using variables described in past studies as being relevant to bicycle traffic including weather, neighborhood socio-demographics, built environment characteristics, and road or bicycle facility type. The models developed were able to explain up to 47% of the variation using a negative binomial modeling approach. The results from Hankey et al. (2012) were derived by scaling (i.e., factoring or extrapolating) short-term two-hour counts to half-day counts (i.e., 12 hour counts) using a standard time-of-day factoring methodology but the authors do not appear to substantiate the reliability of this factoring. The analysis then uses these estimates of 12-hour traffic to compare to the negative binomial and OLS models to test the accuracy of the 12-hour results. Comparing an estimate from one method to an estimate from another in order to assess the predictive capability of one method may lead to spurious conclusions.

Another associated area of research aims to estimate area wide bicycle demand using bicycle counts. For a study that attempts to create a bicycle and pedestrian demand model in San Diego County, researchers used data from two-hour manual counts from 80 locations in conjunction with land use and employment data in order to estimate weekday morning bicycle traffic. A number of different estimation approaches were tried using independent variables including the number of driveway approaches, number of sidewalks, total length of off-street paths, population density, and employment density within a quarter-mile of the count station. A stepwise method using the total length of off-street paths, and employment density was found to be the most reliable and was used to estimate bicycle travel patterns throughout the city of San Diego. (Caltrans 2010)

Griuswold et al. (2011) predict bicycle intersection volumes by estimating a model using 2-hour counts at 81 locations. Using information about the intersections surrounding land use, transportation system, and site characteristics, the authors employed a log linear regression to estimate intersection bicycle volumes in Alameda County. No attempt was made at forecasting daily volumes of traffic.

Other studies attempt to estimate area wide bicycle demand using data sets that gauge different measures of bicycling such as responses from travel surveys and the U.S. Census commute to work survey. For example, Barnes and Krizek (2005) defined a simple model that uses data from the National Household Travel Survey and U.S. Census to estimate total daily adult bicyclist percentage for different geographic scales. The authors attempted to estimate this measure at the state, metropolitan statistical area (MSA) and disaggregate zone level for Minneapolis where data was available. Barnes and Krizek (2005) suggest that estimating bicycle travel from socio-demographic and land use characteristics is not likely to ever produce satisfactory results. They claim that because adjacent land uses do not necessarily generate demand for the facility, using adjacent land uses to predict demand is not always informative. This reality is related to the fact that not all bicycle travel is utilitarian, so relating an estimate of bicycle demand as a function of employment density or another similar measure, does not always hold theoretically. The authors also claim that when land use information is used to explain bicycle traffic it cannot account for the different levels of traffic in the same city. For instance, in Minneapolis one off-street path may exhibit four times as much traffic as an off-street path across town with similar surrounding land use characteristics. Barnes and Krizek (2005) continue by positing that the low levels of bicycling are causing sampling errors thus affecting estimation parameters for models using socio demographic and land use variables as inputs. And lastly, the authors suggest that, as noted by Car and Dill (2003) causation for bicycling and infrastructure go in the opposite direction, with a large number of bicyclists in an area offering the politically favorable conditions to build bicycle infrastructure. Any of these conditions make using socio-demographic and land use characteristics difficult to interpret in explaining bicycle demand.

While other research related to bicycle demand modeling has been done, there has not been a great deal of work published using bicycle count information as the basis for the factor estimations and a review of the error. No work has been done assessing the application of the NBPDP factors, though Jones' (2009) research has been cited frequently when different cities describe their bicycle count program methodology.

3. Data and Analysis

3.1 – Introduction

The following section describes the data and analysis methodology used to address three primary research questions. The first goal of this research is to use available data sets to construct time-of-day expansion factors for comparison with one another and with those derived from study area bicycle count data. This research has access to travel survey information from the 2009 National Household Travel Survey (NHTS), the Oregon Household Activity Survey (OHAS), bicycle traffic count collected throughout the study region, information on factoring from the National Bicycle and Pedestrian Documentation Project (NBPDP), and bicycle count data collected throughout the study area. The second goal seeks to add to the existing literature related to bicycle traffic patterns by describing a “University” pattern using data collected from the study area. Lastly, using time-of-day factors developed from bicycle count data from the study area and the NBPDP, some validation tests will be conducted to determine levels of error associated with applying these factors. This validation analysis will answer the question for the study area: Are locally derived factors more sensible to use than those from the NBPDP?

3.2 – Comparison of Daily Factors from Available Data Sources

3.2.1 – Travel Survey Data Description

The NHTS data set used in this evaluation was collected in 2009 and is considered "the authoritative source of national data on the travel behavior of the American public." The dataset allows analysis of daily travel by all modes, including characteristics of the people traveling, their household, and their vehicles (NHTS 2009). The OHAS data set comes from a detailed study of 17,000 Oregon households collected between April 2009 and June 2012. Detailed information about travel behavior and socio-demographic information is gathered from each member of the surveyed households through the OHAS. These data will be used to inform travel related research for the entire state.

3.2.2 – Study Area Bicycle Traffic Count Data

The CLMPO Regional Bicycle Count Program began collecting data on bicycle traffic during the summer of 2012 in order to provide better information to local planners, policy makers, and the public about the effect of bicycle related infrastructure investments. Data collection began in July of 2012 with 20 sites surveyed using automatic tube counters capable of collecting 24-hour data for as many days as the device is deployed. Data has now been collected at over 50 different sites across the study region with varying number of days of data collection per site. Data collected in summer of 2012 was typically collected for 6 days or more but was limited to 20 count stations. Data collected in fall of 2012 and winter of 2013 focused on only Tuesday and Thursday due to the goals of the CLMPO RBCP (CLMPO 2012), and consists of 41-46 locations. One goal of the RBCP is to count 48 regionally significant count stations each season, though due to device problems and vandalism not all 48 locations are successfully surveyed each season. Table 3.1 below describes the number of count performed in each season. Data collected in summer consists of multiple days, (between 6-10 days) while data collected in fall and winter adhere to the CLMPO RBCP protocol of collecting data on either a Tuesday and Thursday. Table 3.2 details the total number of 24-hour counts by day of the week. Total rainfall observed during deployment days (days when counting devices were recording bike traffic) and average temperature for deployment days are summarized in Table 3.3. Overall summer was warmer and drier than fall. Winter was colder and wetter than both summer and fall.

Table 3.1 – 24-Hour Counts Collected by Season

Number of Sites Counted Each Season		
Summer 2012	**Fall 2012**	**Winter 2013**
20	46	41

Table 3.2 –24-Hour Counts by Day of Week

24-Hour Counts by Day of Week	
Day of week	**24 Hour counts**
Sunday	52
Monday	37
Tuesday	87
Wednesday	38
Thursday	90
Friday	43
Saturday	52
Total	399

Table 3.3 – Count Station Weather Summary

Weather Information on Deployment Days By Season			
Season	**Summer 2012**	**Fall 2012**	**Winter 2013**
Precipitation (Inches)	0.21	4.01	5.16
Mean Temperature (F)	65	53	42

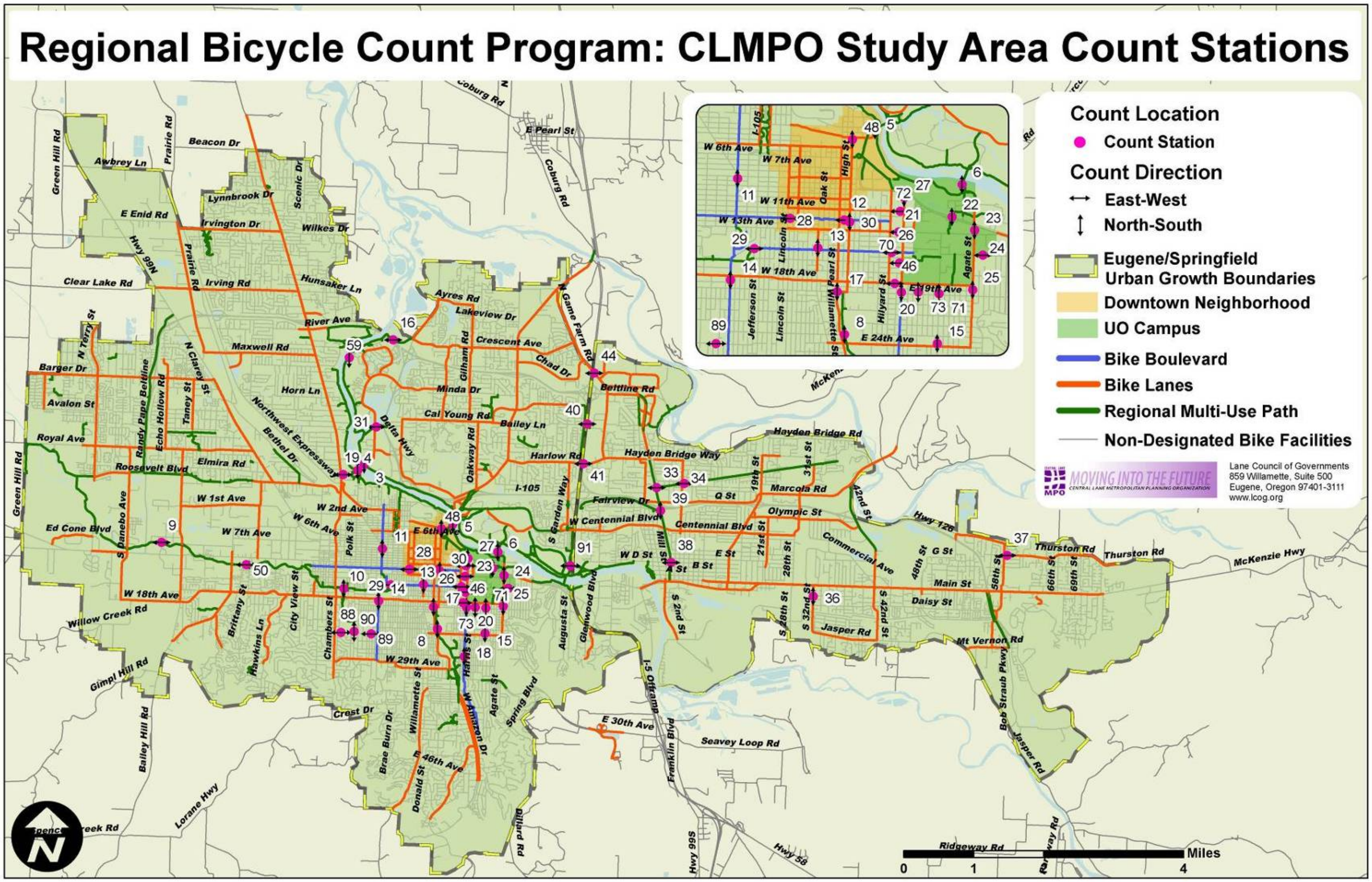
These weather differences combined with fewer students on cmapus in summer result in lower expected average daily traffic values by season represented in Table 3.4 below. For count sites where counts were collected during each season, the differences in total daily counts can be observed. Not unexpectedly, bicycle traffic increases from summer into fall but then drops off again once the rain and cold of winter arrive.

Table 3.4 – Average Tuesday/Thursday Daily Comparison

Count Data Average Weekday (Tuesday-Thursday)			
Count Location	**Summer 2012**	**Fall 2012**	**Winter 2013**
12th West High	365	466	393
15th East Agate	321	1021	814
15th West Alder	462	974	579
Alder South 18th	1215	1862	1085
13th West Alder	1298	2602	1631
18th West Alder	348	646	248
Agate South Franklin	531	576	337
Onyx North Franklin	662	1121	707
DeFazio South River East Bridge	713	566	230
Frohnmayer South River	1142	1691	637

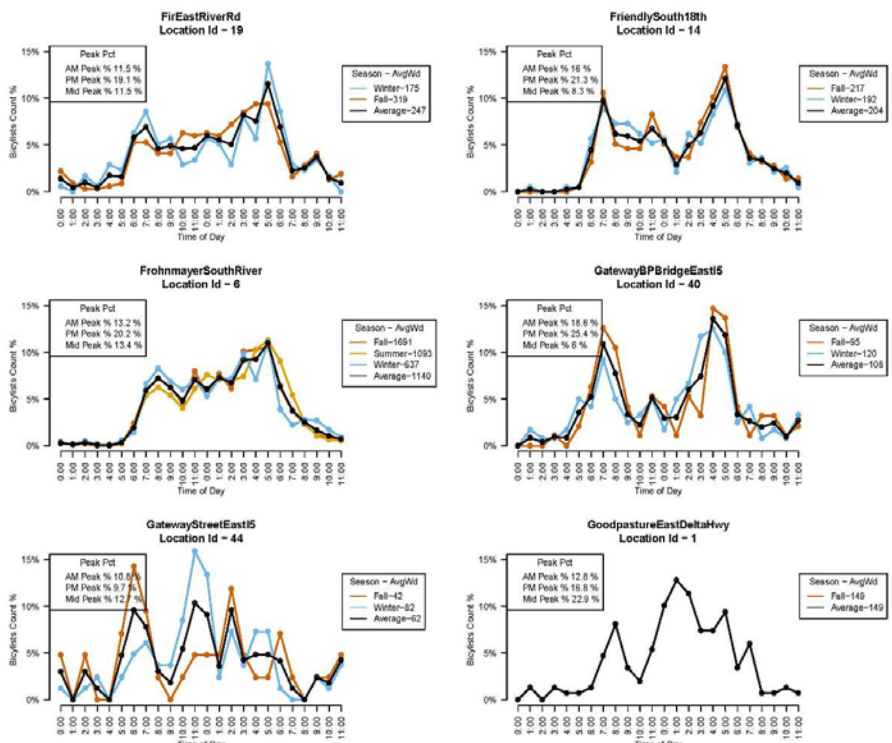
The map in Figure 3.1 describes the count locations throughout the study area over the three different seasons.

Figure 3.1 – Count Station Locations for Study Area



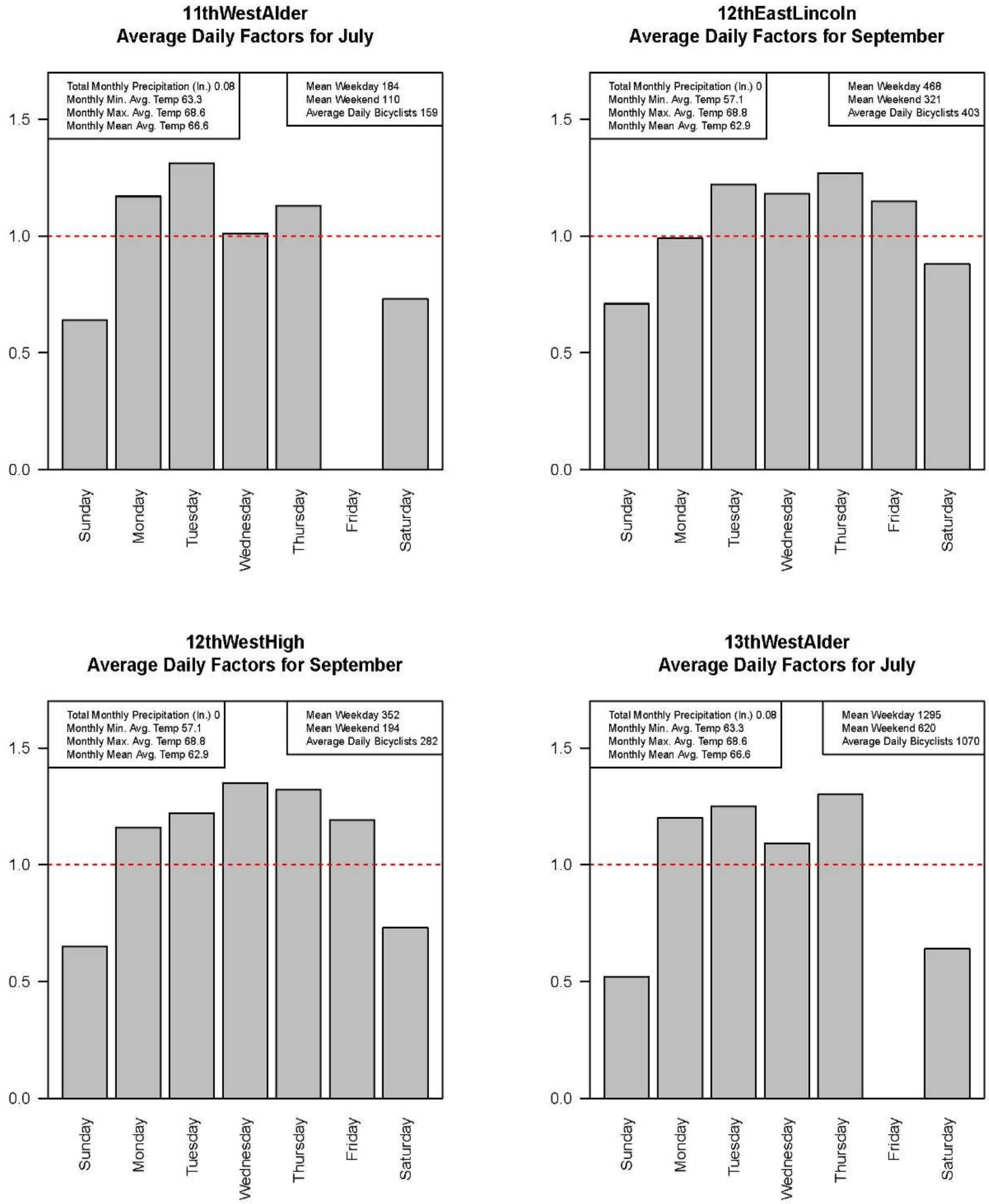
Even though average daily traffic data collected in the study region varies across different seasons, hourly distributions remain relatively stable for most of the locations surveyed. Figure 3.2 below demonstrates the hourly distributions for a subset of count stations where data made comparisons possible, and additional comparisons are available in Appendix A. These plots represent data collected on either a Tuesday or a Thursday and have the total average daily traffic for each season presented in the right hand margin of each plot for context.

Figure 3.2 – Seasonal Comparison of Hourly Distributions



Due to the structure of the data collection program Tuesday and Thursday are the typical days when data is collected. However, for data collected in the summer of 2012, counting devices were deployed for longer periods of up to a week or more. Figure 3.3 provides a summary of these summer data by normalizing each daily traffic summary to the weekly average in order to demonstrate the relative daily traffic by day of the week. This summary also presents the average weekday traffic compared to the average weekend traffic. These pieces of information are informative and allow for some idea of what kinds of users are using the facility. Some days do not have a bar representing the proportion of weekly traffic because no data was collected on that day. Figure 3.3 summarizes four locations' weekday proportions with additional locations weekday proportions presented in Appendix B. Since most locations where multiple days of data were collected are near the University of Oregon, the daily proportions are higher for weekdays compared to weekends. The above data summaries are presented in order to describe the count data collected in the study region. All data including daily and hourly summaries can be found in Appendix C.

Figure 3.3 – Proportion of Weekly Travel by Day of Week



3.3 Creation of Time-of-Day Factors

As described in the Literature Review section, a time-of-day factor adjusts a sub-daily (typically two-hour) count to a total daily count estimate. For example, a common practice for many bike count programs is to count during the morning or evening peak periods, so a time-of-day factor could be employed to extrapolate the counts collected for 2-hours into a total daily estimate. The NHTS and OHAS data sets are both travel surveys with detailed information collected from a sample of Americans about their daily transportation choices, including when they start their trips. In order to construct the factors in the table below, trip arrival time was summarized to the hour in which the trip took place for all trip purposes. There is some geographic resolution to the NHTS since some places could request over sampling in their area in exchange for funding to do so, but the data summarized below represents all households in the data set regardless of location, therefore representing the U.S. average. Factors constructed from OHAS data account for the city in Oregon where surveys were completed and also summarize the state overall. It should be noted that the OHAS data summarized below were done using household weights applied to the trips data where person weights would have been more appropriate. The Oregon Department of Transportation identified issues with the person weights so reformation of these weights is in progress at this time.

The factors constructed from bicycle traffic counts collected in the study region were derived in two ways with each set of results presented in the table. One of the goals of this research is to establish reliable time-of-day factors; therefore two different factor sets have been constructed. The factors in Scenario 1 were created by averaging the AM and PM peak period percentages from data collected in the summer of 2012 by factor groups based on the bicycle facility type in which the counts were collected. Described in more detail in section 3.5.1, factors from Scenario 1 will be applied to independent data collected in the fall of 2012 to determine the levels of error associated with the their application. Also described in more detail below, the factors in Scenario 2 are derived from an iterative process where different factors were tested against all available study area data to determine which factors are best at minimizing error of estimated daily counts. It was found that another factor group should be created to account for differences in bicycle traffic patterns on path facilities. It should also be pointed out that these factors are constructed using data from Tuesday and Thursdays only, therefore minimizing some of the variation that may exist in hourly distributions had all days of the week been used.

Lastly, time-of-day factors derived from the NBPDP data are also presented in the table below. These factors are the factors used in a section 3.5.1 and 3.5.2 of this research and are derived from the NBPDP spreadsheet tool developed to extrapolate short-term counts to longer term estimates. Using the data described above, time-of-day factors have been constructed and are presented below for comparison. These factors are presented in Table 3.5 below.

Table 3.5 – Time-of-Day AM and PM Factor Comparison

Time-of-Day Factor Comparison				
Data set		AM Peak Factor (7-9 AM)	PM Peak Factor (4-6)	Observations in Survey
NHTS		0.11	0.20	9443
OHAS	Oregon	0.20	0.20	3564
	Eugene	0.21	0.19	666
	Springfield	0.06	0.14	42
	Portland	0.21	0.21	1151
	Bend	0.19	0.21	226
Study Area Counts - Scenario 1	Path	0.11	0.21	NA
	Lane	0.13	0.16	NA
	Blvd	0.13	0.18	NA
	No Facility	0.13	0.17	NA
Study Area Counts - Scenario 2	Path - Rec	0.15	0.25	NA
	Path - Commute	0.13	0.21	NA
	Lane	0.15	0.17	NA
	Blvd	0.15	0.19	NA
	No Facility	0.13	0.19	NA
NPBDP Counts		0.10	0.15	NA

As noted above, the NHTS and OHAS factors are derived from trip data for *all* trip purposes. NHTS data looks a bit more reasonable with the AM peak being smaller than the PM peak which is what would be expected based on observations from data collected in the study area. This observation does not apply to some of the OHAS factors however, where each set of factors by city, including the state as a whole, demonstrate nearly identical factors for each peak period. Springfield is the only subset of OHAS data that adheres to the expected result with a higher evening peak relative to the morning peak though the number of observations was minimal for this subset. The use of household weights instead of the more appropriate person level weights may be playing a role in the similarity between AM and PMm peak factors. The study area factors offer a more detailed summary of factors as they have been assigned factor groups based on bicycle facility type (for Scenario 1) and a bicycle facility type and likely user type classification (Scenario 2). When applied in this way, the time-of-day factors base on these factor group specifications yield less error when deployed as time-of-day factors as demonstrated in a later section below. Each set of factors from the study area see larger factors (indicating higher percentage of daily traffic) in the morning compared with the evening which suggests that recreational and other non-work related bicycle travel is occurring. And lastly, the NBPDP factors are consistent with what would be expected with more travel in the PM compared to the AM as reflected in a larger factor for the evening peak as compared to the morning peak.

The NHTS derived factors are similar to some of the factors derived from study area data and the trip information does give some details about trips purpose but without more information about the facility the trip took place on, deriving more detailed factor groups is impossible. The OHAS data does not line up well with factors derived from study area either and would likely be an unreliable source to base time-of-day factors on. Validation of the study area factors will take place in section 3.5.1 and 3.5.2 below.

3.4 – Establishing a "University" Bicycle Traffic Pattern

From a set of continuous count data from several North American cites, Miranda-Moreno (2013) dissect bicycle traffic patterns to create factor groupings based on usage patterns utilizing observed hourly distribution patterns and weekday versus weekend average daily counts. Data collected in the study region suggest consideration of another bicycle traffic pattern related to university travel known as, a "University" travel pattern. Unlike the data used in Miranda-Moreno (2013) which was from multiple continuous counters, data from the study region was collected with temporary tube counters and is therefore limited to at most to 10 days of continuously collected data. Additionally, for a majority of the data, only single day snap shots have been collected, representing either a Tuesday or Thursday. Because of these limitations, definition of a university travel pattern will be limited to exploration only and more data collection will be needed for a firmer classification.

Reviewing the hourly distributions for count stations in the study area, some consistencies are observable that could be useful in classifying certain locations as exhibiting a university travel pattern. The plots in **Figure 3.4** below detail the hourly distributions for a subset of count locations in the study region and display summary statistics that help to establish the university travel pattern. For many of the locations, a generally flat hourly distribution can be observed between the hours of 7 AM and 6 PM. A standard deviation calculation of the hourly percentages between 7 AM and 6

PM is less than .02 for many of the locations near the university. A comparison of this "uniformity" metric (across all count stations where data is available) demonstrates a consistent finding where locations near the university have a uniformity metric of less than 0.02. Table 3.5 details this uniformity metric (StdDev7-6) as well as the AM, PM, and Mid-day (12 PM-2 PM) factors.

Table 3.6 – Summary Statistics of Hourly Distributions

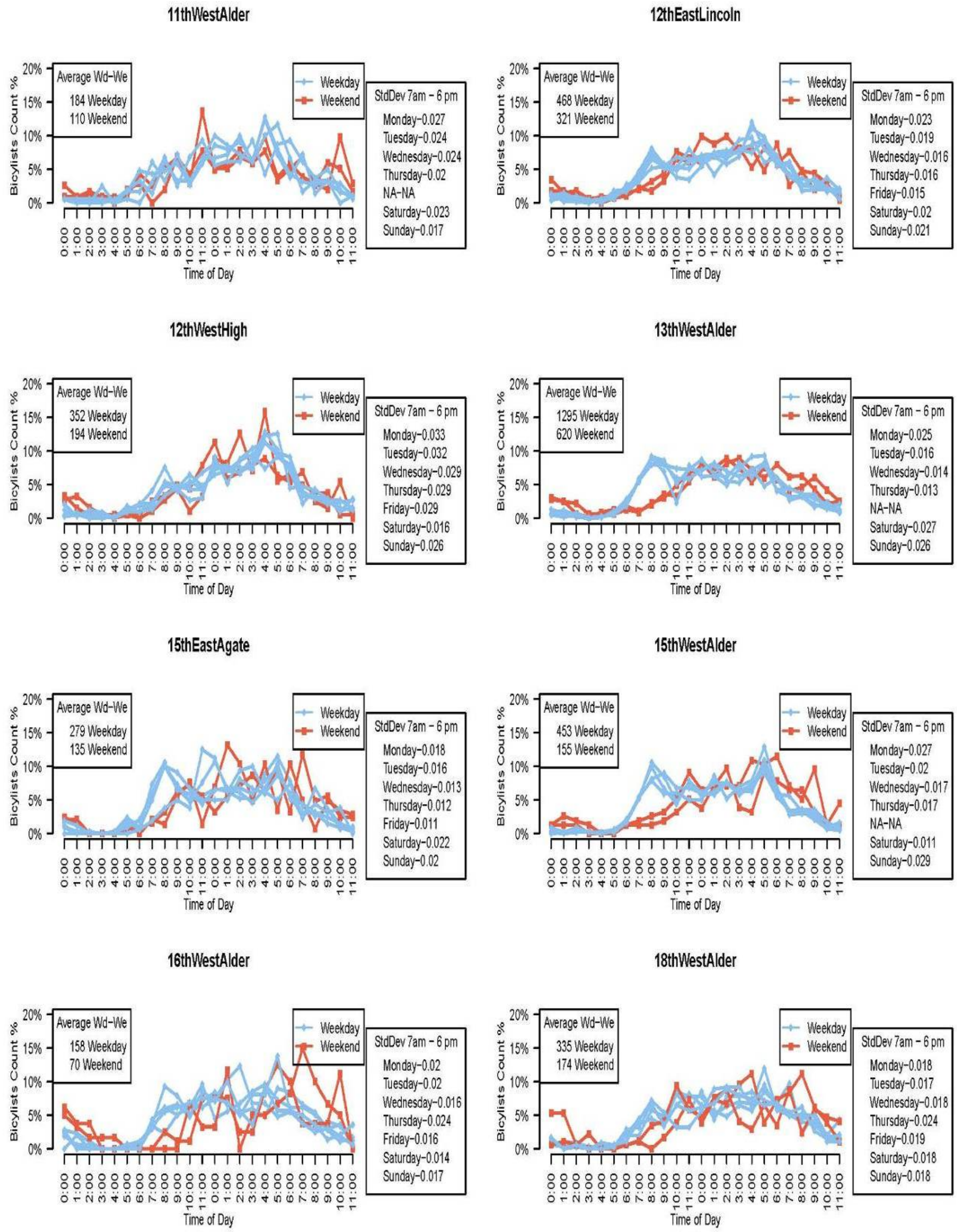
Location	AM Factor	PM Factor	Mid Factor	StdDev7-6 (Uniformity Metric)	Near University
HighSouth4th	0.126	0.15	0.15	**0.012**	FALSE
12thEastLincoln	0.119	0.162	0.162	**0.014**	TRUE
15thEastAgate	0.127	0.146	0.146	**0.014**	TRUE
18thWestAlder	0.107	0.153	0.153	**0.014**	TRUE
13thWestAlder	0.137	0.132	0.132	**0.015**	TRUE
15thWestAlder	0.139	0.174	0.174	**0.016**	TRUE
16thWestAlder	0.11	0.144	0.144	**0.016**	TRUE
12thEastLawrence	0.153	0.158	0.158	**0.017**	TRUE
AgateSouthFranklin	0.148	0.188	0.188	**0.017**	TRUE
AlderSouthFranklin	0.184	0.155	0.155	**0.017**	TRUE
OnyxNorthFranklin	0.153	0.186	0.186	**0.017**	TRUE
PearlSouth19th	0.093	0.176	0.176	**0.017**	TRUE
24thEastFilmore	0.163	0.156	0.156	**0.018**	FALSE
FrohnmayerSouthRiver	0.132	0.202	0.202	**0.018**	TRUE
FirEastRiverRd	0.094	0.188	0.188	**0.019**	FALSE
UniversitySouth18th	0.096	0.19	0.19	**0.019**	TRUE
DefazioSouthRiverEastBridge	0.132	0.201	0.201	0.02	FALSE
HighNorth13th	0.206	0.127	0.127	0.02	TRUE
PolkNorth24th	0.168	0.145	0.145	0.02	FALSE
MonroeSouth8th	0.114	0.194	0.194	0.021	FALSE
WillametteNorth15th	0.059	0.153	0.153	0.021	FALSE
FernRidgeWestChambers	0.137	0.201	0.201	0.022	FALSE
24thWestAdams	0.142	0.172	0.172	0.023	FALSE
UniversitySouth24th	0.128	0.18	0.18	0.023	TRUE

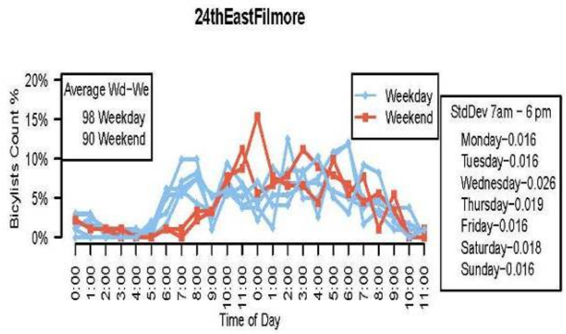
11thWestAlder	0.085	0.207	0.207	0.025	TRUE
12thWestHigh	0.089	0.215	0.215	0.025	TRUE
GWestMohawk	0.126	0.118	0.118	0.025	FALSE
AlderNorth27th	0.17	0.188	0.188	0.026	FALSE
FriendlySouth18th	0.16	0.214	0.214	0.026	FALSE
HarlowEastI5	0.14	0.162	0.162	0.026	FALSE
HeronBridgeSouthFernRidge	0.156	0.204	0.204	0.026	FALSE
15thWestJefferson	0.111	0.228	0.228	0.027	FALSE
32ndSouthOregon	0.144	0.192	0.192	0.027	FALSE
SouthbankSouthGreenwayBr	0.126	0.224	0.224	0.027	FALSE
AmazonPathNorth24th	0.196	0.195	0.195	0.029	FALSE
GatewayStreetEastI5	0.108	0.097	0.097	0.029	FALSE
RichardsonBridge	0.169	0.242	0.242	0.029	FALSE
NorthbankEastKnickerbocker	0.103	0.233	0.233	0.03	FALSE
NorthbankWestDeltaHwy	0.072	0.215	0.215	0.03	FALSE
DEastPioneerPkwyPath	0.128	0.242	0.242	0.031	FALSE
HarrisSouth18th	0.091	0.182	0.182	0.032	FALSE
AgateSouth18th	0.1	0.23	0.23	0.034	TRUE
GoodpastureEastDeltaHwy	0.128	0.168	0.168	0.034	FALSE
UniversityNorth24th	0.105	0.194	0.194	0.035	TRUE
42ndNorthCommercial	0.105	0.186	0.186	0.036	FALSE
FernRidgeEastDanebo	0.177	0.27	0.27	0.036	FALSE
NorthbankSouthOwossoBr	0.105	0.267	0.267	0.037	FALSE
EWEBPathEastPioneerPkwy	0.192	0.256	0.256	0.038	FALSE
NorthbankSouthGreenwayBr	0.102	0.283	0.283	0.038	FALSE
GatewayBPBridgeEastI5	0.186	0.254	0.254	0.039	FALSE
PioneerPkwySouthQ	0.088	0.198	0.198	0.039	FALSE
ThurstonEast58th	0.226	0.14	0.14	0.04	FALSE
DeltaBPBridgeEastGoodPasture	0.126	0.273	0.273	0.041	FALSE
EWEBPathEast5th	0.197	0.184	0.184	0.041	FALSE

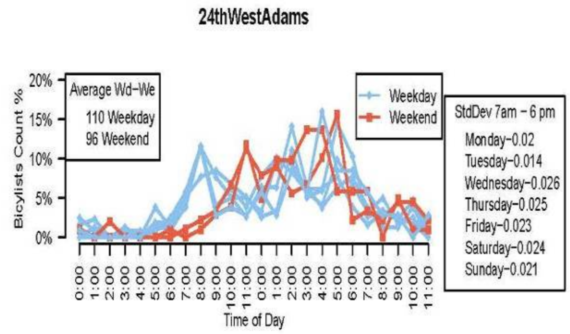
ClearwaterPath	0.2	0.3	0.3	0.075	FALSE

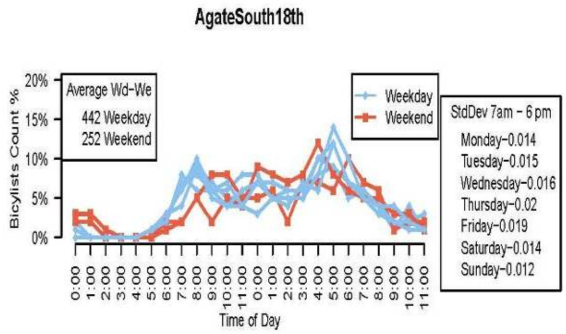
The uniformity metric is good at highlighting locations with relatively flat hourly distributions but does not always point out locations near the university, as three locations with a less than 0.02 uniformity metric are not very close to the university. This might indicate that locations not near the university still experience university related travel, or that the flatness in the hourly distribution is not a good indicator of university related travel. Since 13 of the 15 locations where the uniformity metric indicates a university travel pattern *are* near the university, the former supposition might be more correct.

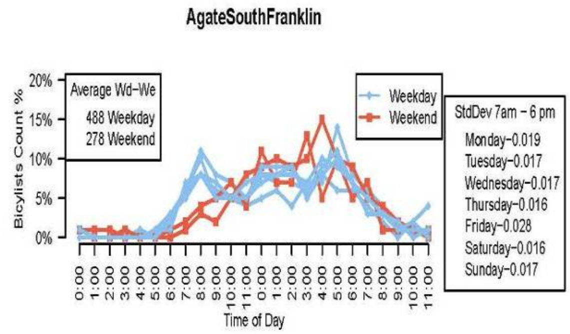
Figure3.4– Hourly Distribution of Study Area Biycle Traffic

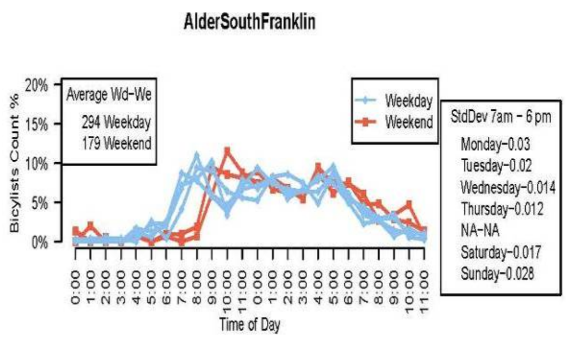


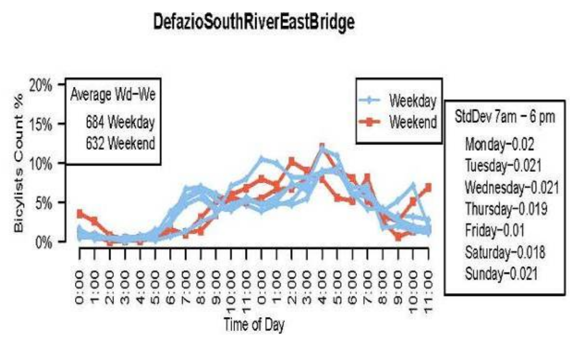

24thEastFilmore
Average Wd-We
98 Weekday
90 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.016
Tuesday-0.016
Wednesday-0.026
Thursday-0.019
Friday-0.016
Saturday-0.018
Sunday-0.016
Bicylists Count %
Time of Day

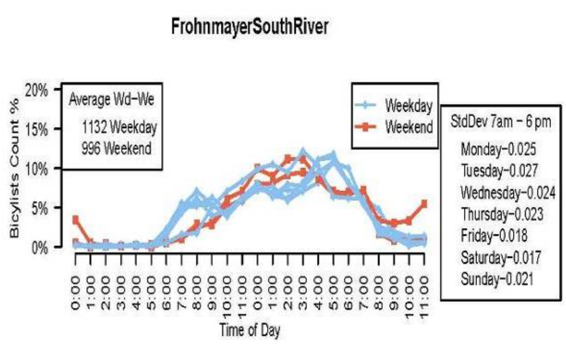

24thWestAdams
Average Wd-We
110 Weekday
96 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.02
Tuesday-0.014
Wednesday-0.026
Thursday-0.025
Friday-0.023
Saturday-0.024
Sunday-0.021
Bicylists Count %
Time of Day

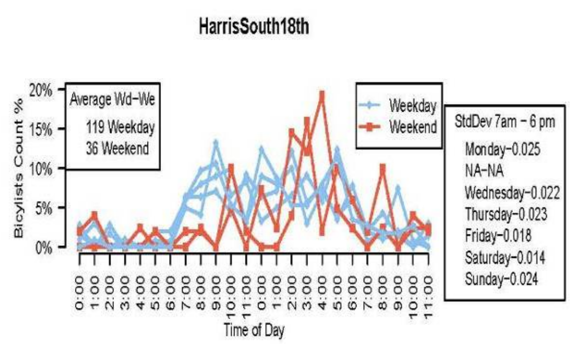

AgateSouth18th
Average Wd-We
442 Weekday
252 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.014
Tuesday-0.015
Wednesday-0.016
Thursday-0.02
Friday-0.019
Saturday-0.014
Sunday-0.012
Bicylists Count %
Time of Day

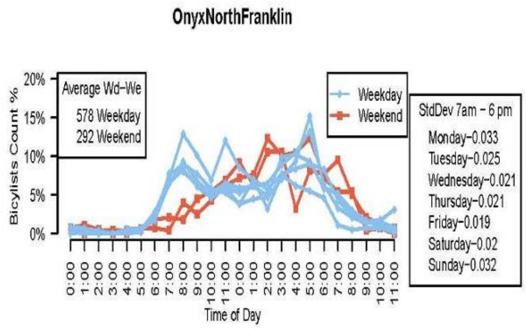

AgateSouthFranklin
Average Wd-We
488 Weekday
278 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.019
Tuesday-0.017
Wednesday-0.017
Thursday-0.016
Friday-0.028
Saturday-0.016
Sunday-0.017
Bicylists Count %
Time of Day

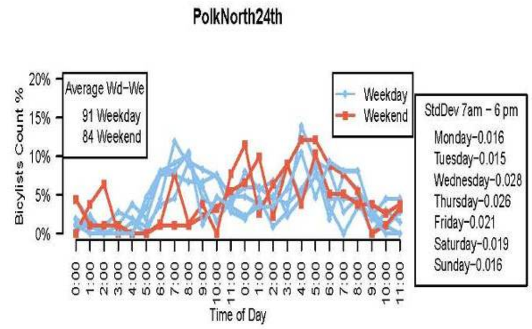

AlderSouthFranklin
Average Wd-We
294 Weekday
179 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.03
Tuesday-0.02
Wednesday-0.014
Thursday-0.012
NA-NA
Saturday-0.017
Sunday-0.028
Bicylists Count %
Time of Day

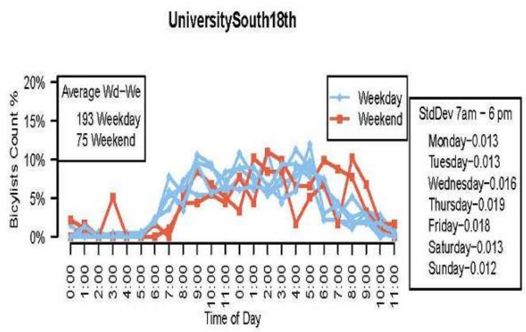

DefazioSouthRiverEastBridge
Average Wd-We
684 Weekday
632 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.02
Tuesday-0.021
Wednesday-0.021
Thursday-0.019
Friday-0.01
Saturday-0.018
Sunday-0.021
Bicylists Count %
Time of Day

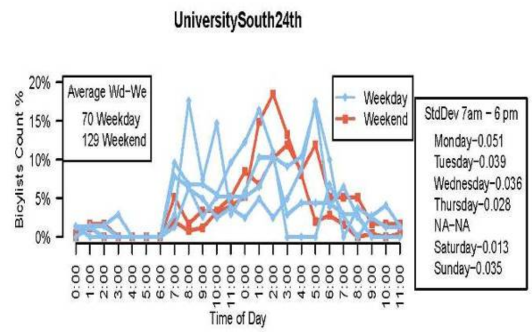

FrohnmayerSouthRiver
Average Wd-We
1132 Weekday
996 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.025
Tuesday-0.027
Wednesday-0.024
Thursday-0.023
Friday-0.018
Saturday-0.017
Sunday-0.021
Bicylists Count %
Time of Day


HarrisSouth18th
Average Wd-We
119 Weekday
36 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.025
NA-NA
Wednesday-0.022
Thursday-0.023
Friday-0.018
Saturday-0.014
Sunday-0.024
Bicylists Count %
Time of Day


OnyxNorthFranklin
Average Wd-We
578 Weekday
292 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.033
Tuesday-0.025
Wednesday-0.021
Thursday-0.021
Friday-0.019
Saturday-0.02
Sunday-0.032
Bicylists Count %
Time of Day

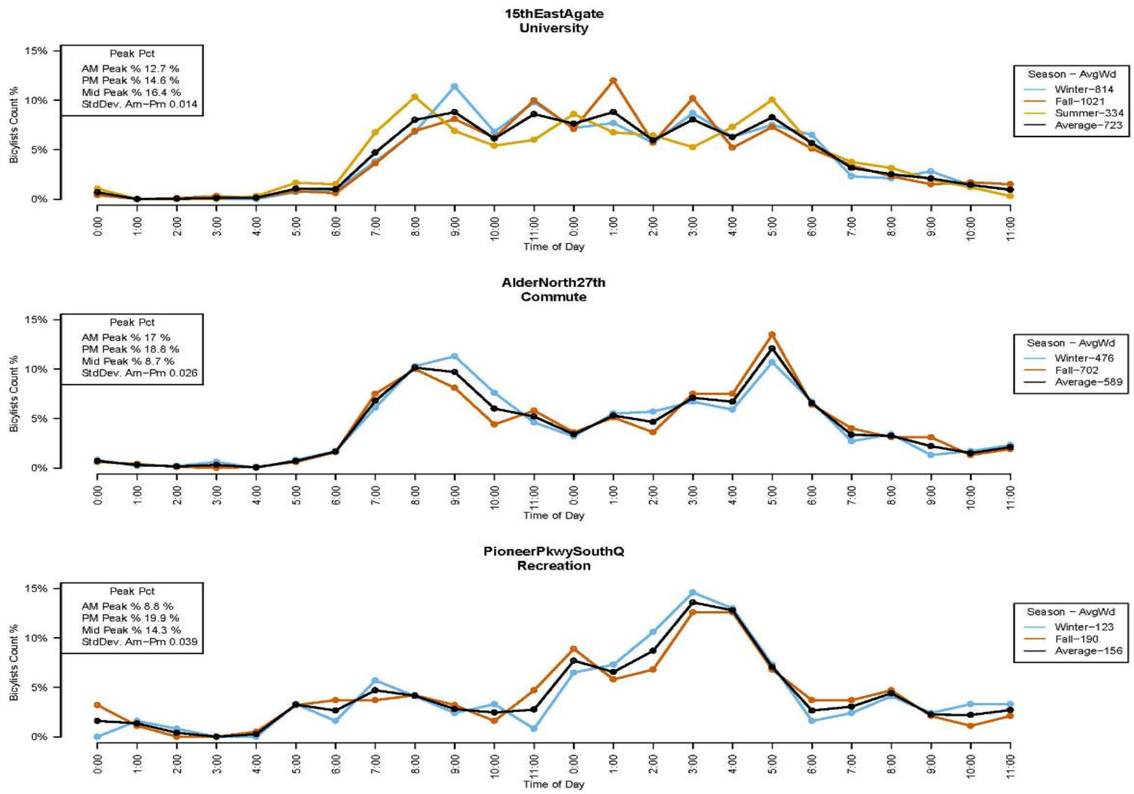

PolkNorth24th
Average Wd-We
91 Weekday
84 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.016
Tuesday-0.015
Wednesday-0.028
Thursday-0.026
Friday-0.021
Saturday-0.019
Sunday-0.016
Bicylists Count %
Time of Day


UniversitySouth18th
Average Wd-We
193 Weekday
75 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.013
Tuesday-0.013
Wednesday-0.016
Thursday-0.019
Friday-0.018
Saturday-0.013
Sunday-0.012
Bicylists Count %
Time of Day


UniversitySouth24th
Average Wd-We
70 Weekday
129 Weekend
Weekday
Weekend
StdDev 7am - 6 pm
Monday-0.051
Tuesday-0.039
Wednesday-0.036
Thursday-0.028
NA-NA
Saturday-0.013
Sunday-0.035
Bicylists Count %
Time of Day

The lack of variation in hourly distributions as measured by the uniformity metric is what would be expected since locations serving primarily university users would probably experience steady traffic throughout the day as university students travel to and from campus as opposed to a standard commute pattern where the hourly distribution exhbits a strong morning and evening peak. To get a clearer idea of the university travel pattern compared to the traffic patterns discussed in Moreno-Miranda (2013), an example of each of the three traffic patterns has been constructed in Figure 3.5 using data gathered in the study area.

Figure 3.5 – Examples of Bicycle Travel Patterns Using Study Area Data



In Figure 3.5, the first plot demonstrates the hourly distribution of a typical university travel pattern while the next two plots display a commute and recreation pattern respectively. The university plot shows how travel remains steady throughout the day while the Commute plot has distinct morning and afternoon peaks. The third plot in Figure 3.5 shows the hourly distribution on a recreational traffic pattern with a distinct and protracted afternoon-evening peak.

Using just the hourly distributions to inform the travel pattern is useful but, Moreno-Miranda (2013) also used the average weekday compared to an average weekend to justify a particular classification. Unfortunately the data set from the study area lacks consistently gathered weekend data so this research cannot use average daily to inform the classification process. Data was collected on weekends at some locations featured in Figure 3.3 (and Appendix B) and would indicate that a university travel pattern has less travel on average, during weekends compared with weekdays. This difference between average weekday and weekend travel would make sense for a university travel pattern since classes are nottypically held on weekends and therefore daily travel overall would be expected to be much lower. Additional data needs to be collected to more firmly establish characteristics of a "University" travel pattern. However, from current data collected from the study region, this research proposes two possible characteristics of a university travel pattern presented in Figure 3.6 below.

Figure 3.6 – Characteristic of University Travel Pattern

1. Generally flat hourly distribution between the morning and evening peak periods

2. Higher levels of traffic observed on weekdays compared to weekends

These characteristics do not result in peak factors that appear to be consistent enough to use as time-of-day extrapolation factors however. Table 3.7 below details the range of AM and PM peak factors for locations exhibiting a university travel pattern and those that do not according to the two characteristics found in Figure 3.7 above. This finding would have implications if a university factor group were to be created and tested as was done using other types of patterns of usage as discussed in the next section.

Table 3.7 – Range of AM and PM Peak Factors for Locations Exhibiting University Travel Patterns

Exhibits University Travel Pattern	AM Range	PM Range
TRUE	9-21%	13-23%
FALSE	6-23%	10-30%

3.5 – Validating the Application of Time-of-Day Factors

Factoring methods aim to improve data coverage in both time and geographic coverage. Factoring methods are also used to extrapolate counts from sites to similar locations, larger geographies or generalize data for modeling purposes. These methods usually use a baseline data set, a sample data set of field data and statistical methods to process data.

The metropolitan planning organization in the study region has been collecting data for over 8 months using automatic pneumatic tube counters capable of observing multiple full day bicycle travel at count stations around the study region. Data collected in the study region will be used to derive two sets (Scenario 1 and Scenario 2) of time-of-day expansion factors based on different factor grouping strategies. These will then be used to estimate 24-hour counts and compared against estimates derived from time-of-day expansion factors taken from the nationally recognized NBPDP bicycle data collection program. The application of each set of factors is a relatively simple calculation with descriptions of the computation below. All of the calculations are performed in the R open source statistical language which allows for quick and repeatable analysis. All R code is available as an appendix (Appendix D).

As discussed in the literature review, federal and state transportation agencies have developed guidance for motorized traffic extrapolation factoring but have yet to do so for non-motorized traffic such as bicycles. Short-term counts are many times the only data collected for bicycle traffic (FHWA 2005; FHWA 2011) and factoring allows for approximating more meaningful estimates (e.g. daily, weekly, monthly, and yearly volumes). This process occurs by first developing factors from multiple long-term counts of typically 24-hours or more. To calculate factors from long term counts, simply calculate the average percentage of traffic observed for each hour or factor period.

To extrapolate a short duration count of two-hours taken during either the morning or evening peaks, the product of the short-term count and the factor will approximate the 24-hour total. A simple equation in Figure 3.7 shows the factoring calculation where $Sample_j$ represents the short term count (2-hour count) and the PeakPct represents the assumed percentage of total daily volumes ($DailyTraffic_i$).

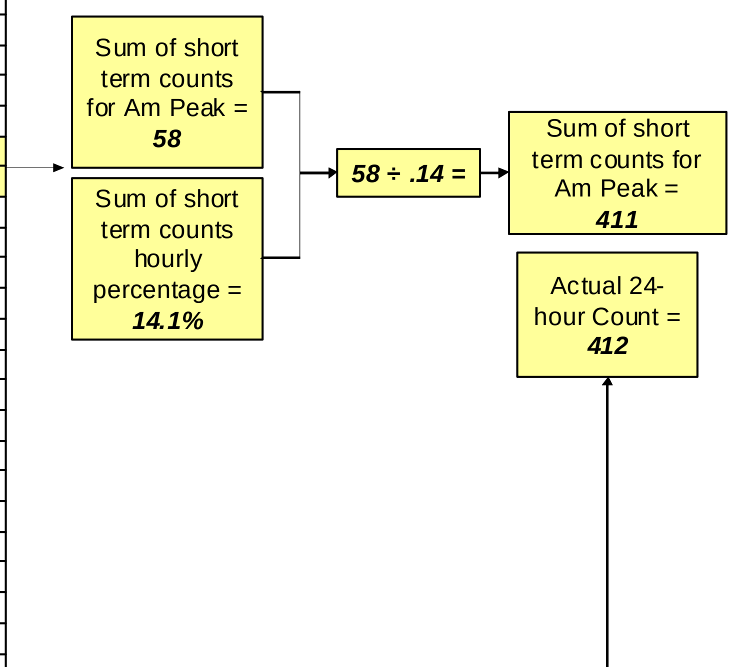
Figure 3.7 - Time-of-Day Factoring

$$DailyTraffic_i = \left(\sum Sample_j \right) \div PeakPct$$

Figure 3.8 uses example data from a single hourly distribution table to derive a short-term count (58 for the AM peak) and the factor (0.141) which when combined in the equation equal 411, which is nearly the observed 24-hour traffic count (minor discrepancy due to rounding). In order for this method to be reliable the peak period traffic proportion in the data where factors are constructed needs to be relatively close to the data in which the short-term count is being done. Reliability is accomplished by the creation of factor groups where count stations are classified by their traffic behavior as described in the section 3.3 above.

Figure 3.8 – Example of Application of Time-of-Day Factor

Time of Day	Total Counts	Percentage of Daily
0	0	0.0%
100	2	0.5%
200	0	0.0%
300	1	0.2%
400	1	0.2%
500	6	1.5%
600	14	3.4%
700	34	8.3%
800	24	5.8%
900	22	5.3%
1000	18	4.4%
1100	16	3.9%
1200	29	7.0%
1300	28	6.8%
1400	33	8.0%
1500	25	6.1%
1600	47	11.4%
1700	54	13.1%
1800	26	6.3%
1900	13	3.2%
2000	8	1.9%
2100	3	0.7%
2200	5	1.2%
2300	3	0.7%
Total	412	100%



3.5.1 – Time-of-Day Factors from Study Area Data – Scenario 1

Data collected from 20 locations within the study area during the summer of 2012 were used to create four groups of time-of-day peak period factors. Factor groups were created by separating the data by bicycle facility type (Multi-use Regional Path, Bike Lane, or Bike Boulevard) or where no bicycle facility existed at all (No Facility). These time-of-day factors are summarized in Table 3.8 below and are the same factors presented in Table 3.5 above for Scenario 1.

Table 3.8 – Scenario 1 Time-of-Day Extrapolation Factors

Time-of-Day Factor Comparison			
Data set		AM Peak Factor (7-9 AM)	PM Peak Factor (4-6)
Study Area Counts - Scenario 1	**Average**	0.13	0.18
	Path	0.11	0.21
	Lane	0.13	0.16
	Blvd	0.13	0.18
	No Facility	0.13	0.17

In order to test the reliability of these time-of-day factors they will be applied to independent data collected in a separate season from the study region**. Figures 3.9 and 3.10** describe the spatial location of each set of data**. Tables 3.9 and 3.10** describe the total daily volumes for Tuesday and Thursday data collected at the factor creation and application sites.

Table 3.9– Scenario 1 Factor Creation Location Daily Volumes

Location	Thursday	Tuesday	Location Id
DefazioSouthRiverEastBridge	650	685	5
11thWestAlder	180	209	72
12thEastLincoln	513	492	28
12thWestHigh	372	344	12
13thWestAlder	1392	1335	21
15thEastAgate	340	327	24
15thWestAlder	469	477	26
16thWestAlder	167	140	70
18thWestAlder	352	349	46
24thEastFilmore	93	101	88
24thWestAdams	117	129	89
AgateSouth18th	545	559	25
AgateSouthFranklin	572	530	23
AlderSouth18th	1227	1130	20
AlderSouthFranklin	345	299	27
FrohnmayerSouthRiver	1094	1084	6
HarrisSouth18th	121	NA	73
OnyxNorthFranklin	702	658	22
PolkNorth24th	105	88	90
UniversitySouth18th	203	213	71

Table 3.10– Scenario 1 Factor Application Location Daily Volumes

Location	Thursday	Tuesday	Location Id
15thWestJefferson	NA	798	29
32ndSouthOregon	878	NA	36
AlderNorth27th	702	NA	18
AmazonPathNorth24th	1023	NA	8
DEastPioneerPkwyPath	75	NA	38
DefazioSouthRiverEastBridge	566	NA	5
DeltaBPBridgeEastGoodPasture	207	NA	31
EastbankSouthOwossoBr	488	NA	59
EWEBPathEast5th	NA	76	34
EWEBPathEastPioneerPkwy	NA	47	33
FernRidgeEastDanebo	NA	178	9
FirEastRiverRd	319	NA	19
FriendlySouth18th	NA	217	14
GatewayBPBridgeEastI5	95	NA	40
GatewayStreetEastI5	42	NA	44
GoodpastureEastDeltaHwy	149	NA	1
GWestMohawk	NA	112	35
HarlowEastI5	55	NA	41
HeronBridgeSouthFernRidge	NA	372	10
HighNorth13th	NA	299	30
HighSouth4th	718	NA	48
MonroeSouth8th	478	NA	11
NorthbankEastKnickerbocker	596	NA	97
NorthbankSouthGreenwayBr	NA	509	3
NorthbankWestDeltaHwy	338	NA	16
PearlSouth19th	119	NA	17
PioneerPkwySouthQ	NA	190	39
RichardsonBridge	NA	427	50
SouthbankSouthGreenwayBr	NA	1098	4
ThurstonEast58th	44	NA	37
UniversityNorth24th	220	NA	15
WillametteNorth15th	NA	330	13

Figure 3.9 – Scenario 1 Time-of-Day Factor Creation Locations (20 locations)

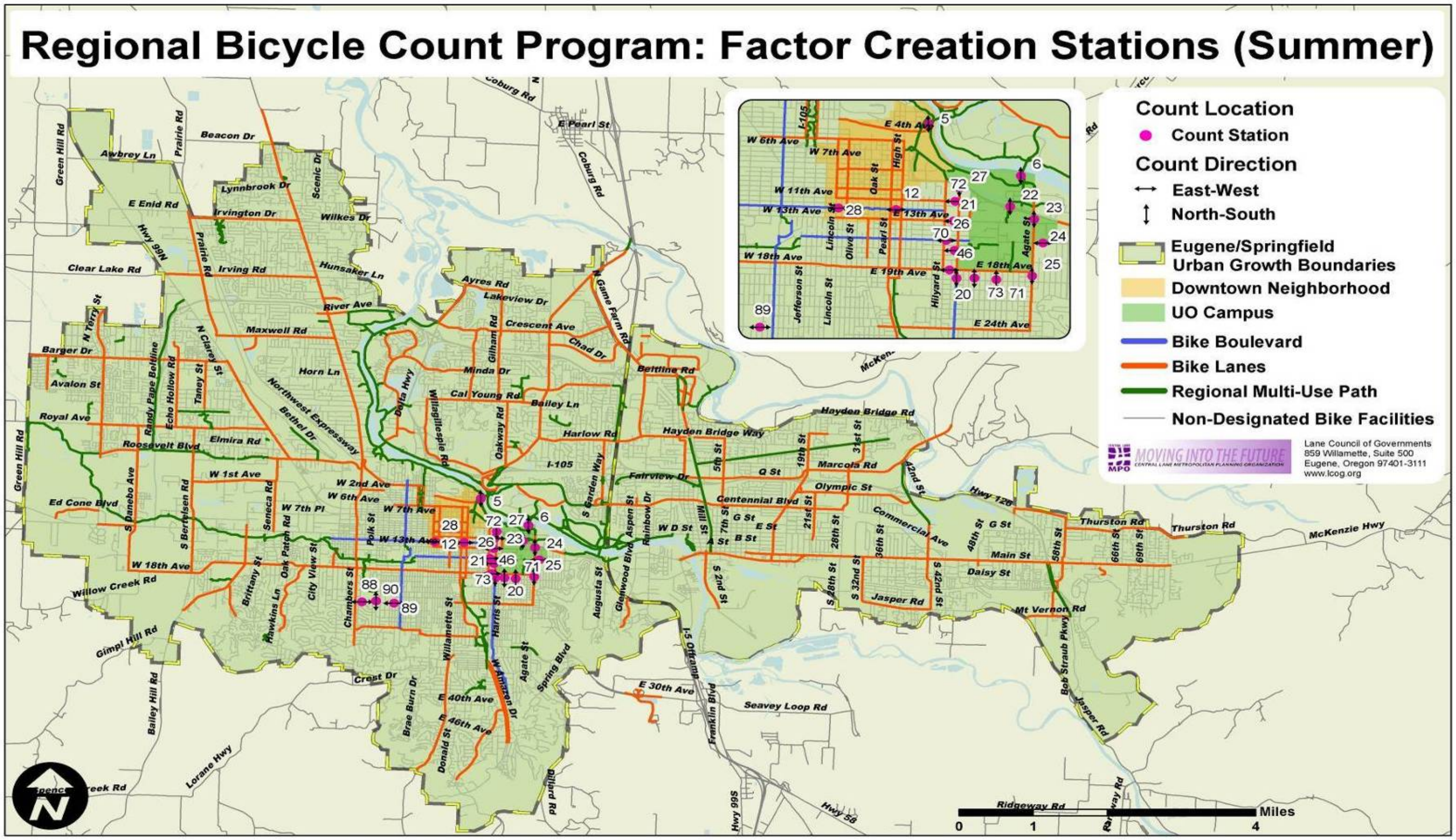
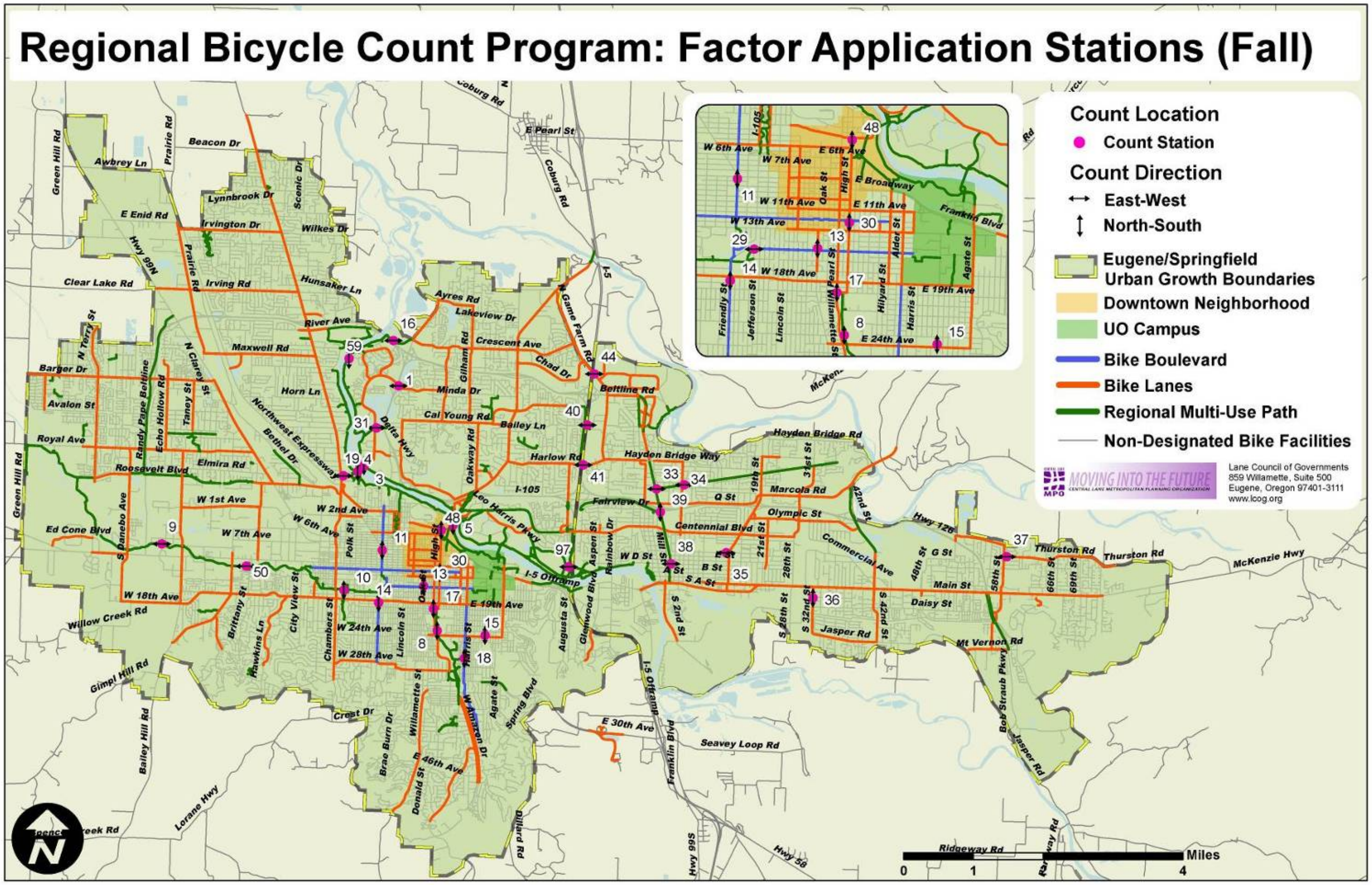


Figure 3.10 – Scenario 1 Time-of-Day Factor Application Locations (32 locations)



Factors from study area data were put into factor groups based on the bicycle facility type(or lack of bike facility) in order to increase the reliability of the estimation process and provide for sensible groupings of factors. Since the data used to create the factors are independent(i.e. different locations) of the data in which the factors are applied this validation will test how well these factor groupings work when appllied simulate how some agencies might actually create and apply time-of-day factors. It is important to point out again that all data are representing travel on either a Tuesday or a Thursday since the structure of the study area's bike count program collects information only on these days.

The factors used from the National Bicycle and Pedestrian Documentation Project (NBPDP) are not broken into detailed factor groups. These factors have been taken from the NBPDP methodology and spreadsheet tool used to estimate daily traffic from short-term counts and the NBPDP methodology only provides two facility types, pedestrian district and off-street path. For the purposes of reasonable comparison with factors derived from study area data, the off-street path factors will be used since that facility type most closely resembles the types of facilities where the study area data were collected. Time of year is considered as well, as the NBPDP factors are broken into two groups, one for April to September and the other for October to March. The application of factors in Scenario 1 will apply time-of-day factors to data collected during the fall, during the months of October and November, so the latter time period will be used for the NPBPD factors since it adheres to a similar time period when study area data was collected.

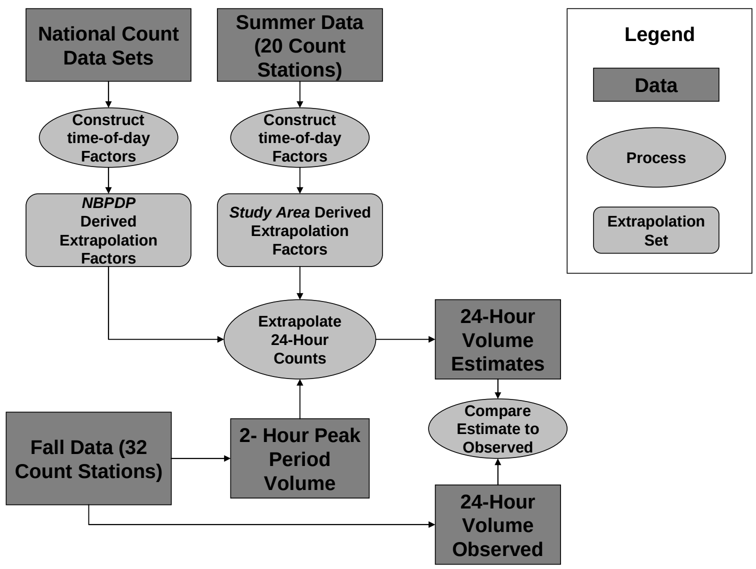
The estimation process using NBPDP factors is similar to the method using study area derived factors described above but uses different time-of-day factors and also has a final step to account for travel not observed in the hourly percentages. According to the NBPDP documentation, the factoring calculation only accounts for the hours between 6:00 AM and 10:00 PM, the time period in which 95% of all bicycle travel occurs. An additional step then accounts for the remaining 5% by using a 1.05 multiplier at the end of the calculation. The equation for the NBPDP calculation is described in Figure 3.11 below, where $Sample_j$ is the sample taken at location i and PeakPct is the average peak percentage assumed by the NBPDP.

Figure 3.11 – NBPDP Time-of-Day Factoring

$$DailyTraffic_i = \left(\sum Sample_j \right) \div PeakPct) \times 1.05$$

The premise of testing the time-of-day factors comes from the current state of the practice for bicycle counts summarized in two Federal Highways Administration reports (FHWA 2007; FHWA 2011) discussed above, that found most count programs consisting of manual 2-hour bicycle traffic counts. This research simulates a possible scenario where 24-hour data is collected for a number of locations where time-of-day factors are derived and then applied to simulated two-hour sample counts. These two-hour sample counts are "simulated" because in reality 24-hours of counts exist, which allows for comparison with the estimated 24-hour count to verify the estimation results. The process of applying the study area factors and NBPDP factors is summarized below in Figure 3.12.

Figure 3.12 – Summary of Application of Time-of-Day Factors for Scenario 1



Using data collected from 20 count sites in the summer of 2012, time-of-day factors have been constructed and applied to sample peak period (both morning and evening) two-hour volumes pulled from observed 24-hour counts done in fall of 2012 collected from independent count stations. The same application process was completed using factors derived from the NBPDP. The results from each application of factors are presented in the tables and figures below.

Tables 3.11 and 3.12 detail the observed and estimated results using study area derived time-of-day factors using morning and evening factors and 2-hour samples. The results table also includes the percent difference and the absolute percent difference. Figure 3.13 describe how these measures of error have been calculated.

Figure 3.13 – Calculation of Measure of Error

Error as % Difference = (DBT_e – DBT) / DBT Error as Absolute % Difference = |(DBT_e – DBT| / DBT where DBT_e = estimated Daily Bicycle Traffic DBT = actual Daily Bicycle Traffic

Results from the application of the NBPDP factors are then presented in Tables 3.13 and 3.14 with the same measures of error included.

Table 3.11 – AMPeak Factor Results using Study Area Factors

Study Area - AM Factor							
Location	**Observed**	**Estimate**	**% Difference**	**Absolute % Difference**	**Factor Group**	**Federal Functional Class**	**Location Id**
GoodpastureEastDeltaHwy	149	148	99%	1%	Lane	Major Collector	1
UniversityNorth24th	220	215	98%	2%	NoFacility	Local	15
DefazioSouthRiverEastBridge	566	591	104%	4%	Path	Path	5
GWestMohawk	112	108	96%	4%	NoFacility	Major Collector	35
HighSouth4th	718	762	106%	6%	NoFacility	Major Collector	48
NorthbankEastKnickerbocker	596	555	93%	7%	Path	Path	97
GatewayStreetEastI5	42	39	93%	7%	Lane	Minor Arterial	44
SouthbankSouthGreenwayBr	1098	1009	92%	8%	Path	Path	4
DEastPioneerPkwyPath	75	69	92%	8%	NoFacility	Local	38
15thWestJefferson	798	867	109%	9%	Blvd	Local	29
DeltaBPBridgeEastGoodPasture	207	227	110%	10%	Path	Path	31
HarlowEastI5	55	62	113%	13%	Lane	Minor Arterial	41
NorthbankSouthGreenwayBr	509	418	82%	18%	Path	Path	3
MonroeSouth8th	478	375	78%	22%	Blvd	Major Collector	11
FriendlySouth18th	217	266	123%	23%	Blvd	Major Collector	14
PioneerPkwySouthQ	190	136	72%	28%	Path	Path	39
PearlSouth19th	119	86	72%	28%	Lane	Major Collector	17
FirEastRiverRd	319	231	72%	28%	NoFacility	Local	19
EastbankSouthOwossoBr	488	336	69%	31%	Path	Path	2
FernRidgeEastDanebo	178	236	133%	33%	Path	Path	9
RichardsonBridge	427	582	136%	36%	Path	Path	32

AlderNorth27th	702	961	137%	37%	Blvd	Local	18
WillametteNorth15th	330	203	62%	38%	Lane	Minor Arterial	13
HeronBridgeSouthFernRidge	372	518	139%	39%	Path	Path	10
NorthbankWestDeltaHwy	338	191	57%	43%	Path	Path	16
32ndSouthOregon	878	445	51%	49%	Lane	Minor Arterial	36
AmazonPathNorth24th	1023	1782	174%	74%	Path	Path	8
EWEBPathEastPioneerPkwy	47	82	174%	74%	Path	Path	33
HighNorth13th	299	523	175%	75%	Lane	Minor Arterial	30
EWEBPathEast5th	76	136	179%	79%	Path	Path	34
GatewayBPBridgeEastI5	95	200	211%	111%	Path	Path	40
ThurstonEast58th	44	117	266%	166%	Lane	Minor Arterial	37

Table 3.12 – PM Peak Factor Results using Study Area Factors

Study Area - PM Factor							
Location	Observed	Estimate	% Difference	Absolute % Difference	Factor Group	Federal Functional Class	Location Id
MonroeSouth8th	478	484	101%	1%	Blvd	Major Collector	11
HighSouth4th	718	713	99%	1%	NoFacility	Major Collector	48
AmazonPathNorth24th	1023	1043	102%	2%	Path	Path	8
GoodpastureEastDeltaHwy	149	154	103%	3%	Lane	<NA>	1
WillametteNorth15th	330	321	97%	3%	Lane	Minor Arterial	13
DefazioSouthRiverEastBridge	566	595	105%	5%	Path	Path	5
PioneerPkwySouthQ	190	176	93%	7%	Path	Path	39
HighNorth13th	299	278	93%	7%	Lane	Minor Arterial	30
HeronBridgeSouthFernRidge	372	405	109%	9%	Path	Path	10
PearlSouth19th	119	130	109%	9%	Lane	Major Collector	17
NorthbankEastKnickerbocker	596	662	111%	11%	Path	Path	97
NorthbankWestDeltaHwy	338	376	111%	11%	Path	Path	16
HarlowEastI5	55	49	89%	11%	Lane	Minor Arterial	41
EWEBPathEast5th	76	67	88%	12%	Path	Path	34
FirEastRiverRd	319	356	112%	12%	NoFacility	Local	19
RichardsonBridge	427	481	113%	13%	Path	Path	32
FernRidgeEastDanebo	178	205	115%	15%	Path	Path	9
GWestMohawk	112	95	85%	15%	NoFacility	Major Collector	35
AlderNorth27th	702	813	116%	16%	Blvd	Local	18
EWEBPathEastPioneerPkwy	47	57	121%	21%	Path	Path	33
SouthbankSouthGreenwayBr	1098	1348	123%	23%	Path	Path	4
UniversityNorth24th	220	273	124%	24%	NoFacility	Local	15

15thWestJefferson	798	1022	128%	28%	Blvd	Local	29
FriendlySouth18th	217	280	129%	29%	Blvd	Major Collector	14
ThurstonEast58th	44	31	70%	30%	Lane	Minor Arterial	37
GatewayBPBridgeEastI5	95	129	136%	36%	Path	Path	40
EastbankSouthOwossoBr	488	676	139%	39%	Path	Path	2
NorthbankSouthGreenwayBr	509	729	143%	43%	Path	Path	3
DEastPioneerPkwyPath	75	113	151%	51%	NoFacility	Local	38
32ndSouthOregon	878	1333	152%	52%	Lane	Minor Arterial	36
DeltaBPBridgeEastGoodPasture	207	329	159%	59%	Path	Path	31
GatewayStreetEastI5	42	12	0.29	71%	Lane	Minor Arterial	44

Table 3.13 – AM Peak Factor Results using NBPDP Factors

Location	Observed	Estimate	% Difference	Absolute % Difference	Factor Group	Federal Functional Class	Location Id
	NBPDP - AM Factor						
FirEastRiverRd	319	315	99%	1%	NoFacility	Local	19
PearlSouth19th	119	116	97%	3%	Lane	Major Collector	17
NorthbankSouthGreenwayBr	509	483	95%	5%	Path	Path	3
MonroeSouth8th	478	504	105%	5%	Blvd	Major Collector	11
SouthbankSouthGreenwayBr	1098	1166	106%	6%	Path	Path	4
NorthbankEastKnickerbocker	596	640	107%	7%	Path	Path	97
PioneerPkwySouthQ	190	158	83%	17%	Path	Path	39
WillametteNorth15th	330	273	83%	17%	Lane	Minor Arterial	13
DefazioSouthRiverEastBridge	566	682	120%	20%	Path	Path	5
EastbankSouthOwossoBr	488	388	80%	20%	Path	Path	2
GatewayStreetEastI5	42	52	124%	24%	Lane	Minor Arterial	44
DEastPioneerPkwyPath	75	94	125%	25%	NoFacility	Local	38
DeltaBPBridgeEastGoodPasture	207	262	127%	27%	Path	Path	31
GWestMohawk	112	147	131%	31%	NoFacility	Major Collector	35
32ndSouthOregon	878	598	68%	32%	Lane	Minor Arterial	36
GoodpastureEastDeltaHwy	149	200	134%	34%	Lane	<NA>	1
UniversityNorth24th	220	294	134%	34%	NoFacility	Local	15
NorthbankWestDeltaHwy	338	220	65%	35%	Path	Path	16
HighSouth4th	718	1040	145%	45%	NoFacility	Major Collector	48
15thWestJefferson	798	1166	146%	46%	Blvd	Local	29
FernRidgeEastDanebo	178	273	153%	53%	Path	Path	9
HarlowEastI5	55	84	153%	53%	Lane	Minor Arterial	41

RichardsonBridge	427	672	157%	57%	Path	Path	32
HeronBridgeSouthFernRidge	372	598	161%	61%	Path	Path	10
FriendlySouth18th	217	357	165%	65%	Blvd	Major Collector	14
AlderNorth27th	702	1292	184%	84%	Blvd	Local	18
EWEBPathEastPioneerPkwy	47	94	200%	100%	Path	Path	33
AmazonPathNorth24th	1023	2058	201%	101%	Path	Path	8
EWEBPathEast5th	76	158	208%	108%	Path	Path	34
HighNorth13th	299	704	235%	135%	Lane	Minor Arterial	30
GatewayBPBridgeEastI5	95	231	243%	143%	Path	Path	40
ThurstonEast58th	44	158	3.59	259%	Lane	Minor Arterial	37

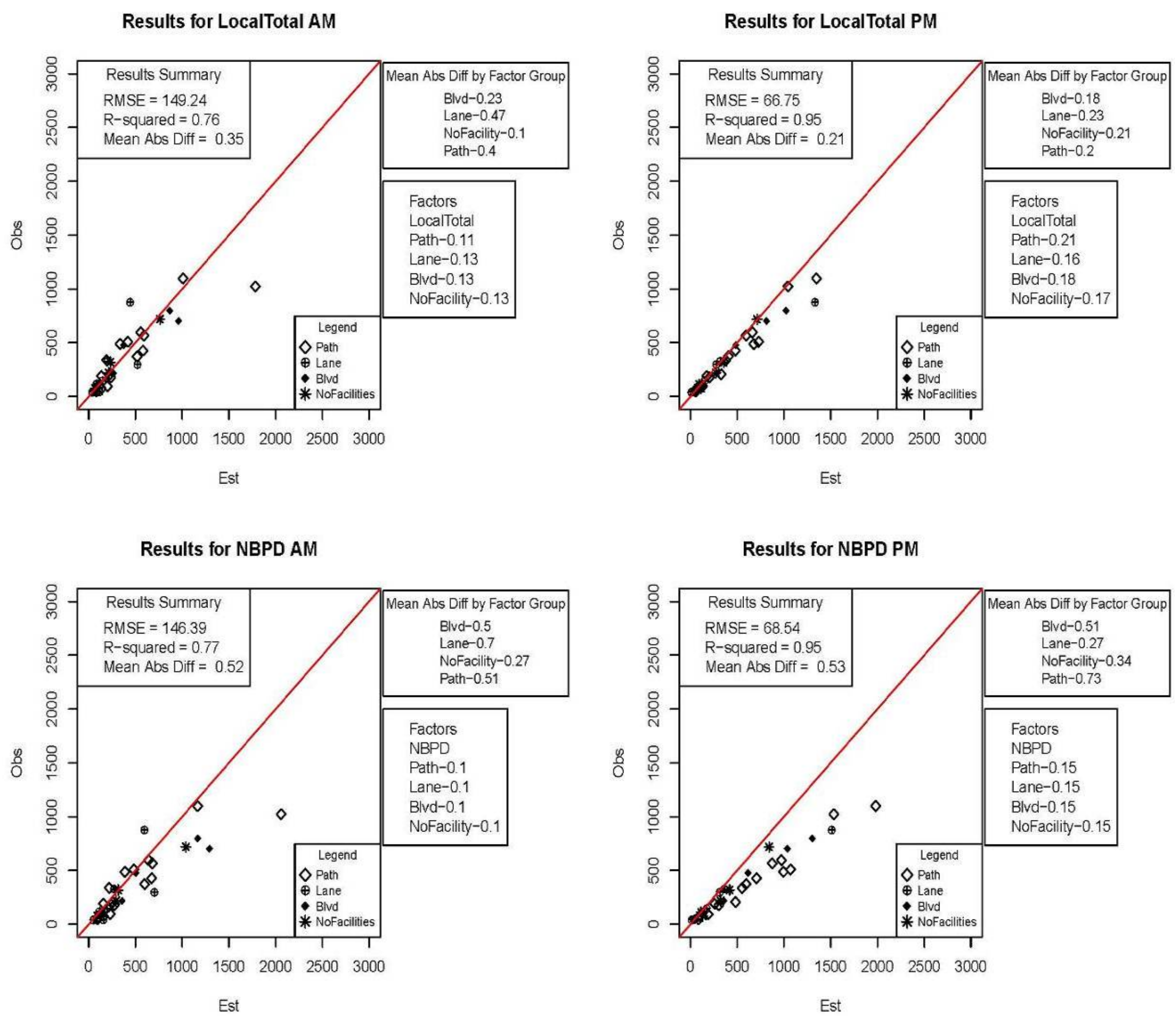
Table 3.14 – PM Peak Factor Results using NBPD Factors

	NBPDP - PM Factor							
Location	Observed	Estimate	% Difference	Absolute % Difference	Factor Group	Federal Functional Class	Location Id
GWestMohawk	112	112	100%	0%	NoFacility	Major Collector	35
HarlowEastI5	55	56	102%	2%	Lane	Minor Arterial	41
HighNorth13th	299	315	105%	5%	Lane	Minor Arterial	30
WillametteNorth15th	330	364	110%	10%	Lane	Minor Arterial	13
GoodpastureEastDeltaHwy	149	175	117%	17%	Lane	<NA>	1
HighSouth4th	718	840	117%	17%	NoFacility	Major Collector	48
ThurstonEast58th	44	35	80%	20%	Lane	Minor Arterial	37
PearlSouth19th	119	147	124%	24%	Lane	Major Collector	17
EWEBPathEast5th	76	98	129%	29%	Path	Path	34
MonroeSouth8th	478	616	129%	29%	Blvd	Major Collector	11
FirEastRiverRd	319	420	132%	32%	NoFacility	Local	19
PioneerPkwySouthQ	190	259	136%	36%	Path	Path	39
UniversityNorth24th	220	322	146%	46%	NoFacility	Local	15
AlderNorth27th	702	1036	148%	48%	Blvd	Local	18
AmazonPathNorth24th	1023	1533	150%	50%	Path	Path	8
DefazioSouthRiverEastBridge	566	875	155%	55%	Path	Path	5
HeronBridgeSouthFernRidge	372	595	160%	60%	Path	Path	10
NorthbankEastKnickerbocker	596	973	163%	63%	Path	Path	97
15thWestJefferson	798	1302	163%	63%	Blvd	Local	29
NorthbankWestDeltaHwy	338	553	164%	64%	Path	Path	16
FriendlySouth18th	217	357	165%	65%	Blvd	Major Collector	14

RichardsonBridge	427	707	166%	66%	Path	Path	32
GatewayStreetEastI5	42	14	33%	67%	Lane	Minor Arterial	44
FernRidgeEastDanebo	178	301	169%	69%	Path	Path	9
32ndSouthOregon	878	1512	172%	72%	Lane	Minor Arterial	36
DEastPioneerPkwyPath	75	133	177%	77%	NoFacility	Local	38
EWEBPathEastPioneerPkwy	47	84	179%	79%	Path	Path	33
SouthbankSouthGreenwayBr	1098	1981	180%	80%	Path	Path	4
GatewayBPBridgeEastI5	95	189	199%	99%	Path	Path	40
EastbankSouthOwossoBr	488	994	204%	104%	Path	Path	2
NorthbankSouthGreenwayBr	509	1071	210%	110%	Path	Path	3
DeltaBPBridgeEastGoodPasture	207	483	233%	133%	Path	Path	31

Figure 3.14 below plots each the results in Scenario 1 using both peak periods for each time-of-day factor set for a visual representation which includes some summary statistics for the overall performance for the estimation. Results using factors generated from study area data are featured in the top two plots with the NBPDP results in the bottom half of the figure.

Figure 3.14– Results for Scenario 1 Study Area Factors Compared to NBPDP Factors



Points in the plots in Figure 3.14 that appear above the line indicate an under estimation while points on the plot below the red line indicate an over estimation. The application of each set of factors produce different outcomes. Measures of R-squared of the observed and the estimates as well as the root mean squared error and average absolute percentage difference are displayed in the top right corner of each plot. The average absolute percentage differences by factor group are also presented in the outer box in the top right hand corner of each plot. Factors used in the extrapolation process are described in the outer box to the right of each plot. The application of study area time-of-day factors using PM samples demonstrate better results compared to the morning peak which is the opposite of what is observed for the application of the NBPDP time-of-day factors which shows the AM results produce less error. The factors that produce the least error are the application of study area factors using the PM peak period factors and samples. The average absolute error is 23% which over generalizes the results somewhat since a few estimates of the factoring are very poor and skew the average. Some of this may be due to a poor initial sample used in the extrapolation calculation. One of the results with substantial error comes from location 44 (Gateway Street East I-5) where the PM study area factors produced an estimate significantly different that the observed, 12 versus 42. With such low number of daily bicyclists it could be that this particular location is highly variable by hour and the counts used in the extrapolation calculation were not representative of the travel for that location. For this particular implementation of factors, the average absolute difference for locations that observed less than 100 bicyclists per day is 56% compared to 13% for locations observing 100 bicyclist or more. That being stated, there are results where daily bicyclists were less than 100 but the absolute difference was not less than 15%. The results from stations with more than 100 daily bicyclists are generally better in each of the application of time-of-day factors however. Table 3.15 details the average absolute percent difference separated by count stations with more or less than 100 observed daily bicyclists.

Table 3.15 – Exploring Effect of *Outliers*- Average Absolute % Difference Results Comparison

Factor Set Used	Average Absolute % Difference	Average Absolute % Difference for locations *less than* 100 Daily Bicyclists	Average Absolute % Difference for locations *more than* 100 Daily Bicyclists	Period
Study Area	35%	65%	26%	AM
Study Area	21%	33%	17%	PM
NBPDP	52%	102%	38%	AM
NBPDP	53%	53%	53%	PM
Observations	32%	7	25	

Locations with less than 100 daily bicyclists might represent some kind of outlier since hourly observations can be skewed more easily by a small number of bicyclists, producing poorer results using these hourly observations in any extrapolation process.

Table 3.16 presents the average absolute percent difference results by factor group for all estimates. For the PM results for the study area factors, absolute percent difference is less than the NBPDP factors for all factor groups. This table demonstrates that the bike boulevard (Blvd) generally resulted in the best overall result for PM study area factors with an absolute percentage difference of 18%.

Table 3.16 – Average Absolute % Difference Results Comparison by Factor Group

	Average Absolute % Difference by Factor Group				
Factor Group	**Blvd**	**Lane**	**No Facility**	**Path**	**Period**
Study Area	23%	47%	10%	40%	AM
Study Area	18%	23%	21%	20%	PM
NBPDP	50%	70%	27%	51%	AM
NBPDP	51%	27%	34%	73%	PM

In general, the estimates from each factor set implementation result in over estimation of observed counts though the study area factors over estimate by less than the NBPDP factors. Table 3.17 below demonstrates the sum of all estimates relative to the sum of observed traffic for all count stations where estimates were provided. The study area factors over estimate daily counts by 6-17 % while the NBPDP factors over estimate by 32 - 57% when reviewed this way. These results are summarized in Table 3.15 below.

Table 3.17- Relative Levels of Over-estimation

Factors	Sum of All Estimates	Observed	Percent Difference
Study Area AM	12,476	11,765	106%
Study Area PM	13,735	11,765	117%
NBPDP AM	15,477	11,765	132%
NBPDP PM	18,452	11,765	157%

Evaluated in a few ways, the best results come from applying the study area factors using the PM peak period. Of the 32 estimates from the PM study area factors, 18 of estimates had 15% error or less while only 6 of the NBPDP estimates were less than 15% error. More discussion of the implications of this level of error will follow the next section's testing of additional study area derived factors.

3.5.2 – Time-of-Day Factors from Study Area Data – Scenario 2

The above application of factors created time-of-day expansion factors from study area data using bicycle counts collected in one season (summer) at one set of locations and applied them to count data collected in another season (fall) from a separate set of locations. This process of development and application of factors produces considerable error in some cases. Even in the best results, those using evening peak factors derived from study area data, error is as much as 59% for count locations with more than 100 daily bicyclists (up to 159% error for all locations where factors were applied). In order to decrease levels of error, an approach was developed using iterative programming in R to test different factors and report the level of error derived from each tested factor set looking for factors that produce the best estimates overall. These simulated factors were applied based on a factor grouping derived from the bicycle facility type where each count location was located. An additional factor grouping was added to those tried in Scenario 1 by splitting the “Path” facility into a “Path-Commute” and a “Path-Recreation” based on a review of the hourly distributions (see Figure 3.5 below and related appendix below). Path facilities with a wider evening peak period are classified as Path-Recreation while locations on paths with a more pronounced morning and afternoon peak were characterized as Path-Commute. This classification approach uses some of the methods employed by Moreno-Miranda (2012) to classify bicycle count locations except that this approach does not have weekend daily totals to inform the classification process.

Data for this application of factors uses 24-hour counts collected on either a Tuesday or Thursday for each of the three seasons where data was available resulting in 123 days of data after cleaning out anomalous data. A process was developed in the R statistical software which iteratively tested different factors on an expanded factor grouping. The "Path" factor group used in Scenario 1 was split into two separate groups based on the hourly distribution, one for path facilities assumed to carry more commute travel and another assumed to carry more recreational travel. The process developed in R iterated through a vector of possible peak period factor values from 0.05 to 0.30 by increments of 0.01 and stored the results for each application of factors to determine the overall error associated with each elemental factor. By doing this, a set of factors was obtained that minimized the level of error to the greatest extent possible given the factor groupings. Figure 3.15 below describes graphically the process of the iterating through each test factor and applying the factor to each of the 123 daily counts and storing the results. After iterating through all test factors, results are reviewed to determine which factors produce the best results. The factors derived from the iterative process that produced the least amount of error are presented in Table 3.16 below.

Figure 3.15 – Iterative Process for Determining Most Effective

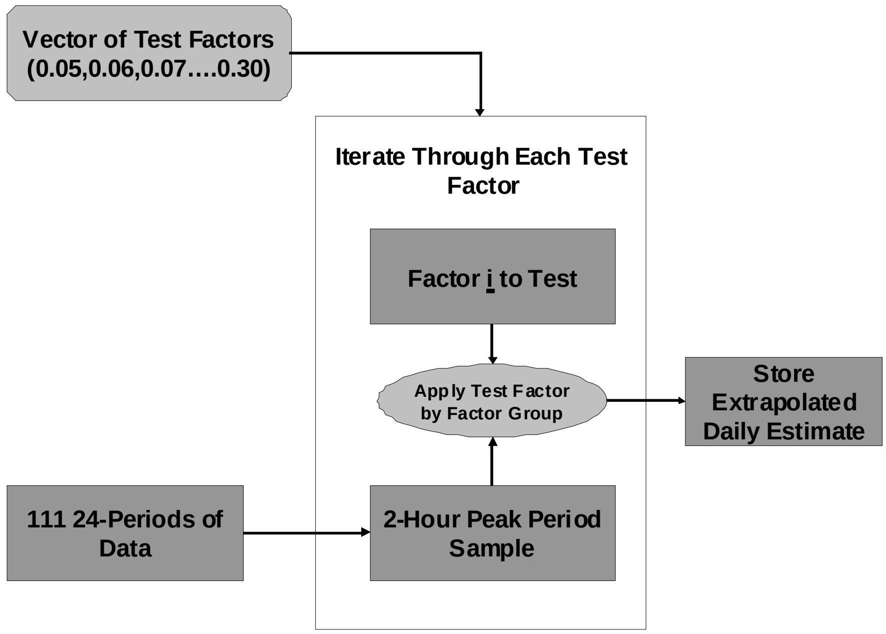


Table 3.18 – Scenario 2 Time-of-Day Extrapolation Factors

Time-of-Day Factor Comparison			
Data set		AM Peak Factor (7-9 AM)	PM Peak Factor (4-6)
Study Area Counts - Scenario 2	Path - Rec	0.15	0.25
	Path - Commute	0.13	0.21
	Lane	0.15	0.17
	Blvd	0.15	0.19
	No Facility	0.13	0.19

This approach to developing factors represents a completely different method of constructing factors compared to what was done in Scenario 1. It uses some simple iterative programming to determine factors that produce the least amount of error within the factor groups that were tried.

The result of this implementation is that the levels of error associated with the application of the Scenario 2 factors have been reduced. Tables 3.19 – 3.22 detail the results for each location for each season where data was available. The tables also denote the day of the week since some of the data come from bicycle traffic collected on Tuesday and some on Thursday.

Table 3.19 – Scenario 2 AM Peak Factor Results using Study Area Factors

tudy Area - AM Factor										
Location	Season	Observed	Estimate	Weekday	% Difference	Absolute % Difference	Bike Facility	Factor Group	Federal Functional Class	Location Id
13thWestAlder	Winter	1631	1627	Tuesday	100%	0%	Lane	Lane	Major Collector	21
16thWestAlder	Summer	140	138	Tuesday	99%	1%	NoFacility	NoFacility	Local	70
AgateSouth18th	Summer	438	433	Thursday	99%	1%	Lane	Lane	Minor Arterial	25
FernRidgeWestChambers	Winter	497	492	Thursday	99%	1%	Path	Path-Commute	Path	95
FrohnmayerSouthRiver	Fall	1691	1700	Tuesday	101%	1%	Path	Path-Commute	Path	6
SouthbankSouthGreenwayBr	Winter	576	580	Thursday	101%	1%	Path	Path-Rec	Path	4
12thEastLawrence	Winter	495	507	Tuesday	102%	2%	Blvd	Blvd	Major Collector	96
15thWestAlder	Summer	477	487	Tuesday	102%	2%	Blvd	Blvd	Local	26
GWestMohawk	Winter	63	62	Thursday	98%	2%	NoFacility	NoFacility	Major Collector	35
UniversityNorth24th	Fall	220	215	Thursday	98%	2%	NoFacility	NoFacility	Local	15
13thWestAlder	Summer	1335	1300	Tuesday	97%	3%	Lane	Lane	Major Collector	21
24thWestAdams	Summer	129	133	Tuesday	103%	3%	Lane	Lane	Major Collector	89
DefazioSouthRiverEastBridge	Summer	650	631	Thursday	97%	3%	Path	Path-Commute	Path	5
DEastPioneerPkwyPath	Winter	74	77	Tuesday	104%	4%	NoFacility	NoFacility	Local	38
GWestMohawk	Fall	112	108	Tuesday	96%	4%	NoFacility	NoFacility	Major Collector	35
HarlowEastI5	Fall	55	53	Thursday	96%	4%	Lane	Lane	Minor Arterial	41
AgateSouthFranklin	Summer	570	540	Thursday	95%	5%	Lane	Lane	Minor Arterial	23
FriendlySouth18th	Fall	217	227	Tuesday	105%	5%	Blvd	Blvd	Major Collector	14
OnyxNorthFranklin	Fall	1121	1177	Tuesday	105%	5%	NoFacility	NoFacility	<NA>	22
FirEastRiverRd	Winter	175	185	Thursday	106%	6%	NoFacility	NoFacility	Local	19
FrohnmayerSouthRiver	Summer	1094	1031	Thursday	94%	6%	Path	Path-Commute	Path	6
GatewayBPBridgeEastI5	Winter	120	113	Thursday	94%	6%	Path	Path-Rec	Path	40
HighSouth4th	Fall	718	762	Thursday	106%	6%	NoFacility	NoFacility	Major Collector	48
15thWestAlder	Winter	579	540	Tuesday	93%	7%	Blvd	Blvd	Local	26
15thWestJefferson	Fall	798	740	Tuesday	93%	7%	Blvd	Blvd	Local	29
15thEastAgate	Summer	327	353	Tuesday	108%	8%	Blvd	Blvd	Local	24
18thWestAlder	Winter	248	227	Tuesday	92%	8%	Lane	Lane	Minor Arterial	46

DEastPioneerPkwyPath	Fall	75	69	Thursday	92%	8%	NoFacility	NoFacility	Local	38
FriendlySouth18th	Winter	192	207	Tuesday	108%	8%	Blvd	Blvd	Major Collector	14
13thWestAlder	Summer	1392	1260	Thursday	91%	9%	Lane	Lane	Major Collector	21
AlderNorth27th	Winter	476	520	Thursday	109%	9%	Blvd	Blvd	Local	18
DefazioSouthRiverEastBridge	Summer	685	623	Tuesday	91%	9%	Path	Path-Commute	Path	5
15thWestAlder	Summer	469	420	Thursday	90%	10%	Blvd	Blvd	Local	26
15thWestAlder	Fall	974	873	Tuesday	90%	10%	Blvd	Blvd	Local	26
AgateSouthFranklin	Summer	527	473	Tuesday	90%	10%	Lane	Lane	Minor Arterial	23
AlderSouthFranklin	Summer	345	380	Thursday	110%	10%	Blvd	Blvd	Major Collector	27
PolkNorth24th	Summer	105	115	Thursday	110%	10%	NoFacility	NoFacility	Local	90
UniversitySouth24th	Summer	77	85	Tuesday	110%	10%	NoFacility	NoFacility	Major Collector	65
HarlowEastI5	Winter	434	387	Thursday	89%	11%	Lane	Lane	Minor Arterial	41
DefazioSouthRiverEastBridge	Fall	566	500	Thursday	88%	12%	Path	Path-Commute	Path	5
EastbankSouthOwossoBr	Winter	136	120	Tuesday	88%	12%	Path	Path-Rec	Path	2
FernRidgeEastDanebo	Fall	178	200	Tuesday	112%	12%	Path	Path-Commute	Path	9
HighSouth4th	Winter	331	292	Thursday	88%	12%	NoFacility	NoFacility	Major Collector	48
DeltaBPBridgeEastGoodPasture	Winter	61	53	Tuesday	87%	13%	Path	Path-Rec	Path	31
24thEastFilmore	Summer	93	80	Thursday	86%	14%	Lane	Lane	Minor Arterial	88
AgateSouth18th	Summer	471	407	Tuesday	86%	14%	Lane	Lane	Minor Arterial	25
MonroeSouth8th	Winter	304	260	Tuesday	86%	14%	Blvd	Blvd	Major Collector	11
12thEastLincoln	Summer	492	420	Tuesday	85%	15%	Blvd	Blvd	Local	28
24thWestAdams	Summer	117	100	Thursday	85%	15%	Lane	Lane	Major Collector	89
FernRidgeWestChambers	Winter	537	454	Tuesday	85%	15%	Path	Path-Commute	Path	95
FrohnmayerSouthRiver	Winter	637	731	Thursday	115%	15%	Path	Path-Commute	Path	6
GoodpastureEastDeltaHwy	Fall	149	127	Thursday	85%	15%	Lane	Lane	Major Collector	1
RichardsonBridge	Fall	427	492	Tuesday	115%	15%	Path	Path-Commute	Path	32
FrohnmayerSouthRiver	Summer	1084	915	Tuesday	84%	16%	Path	Path-Commute	Path	6
AlderNorth27th	Fall	702	820	Thursday	117%	17%	Blvd	Blvd	Local	18
AgateSouthFranklin	Fall	563	460	Tuesday	82%	18%	Lane	Lane	Minor Arterial	23
AlderSouthFranklin	Summer	299	353	Tuesday	118%	18%	Blvd	Blvd	Major Collector	27
HeronBridgeSouthFernRidge	Fall	372	438	Tuesday	118%	18%	Path	Path-Commute	Path	10

DeltaBPBridgeEastGoodPasture	Fall	207	167	Thursday	81%	19%	Path	Path-Rec	Path	31
15thEastAgate	Summer	340	407	Thursday	120%	20%	Blvd	Blvd	Local	24
OnyxNorthFranklin	Summer	658	792	Tuesday	120%	20%	NoFacility	NoFacility	<NA>	22
13thWestAlder	Fall	2602	2067	Tuesday	79%	21%	Lane	Lane	Major Collector	21
GatewayStreetEastI5	Fall	42	33	Thursday	79%	21%	Lane	Lane	Minor Arterial	44
HeronBridgeSouthFernRidge	Winter	342	415	Tuesday	121%	21%	Path	Path-Commute	Path	10
NorthbankEastKnickerbocker	Fall	596	469	Thursday	79%	21%	Path	Path-Commute	Path	97
12thWestHigh	Summer	344	267	Tuesday	78%	22%	Blvd	Blvd	Local	12
OnyxNorthFranklin	Summer	702	854	Thursday	122%	22%	NoFacility	NoFacility	Major Collector	22
18thWestAlder	Summer	349	267	Tuesday	77%	23%	Lane	Lane	Minor Arterial	46
AgateSouthFranklin	Winter	329	407	Thursday	124%	24%	Lane	Lane	Minor Arterial	23
DefazioSouthRiverEastBridge	Winter	230	285	Thursday	124%	24%	Path	Path-Commute	Path	5
NorthbankSouthGreenwayBr	Winter	158	120	Tuesday	76%	24%	Path	Path-Rec	Path	3
UniversitySouth18th	Summer	213	162	Tuesday	76%	24%	NoFacility	NoFacility	Local	71
ThurstonEast58th	Winter	36	27	Thursday	75%	25%	Lane	Lane	Minor Arterial	37
HighNorth13th	Winter	292	367	Tuesday	126%	26%	Lane	Lane	Minor Arterial	30
OnyxNorthFranklin	Winter	707	892	Tuesday	126%	26%	NoFacility	NoFacility	Major Collector	22
12thEastLincoln	Summer	513	373	Thursday	73%	27%	Blvd	Blvd	Local	28
EWEBPathEastPioneerPkwy	Fall	47	60	Tuesday	128%	28%	Path	Path-Rec	Path	33
FirEastRiverRd	Fall	319	231	Thursday	72%	28%	NoFacility	NoFacility	Local	19
UniversitySouth18th	Summer	203	146	Thursday	72%	28%	NoFacility	NoFacility	Local	71
15thEastAgate	Fall	1021	713	Thursday	70%	30%	Blvd	Blvd	Local	24
15thEastAgate	Winter	814	573	Tuesday	70%	30%	Blvd	Blvd	Local	24
42ndNorthCommercial	Winter	189	133	Thursday	70%	30%	Lane	Lane	Minor Arterial	45
AgateSouth18th	Winter	295	207	Thursday	70%	30%	Lane	Lane	Minor Arterial	25
ClearwaterPath	Winter	10	13	Thursday	130%	30%	Path	Path-Rec	Path	98
HarrisSouth18th	Summer	121	85	Thursday	70%	30%	NoFacility	NoFacility	Major Collector	73
16thWestAlder	Summer	167	115	Thursday	69%	31%	NoFacility	NoFacility	Local	70
24thEastFilmore	Summer	101	133	Tuesday	132%	32%	Lane	Lane	Minor Arterial	88
AlderSouthFranklin	Winter	293	387	Tuesday	132%	32%	Blvd	Blvd	Major Collector	27
EWEBPathEast5th	Fall	76	100	Tuesday	132%	32%	Path	Path-Rec	Path	34
13thEastHigh	Fall	623	827	Thursday	133%	33%	Lane	Lane	<NA>	52
MonroeSouth8th	Fall	478	320	Thursday	67%	33%	Blvd	Blvd	Major Collector	11
SouthbankSouthGreenwayBr	Fall	1098	740	Tuesday	67%	33%	Path	Path-Rec	Path	4
GatewayStreetEastI5	Winter	82	53	Thursday	65%	35%	Lane	Lane	Minor Arterial	44
PioneerPkwySouthQ	Winter	123	80	Tuesday	65%	35%	Path	Path-Rec	Path	39
11thWestAlder	Summer	180	113	Thursday	63%	37%	Lane	Lane	Minor Arterial	72

12thWestHigh	Fall	466	293	Tuesday	63%	37%	Blvd	Blvd	Local	12
NorthbankWestDeltaHwy	Winter	147	92	Tuesday	63%	37%	Path	Path-Commute	Path	16
UniversityNorth24th	Winter	184	115	Thursday	62%	38%	NoFacility	NoFacility	Local	15
PearlSouth19th	Fall	119	73	Thursday	61%	39%	Lane	Lane	Major Collector	17
NorthbankSouthGreenwayBr	Fall	509	307	Tuesday	60%	40%	Path	Path-Rec	Path	3
18thWestAlder	Fall	646	373	Thursday	58%	42%	Lane	Lane	Minor Arterial	46
15thWestJefferson	Winter	348	193	Thursday	55%	45%	Blvd	Blvd	Local	29
18thWestAlder	Summer	352	193	Thursday	55%	45%	Lane	Lane	Minor Arterial	46
RichardsonBridge	Winter	387	562	Tuesday	145%	45%	Path	Path-Commute	Path	32
32ndSouthOregon	Winter	36	53	Thursday	147%	47%	Lane	Lane	Minor Arterial	36
AmazonPathNorth24th	Fall	1023	1508	Thursday	147%	47%	Path	Path-Commute	Path	8
PioneerPkwySouthQ	Fall	190	100	Tuesday	53%	47%	Path	Path-Rec	Path	39
WillametteNorth15th	Fall	330	173	Tuesday	52%	48%	Lane	Lane	Minor Arterial	13
11thWestAlder	Summer	209	107	Tuesday	51%	49%	Lane	Lane	Minor Arterial	72
12thWestHigh	Winter	393	200	Tuesday	51%	49%	Blvd	Blvd	Local	12
EastbankSouthOwossoBr	Fall	488	247	Thursday	51%	49%	Path	Path-Rec	Path	2
HighNorth13th	Fall	299	447	Tuesday	149%	49%	Lane	Lane	Minor Arterial	30
PolkNorth24th	Summer	88	131	Tuesday	149%	49%	NoFacility	NoFacility	Local	90
12thWestHigh	Summer	372	187	Thursday	50%	50%	Blvd	Blvd	Local	12
NorthbankWestDeltaHwy	Fall	338	162	Thursday	48%	52%	Path	Path-Commute	Path	16
AmazonPathNorth24th	Winter	538	831	Thursday	154%	54%	Path	Path-Commute	Path	8
GatewayBPBridgeEastI5	Fall	95	147	Thursday	155%	55%	Path	Path-Rec	Path	40
32ndSouthOregon	Fall	878	380	Thursday	43%	57%	Lane	Lane	Minor Arterial	36
UniversitySouth24th	Summer	68	108	Thursday	159%	59%	NoFacility	NoFacility	Major	65
FernRidgeEastDanebo	Winter	144	231	Tuesday	160%	60%	Path	Path-Commute	Path	9
WillametteNorth15th	Winter	311	80	Tuesday	26%	74%	Lane	Lane	Minor Arterial	13
DefazioNorthRiverWestBridge	Winter	104	200	Thursday	192%	92%	Path	Path-Commute	Path	47
ThurstonEast58th	Fall	44	100	Thursday	227%	127%	Lane	Lane	Minor Arterial	37

Table 3.20 – Scenario 2 PM Peak Factor Results using Study Area Factors

Study Area - PM Factor										
Location	Season	Observed	Estimate	Weekday	% Difference	Absolute % Difference	Bike Facility	Factor Group	Federal Functional Class	Location Id
FernRidgeWestChambers	Winter	537	538	Tuesday	100%	0%	Path	Path-Commute	Path	95
FrohnmayerSouthRiver	Fall	1691	1686	Tuesday	100%	0%	Path	Path-Commute	Path	6
18thWestAlder	Fall	646	641	Thursday	99%	1%	Lane	Lane	Minor Arterial	46
FirEastRiverRd	Fall	319	316	Thursday	99%	1%	NoFacility	NoFacility	Local	19
GoodpastureEastDeltaHwy	Fall	149	147	Thursday	99%	1%	Lane	Lane	<NA>	1
AmazonPathNorth24th	Fall	1023	1043	Thursday	102%	2%	Path	Path-Commute	Path	8
EWEBPathEastPioneerPkwy	Fall	47	48	Tuesday	102%	2%	Path	Path-Rec	Path	33
FirEastRiverRd	Winter	175	179	Thursday	102%	2%	NoFacility	NoFacility	Local	19
FriendlySouth18th	Winter	192	195	Tuesday	102%	2%	Blvd	Blvd	Major Collector	14
OnyxNorthFranklin	Summer	658	674	Tuesday	102%	2%	NoFacility	NoFacility	<NA>	22
EastbankSouthOwossoBr	Winter	136	132	Tuesday	97%	3%	Path	Path-Rec	Path	2
FrohnmayerSouthRiver	Summer	1084	1048	Tuesday	97%	3%	Path	Path-Commute	Path	6
MonroeSouth8th	Fall	478	463	Thursday	97%	3%	Blvd	Blvd	Major Collector	11
SouthbankSouthGreenwayBr	Fall	1098	1132	Tuesday	103%	3%	Path	Path-Rec	Path	4
ThurstonEast58th	Winter	36	35	Thursday	97%	3%	Lane	Lane	Minor Arterial	37
AgateSouthFranklin	Winter	329	341	Thursday	104%	4%	Lane	Lane	Minor Arterial	23
HarlowEastI5	Winter	434	453	Thursday	104%	4%	Lane	Lane	Minor Arterial	41
HarrisSouth18th	Summer	121	116	Thursday	96%	4%	NoFacility	NoFacility	Major Collector	73
PearlSouth19th	Fall	119	124	Thursday	104%	4%	Lane	Lane	Major Collector	17
DefazioSouthRiverEastBridge	Fall	566	595	Thursday	105%	5%	Path	Path-Commute	Path	5
UniversityNorth24th	Winter	184	174	Thursday	95%	5%	NoFacility	NoFacility	Local	15
15thWestAlder	Summer	469	442	Thursday	94%	6%	Blvd	Blvd	Local	26
NorthbankSouthGreenwayBr	Winter	158	168	Tuesday	106%	6%	Path	Path-Rec	Path	3
NorthbankWestDeltaHwy	Winter	147	138	Tuesday	94%	6%	Path	Path-Commute	Path	16
UniversitySouth18th	Summer	213	200	Tuesday	94%	6%	NoFacility	NoFacility	Local	71
UniversitySouth18th	Summer	203	216	Thursday	106%	6%	NoFacility	NoFacility	Local	71
15thEastAgate	Summer	340	316	Thursday	93%	7%	Blvd	Blvd	Local	24
15thWestAlder	Fall	974	905	Tuesday	93%	7%	Blvd	Blvd	Local	26
18thWestAlder	Summer	349	324	Tuesday	93%	7%	Lane	Lane	Minor Arterial	46

MonroeSouth8th	Winter	304	326	Tuesday	107%	7%	Blvd	Blvd	Major Collector	11
WillametteNorth15th	Fall	330	306	Tuesday	93%	7%	Lane	Lane	Minor Arterial	13
24thEastFilmore	Summer	93	100	Thursday	108%	8%	Lane	Lane	Minor Arterial	88
AlderSouthFranklin	Summer	345	316	Thursday	92%	8%	Blvd	Blvd	Major Collector	27
DefazioSouthRiverEastBridge	Summer	685	743	Tuesday	108%	8%	Path	Path-Commute	Path	5
12thWestHigh	Summer	344	374	Tuesday	109%	9%	Blvd	Blvd	Local	12
15thWestAlder	Winter	579	526	Tuesday	91%	9%	Blvd	Blvd	Local	26
42ndNorthCommercial	Winter	189	206	Thursday	109%	9%	Lane	Lane	Minor Arterial	45
AgateSouth18th	Summer	438	476	Thursday	109%	9%	Lane	Lane	Minor Arterial	25
AgateSouthFranklin	Fall	563	612	Tuesday	109%	9%	Lane	Lane	Minor Arterial	23
DefazioNorthRiverWestBridge	Winter	104	95	Thursday	91%	9%	Path	Path-Commute	Path	47
FrohnmayerSouthRiver	Summer	1094	1190	Thursday	109%	9%	Path	Path-Commute	Path	6
HeronBridgeSouthFernRidge	Fall	372	405	Tuesday	109%	9%	Path	Path-Commute	Path	10
OnyxNorthFranklin	Summer	702	642	Thursday	91%	9%	NoFacility	NoFacility	<NA>	22
OnyxNorthFranklin	Winter	707	768	Tuesday	109%	9%	NoFacility	NoFacility	<NA>	22
15thEastAgate	Summer	327	295	Tuesday	90%	10%	Blvd	Blvd	Local	24
GatewayBPBridgeEastI5	Winter	120	108	Thursday	90%	10%	Path	Path-Rec	Path	40
UniversityNorth24th	Fall	220	242	Thursday	110%	10%	NoFacility	NoFacility	Local	15
12thEastLincoln	Summer	492	437	Tuesday	89%	11%	Blvd	Blvd	Local	28
AlderNorth27th	Fall	702	779	Thursday	111%	11%	Blvd	Blvd	Local	18
HighNorth13th	Fall	299	265	Tuesday	89%	11%	Lane	Lane	Minor Arterial	30
NorthbankEastKnickerbocker	Fall	596	662	Thursday	111%	11%	Path	Path-Commute	Path	97
NorthbankWestDeltaHwy	Fall	338	376	Thursday	111%	11%	Path	Path-Commute	Path	16
12thWestHigh	Fall	466	521	Tuesday	112%	12%	Blvd	Blvd	Local	12
12thWestHigh	Winter	393	442	Tuesday	112%	12%	Blvd	Blvd	Local	12
HighSouth4th	Fall	718	632	Thursday	88%	12%	NoFacility	NoFacility	Major Collector	48
OnyxNorthFranklin	Fall	1121	984	Tuesday	88%	12%	NoFacility	NoFacility	<NA>	22
AlderNorth27th	Winter	476	416	Thursday	87%	13%	Blvd	Blvd	Local	18
FrohnmayerSouthRiver	Winter	637	552	Thursday	87%	13%	Path	Path-Commute	Path	6
GatewayStreetEastI5	Winter	82	71	Thursday	87%	13%	Lane	Lane	Minor Arterial	44
RichardsonBridge	Fall	427	481	Tuesday	113%	13%	Path	Path-Commute	Path	32
WillametteNorth15th	Winter	311	271	Tuesday	87%	13%	Lane	Lane	Minor Arterial	13
15thWestAlder	Summer	477	411	Tuesday	86%	14%	Blvd	Blvd	Local	26
DefazioSouthRiverEastBridge	Summer	650	557	Thursday	86%	14%	Path	Path-Commute	Path	5

GatewayBPBridgeEastI5	Fall	95	108	Thursday	114%	14%	Path	Path-Rec	Path	40
11thWestAlder	Summer	209	241	Tuesday	115%	15%	Lane	Lane	Minor Arterial	72
DefazioSouthRiverEastBridge	Winter	230	195	Thursday	85%	15%	Path	Path-Commute	Path	5
DeltaBPBridgeEastGoodPasture	Winter	61	52	Tuesday	85%	15%	Path	Path-Rec	Path	31
FernRidgeEastDanebo	Fall	178	205	Tuesday	115%	15%	Path	Path-Commute	Path	9
HarlowEastI5	Fall	55	47	Thursday	85%	15%	Lane	Lane	Minor Arterial	41
HeronBridgeSouthFernRidge	Winter	342	290	Tuesday	85%	15%	Path	Path-Commute	Path	10
15thWestJefferson	Winter	348	405	Thursday	116%	16%	Blvd	Blvd	Local	29
18thWestAlder	Summer	352	294	Thursday	84%	16%	Lane	Lane	Minor Arterial	46
AgateSouthFranklin	Summer	527	612	Tuesday	116%	16%	Lane	Lane	Minor Arterial	23
AmazonPathNorth24th	Winter	538	452	Thursday	84%	16%	Path	Path-Commute	Path	8
EastbankSouthOwossoBr	Fall	488	568	Thursday	116%	16%	Path	Path-Rec	Path	2
12thEastLawrence	Winter	495	411	Tuesday	83%	17%	Blvd	Blvd	<NA>	96
12thEastLincoln	Summer	513	426	Thursday	83%	17%	Blvd	Blvd	Local	28
13thWestAlder	Summer	1335	1112	Tuesday	83%	17%	Lane	Lane	Major Collector	21
18thWestAlder	Winter	248	206	Tuesday	83%	17%	Lane	Lane	Minor Arterial	46
AlderSouthFranklin	Summer	299	247	Tuesday	83%	17%	Blvd	Blvd	Major Collector	27
13thWestAlder	Fall	2602	2129	Tuesday	82%	18%	Lane	Lane	Major Collector	21
24thWestAdams	Summer	129	106	Tuesday	82%	18%	Lane	Lane	Major Collector	89
FernRidgeWestChambers	Winter	497	410	Thursday	82%	18%	Path	Path-Commute	Path	95
RichardsonBridge	Winter	387	457	Tuesday	118%	18%	Path	Path-Commute	Path	32
32ndSouthOregon	Winter	36	29	Thursday	81%	19%	Lane	Lane	Minor Arterial	36
PioneerPkwySouthQ	Winter	123	100	Tuesday	81%	19%	Path	Path-Rec	Path	39
ClearwaterPath	Winter	10	12	Thursday	120%	20%	Path	Path-Rec	Path	98
DEastPioneerPkwyPath	Winter	74	89	Tuesday	120%	20%	NoFacility	NoFacility	Local	38
NorthbankSouthGreenwayBr	Fall	509	612	Tuesday	120%	20%	Path	Path-Rec	Path	3
16thWestAlder	Summer	140	111	Tuesday	79%	21%	NoFacility	NoFacility	Local	70
24thWestAdams	Summer	117	141	Thursday	121%	21%	Lane	Lane	Major Collector	89
12thWestHigh	Summer	372	453	Thursday	122%	22%	Blvd	Blvd	Local	12
PioneerPkwySouthQ	Fall	190	148	Tuesday	78%	22%	Path	Path-Rec	Path	39
15thWestJefferson	Fall	798	979	Tuesday	123%	23%	Blvd	Blvd	Local	29
AgateSouthFranklin	Summer	570	700	Thursday	123%	23%	Lane	Lane	Minor Arterial	23
PolkNorth24th	Summer	88	68	Tuesday	77%	23%	NoFacility	NoFacility	Local	90
FriendlySouth18th	Fall	217	268	Tuesday	124%	24%	Blvd	Blvd	Major Collector	14

SouthbankSouthGreenwayBr	Winter	576	436	Thursday	76%	24%	Path	Path-Rec	Path	4
24thEastFilmore	Summer	101	76	Tuesday	75%	25%	Lane	Lane	Minor Arterial	88
AlderSouthFranklin	Winter	293	221	Tuesday	75%	25%	Blvd	Blvd	Major Collector	27
GWestMohawk	Fall	112	84	Tuesday	75%	25%	NoFacility	NoFacility	Major Collector	35
PolkNorth24th	Summer	105	79	Thursday	75%	25%	NoFacility	NoFacility	Local	90
13thWestAlder	Winter	1631	1200	Tuesday	74%	26%	Lane	Lane	Major Collector	21
EWEBPathEast5th	Fall	76	56	Tuesday	74%	26%	Path	Path-Rec	Path	34
11thWestAlder	Summer	180	229	Thursday	127%	27%	Lane	Lane	Minor Arterial	72
15thEastAgate	Winter	814	589	Tuesday	72%	28%	Blvd	Blvd	Local	24
16thWestAlder	Summer	167	121	Thursday	72%	28%	NoFacility	NoFacility	Local	70
13thWestAlder	Summer	1392	988	Thursday	71%	29%	Lane	Lane	Major Collector	21
HighSouth4th	Winter	331	232	Thursday	70%	30%	NoFacility	NoFacility	Major Collector	48
AgateSouth18th	Summer	471	624	Tuesday	132%	32%	Lane	Lane	Minor Arterial	25
DEastPioneerPkwyPath	Fall	75	100	Thursday	133%	33%	NoFacility	NoFacility	Local	38
DeltaBPBridgeEastGoodPasture	Fall	207	276	Thursday	133%	33%	Path	Path-Rec	Path	31
15thEastAgate	Fall	1021	674	Thursday	66%	34%	Blvd	Blvd	Local	24
ThurstonEast58th	Fall	44	29	Thursday	66%	34%	Lane	Lane	Minor Arterial	37
AgateSouth18th	Winter	295	400	Thursday	136%	36%	Lane	Lane	Minor Arterial	25
13thEastHigh	Fall	623	394	Thursday	63%	37%	Lane	Lane	<NA>	52
HighNorth13th	Winter	292	176	Tuesday	60%	40%	Lane	Lane	Minor Arterial	30
FernRidgeEastDanebo	Winter	144	205	Tuesday	142%	42%	Path	Path-Commute	Path	9
UniversitySouth24th	Summer	77	111	Tuesday	144%	44%	NoFacility	NoFacility	<NA>	65
32ndSouthOregon	Fall	878	1271	Thursday	145%	45%	Lane	Lane	Minor Arterial	36
GWestMohawk	Winter	63	32	Thursday	51%	49%	NoFacility	NoFacility	Major Collector	35
UniversitySouth24th	Summer	68	32	Thursday	47%	53%	NoFacility	NoFacility	<NA>	65
GatewayStreetEastI5	Fall	42	12	Thursday	29%	71%	Lane	Lane	Minor Arterial	44

Table 3.21 – Scenario 2 AM Peak Factor Results NBPDP Factors

NBPDP AM Factor										
Location	Season	Observed	Estimate	Weekday	% Difference	Absolute % Difference	Bike Facility	Factor Group	Federal Functional Class	Location Id
11thWestAlder	Summer	180	179	Thursday	99%	1%	Lane	Lane	Minor Arterial	72
12thWestHigh	Fall	466	462	Tuesday	99%	1%	Blvd	Blvd	Local	12
FirEastRiverRd	Fall	319	315	Thursday	99%	1%	NoFacility	NoFacility	Local	19
GatewayStreetEastI5	Winter	82	84	Thursday	102%	2%	Lane	Lane	Minor Arterial	44
PioneerPkwySouthQ	Winter	123	126	Tuesday	102%	2%	Path	Path-Rec	Path	39
UniversitySouth18th	Summer	203	200	Thursday	98%	2%	NoFacility	NoFacility	Local	71
PearlSouth19th	Fall	119	116	Thursday	97%	3%	Lane	Lane	Major Collector	17
UniversitySouth18th	Summer	213	221	Tuesday	104%	4%	NoFacility	NoFacility	Local	71
HarrisSouth18th	Summer	121	116	Thursday	95%	5%	NoFacility	NoFacility	Major Collector	73
MonroeSouth8th	Fall	478	504	Thursday	105%	5%	Blvd	Blvd	Major Collector	11
NorthbankSouthGreenwayBr	Fall	509	483	Tuesday	95%	5%	Path	Path-Rec	Path	3
16thWestAlder	Summer	167	158	Thursday	94%	6%	NoFacility	NoFacility	Local	70
SouthbankSouthGreenwayBr	Fall	1098	1166	Tuesday	106%	6%	Path	Path-Rec	Path	4
NorthbankEastKnickerbocker	Fall	596	641	Thursday	107%	7%	Path	Path-Commute	Path	97
18thWestAlder	Fall	646	588	Thursday	91%	9%	Lane	Lane	Minor Arterial	46
15thEastAgate	Fall	1021	1124	Thursday	110%	10%	Blvd	Blvd	Local	24
AgateSouth18th	Winter	295	326	Thursday	110%	10%	Lane	Lane	Minor Arterial	25
15thEastAgate	Winter	814	903	Tuesday	111%	11%	Blvd	Blvd	Local	24
42ndNorthCommercial	Winter	189	210	Thursday	111%	11%	Lane	Lane	Minor Arterial	45
15thWestJefferson	Winter	348	305	Thursday	88%	12%	Blvd	Blvd	Local	29
18thWestAlder	Summer	352	305	Thursday	87%	13%	Lane	Lane	Minor Arterial	46
NorthbankWestDeltaHwy	Winter	147	126	Tuesday	86%	14%	Path	Path-Commute	Path	16
UniversityNorth24th	Winter	184	158	Thursday	86%	14%	NoFacility	NoFacility	Local	15
12thEastLincoln	Summer	513	588	Thursday	115%	15%	Blvd	Blvd	Local	28
FernRidgeWestChambers	Winter	537	620	Tuesday	115%	15%	Path	Path-Commute	Path	95
FrohnmayerSouthRiver	Summer	1084	1250	Tuesday	115%	15%	Path	Path-Commute	Path	6
PioneerPkwySouthQ	Fall	190	158	Tuesday	83%	17%	Path	Path-Rec	Path	39
ThurstonEast58th	Winter	36	42	Thursday	117%	17%	Lane	Lane	Minor Arterial	37
WillametteNorth15th	Fall	330	273	Tuesday	83%	17%	Lane	Lane	Minor Arterial	13
11thWestAlder	Summer	209	168	Tuesday	80%	20%	Lane	Lane	Minor Arterial	72
12thWestHigh	Winter	393	315	Tuesday	80%	20%	Blvd	Blvd	Local	12

18thWestAlder	Summer	349	420	Tuesday	120%	20%	Lane	Lane	Minor Arterial	46
EastbankSouthOwossoBr	Fall	488	389	Thursday	80%	20%	Path	Path-Rec	Path	2
NorthbankSouthGreenwayBr	Winter	158	189	Tuesday	120%	20%	Path	Path-Rec	Path	3
12thWestHigh	Summer	372	294	Thursday	79%	21%	Blvd	Blvd	Local	12
DefazioSouthRiverEastBridge	Fall	566	683	Thursday	121%	21%	Path	Path-Commute	Path	5
HighSouth4th	Winter	331	399	Thursday	121%	21%	NoFacility	NoFacility	Major Collector	48
12thWestHigh	Summer	344	420	Tuesday	122%	22%	Blvd	Blvd	Local	12
DefazioSouthRiverEastBridge	Summer	685	851	Tuesday	124%	24%	Path	Path-Commute	Path	5
13thWestAlder	Fall	2602	3255	Tuesday	125%	25%	Lane	Lane	Major Collector	21
GatewayStreetEastI5	Fall	42	53	Thursday	125%	25%	Lane	Lane	Minor Arterial	44
DEastPioneerPkwyPath	Fall	75	95	Thursday	126%	26%	NoFacility	NoFacility	Local	38
DeltaBPBridgeEastGoodPasture	Fall	207	263	Thursday	127%	27%	Path	Path-Rec	Path	31
AgateSouthFranklin	Fall	563	725	Tuesday	129%	29%	Lane	Lane	Minor Arterial	23
FrohnmayerSouthRiver	Summer	1094	1407	Thursday	129%	29%	Path	Path-Commute	Path	6
GWestMohawk	Fall	112	147	Tuesday	131%	31%	NoFacility	NoFacility	Major Collector	35
32ndSouthOregon	Fall	878	599	Thursday	68%	32%	Lane	Lane	Minor Arterial	36
DefazioSouthRiverEastBridge	Summer	650	861	Thursday	132%	32%	Path	Path-Commute	Path	5
GWestMohawk	Winter	63	84	Thursday	133%	33%	NoFacility	NoFacility	Major Collector	35
12thEastLincoln	Summer	492	662	Tuesday	134%	34%	Blvd	Blvd	Local	28
GoodpastureEastDeltaHwy	Fall	149	200	Thursday	134%	34%	Lane	Lane	Major Collector	1
UniversityNorth24th	Fall	220	294	Thursday	134%	34%	NoFacility	NoFacility	Local	15
16thWestAlder	Summer	140	189	Tuesday	135%	35%	NoFacility	NoFacility	Local	70
24thEastFilmore	Summer	93	126	Thursday	135%	35%	Lane	Lane	Minor Arterial	88
24thWestAdams	Summer	117	158	Thursday	135%	35%	Lane	Lane	Major Collector	89
FernRidgeWestChambers	Winter	497	672	Thursday	135%	35%	Path	Path-Commute	Path	95
MonroeSouth8th	Winter	304	410	Tuesday	135%	35%	Blvd	Blvd	Major Collector	11
NorthbankWestDeltaHwy	Fall	338	221	Thursday	65%	35%	Path	Path-Commute	Path	16
AgateSouth18th	Summer	471	641	Tuesday	136%	36%	Lane	Lane	Minor Arterial	25
FrohnmayerSouthRiver	Fall	1691	2321	Tuesday	137%	37%	Path	Path-Commute	Path	6
DeltaBPBridgeEastGoodPasture	Winter	61	84	Tuesday	138%	38%	Path	Path-Rec	Path	31
EastbankSouthOwossoBr	Winter	136	189	Tuesday	139%	39%	Path	Path-Rec	Path	2
HarlowEastI5	Winter	434	609	Thursday	140%	40%	Lane	Lane	Minor Arterial	41
15thWestAlder	Summer	469	662	Thursday	141%	41%	Blvd	Blvd	Local	26

15thWestAlder	Fall	974	1376	Tuesday	141%	41%	Blvd	Blvd	Local	26
AgateSouthFranklin	Summer	527	746	Tuesday	141%	41%	Lane	Lane	Minor Arterial	23
DEastPioneerPkwyPath	Winter	74	105	Tuesday	142%	42%	NoFacility	NoFacility	Local	38
13thWestAlder	Summer	1392	1985	Thursday	143%	43%	Lane	Lane	Major Collector	21
OnyxNorthFranklin	Fall	1121	1607	Tuesday	143%	43%	NoFacility	NoFacility	Major Collector	22
18thWestAlder	Winter	248	357	Tuesday	144%	44%	Lane	Lane	Minor Arterial	46
FirEastRiverRd	Winter	175	252	Thursday	144%	44%	NoFacility	NoFacility	Local	19
HighSouth4th	Fall	718	1040	Thursday	145%	45%	NoFacility	NoFacility	Major Collector	48
15thWestJefferson	Fall	798	1166	Tuesday	146%	46%	Blvd	Blvd	Local	29
15thWestAlder	Winter	579	851	Tuesday	147%	47%	Blvd	Blvd	Local	26
AgateSouthFranklin	Summer	570	851	Thursday	149%	49%	Lane	Lane	Minor Arterial	23
GatewayBPBridgeEastI5	Winter	120	179	Thursday	149%	49%	Path	Path-Rec	Path	40
PolkNorth24th	Summer	105	158	Thursday	150%	50%	NoFacility	NoFacility	Local	90
UniversitySouth24th	Summer	77	116	Tuesday	150%	50%	NoFacility	NoFacility	Major Collector	65
13thWestAlder	Summer	1335	2048	Tuesday	153%	53%	Lane	Lane	Major Collector	21
FernRidgeEastDanebo	Fall	178	273	Tuesday	153%	53%	Path	Path-Commute	Path	9
HarlowEastI5	Fall	55	84	Thursday	153%	53%	Lane	Lane	Minor Arterial	41
AgateSouth18th	Summer	438	683	Thursday	156%	56%	Lane	Lane	Minor Arterial	25
13thWestAlder	Winter	1631	2562	Tuesday	157%	57%	Lane	Lane	Major Collector	21
FrohnmayerSouthRiver	Winter	637	998	Thursday	157%	57%	Path	Path-Commute	Path	6
RichardsonBridge	Fall	427	672	Tuesday	157%	57%	Path	Path-Commute	Path	32
SouthbankSouthGreenwayBr	Winter	576	914	Thursday	159%	59%	Path	Path-Rec	Path	4
WillametteNorth15th	Winter	311	126	Tuesday	41%	59%	Lane	Lane	Minor Arterial	13
12thEastLawrence	Winter	495	798	Tuesday	161%	61%	Blvd	Blvd	Major Collector	96
15thWestAlder	Summer	477	767	Tuesday	161%	61%	Blvd	Blvd	Local	26
HeronBridgeSouthFernRidge	Fall	372	599	Tuesday	161%	61%	Path	Path-Commute	Path	10
24thWestAdams	Summer	129	210	Tuesday	163%	63%	Lane	Lane	Major Collector	89
OnyxNorthFranklin	Summer	658	1082	Tuesday	164%	64%	NoFacility	NoFacility	Major Collector	22
FriendlySouth18th	Fall	217	357	Tuesday	165%	65%	Blvd	Blvd	Major Collector	14
HeronBridgeSouthFernRidge	Winter	342	567	Tuesday	166%	66%	Path	Path-Commute	Path	10
OnyxNorthFranklin	Summer	702	1166	Thursday	166%	66%	NoFacility	NoFacility	Major Collector	22

DefazioSouthRiverEastBridge	Winter	230	389	Thursday	169%	69%	Path	Path-Commute	Path	5
15thEastAgate	Summer	327	557	Tuesday	170%	70%	Blvd	Blvd	Local	24
FriendlySouth18th	Winter	192	326	Tuesday	170%	70%	Blvd	Blvd	Major Collector	14
AlderNorth27th	Winter	476	819	Thursday	172%	72%	Blvd	Blvd	Local	18
OnyxNorthFranklin	Winter	707	1218	Tuesday	172%	72%	NoFacility	NoFacility	Major Collector	22
AlderSouthFranklin	Summer	345	599	Thursday	173%	73%	Blvd	Blvd	Major Collector	27
AlderNorth27th	Fall	702	1292	Thursday	184%	84%	Blvd	Blvd	Local	18
AlderSouthFranklin	Summer	299	557	Tuesday	186%	86%	Blvd	Blvd	Major Collector	27
15thEastAgate	Summer	340	641	Thursday	188%	88%	Blvd	Blvd	Local	24
AgateSouthFranklin	Winter	329	641	Thursday	195%	95%	Lane	Lane	Minor Arterial	23
HighNorth13th	Winter	292	578	Tuesday	198%	98%	Lane	Lane	Minor Arterial	30
RichardsonBridge	Winter	387	767	Tuesday	198%	98%	Path	Path-Commute	Path	32
AmazonPathNorth24th	Fall	1023	2058	Thursday	201%	101%	Path	Path-Commute	Path	8
EWEBPathEastPioneerPkwy	Fall	47	95	Tuesday	201%	101%	Path	Path-Rec	Path	33
PolkNorth24th	Summer	88	179	Tuesday	203%	103%	NoFacility	NoFacility	Local	90
EWEBPathEast5th	Fall	76	158	Tuesday	207%	107%	Path	Path-Rec	Path	34
24thEastFilmore	Summer	101	210	Tuesday	208%	108%	Lane	Lane	Minor Arterial	88
AlderSouthFranklin	Winter	293	609	Tuesday	208%	108%	Blvd	Blvd	Major Collector	27
13thEastHigh	Fall	623	1302	Thursday	209%	109%	Lane	Lane	Major Collector	52
ClearwaterPath	Winter	10	21	Thursday	210%	110%	Path	Path-Rec	Path	98
AmazonPathNorth24th	Winter	538	1134	Thursday	211%	111%	Path	Path-Commute	Path	8
UniversitySouth24th	Summer	68	147	Thursday	216%	116%	NoFacility	NoFacility	Major Collector	65
FernRidgeEastDanebo	Winter	144	315	Tuesday	219%	119%	Path	Path-Commute	Path	9
32ndSouthOregon	Winter	36	84	Thursday	233%	133%	Lane	Lane	Minor Arterial	36
HighNorth13th	Fall	299	704	Tuesday	235%	135%	Lane	Lane	Minor Arterial	30
GatewayBPBridgeEastI5	Fall	95	231	Thursday	243%	143%	Path	Path-Rec	Path	40
DefazioNorthRiverWestBridge	Winter	104	273	Thursday	262%	162%	Path	Path-Commute	Path	47
ThurstonEast58th	Fall	44	158	Thursday	358%	258%	Lane	Lane	Minor Arterial	37

Table 3.22 – Scenario 2 PM Peak Factor Results NBPDP Factors

NBPDP PM Factor										
Location	Season	Observed	Estimate	Weekday	% Difference	Absolute % Difference	Bike Facility	Factor Group	Federal Functional Class	Location Id
AlderSouthFranklin	Winter	293	294	Tuesday	100%	0%	Blvd	Blvd	Major Collector	27
GWestMohawk	Fall	112	112	Tuesday	100%	0%	NoFacility	NoFacility	Major Collector	35
PolkNorth24th	Summer	105	105	Thursday	100%	0%	NoFacility	NoFacility	Local	90
13thWestAlder	Summer	1335	1323	Tuesday	99%	1%	Lane	Lane	Major Collector	21
18thWestAlder	Summer	352	350	Thursday	99%	1%	Lane	Lane	Minor Arterial	46
18thWestAlder	Winter	248	245	Tuesday	99%	1%	Lane	Lane	Minor Arterial	46
HarlowEastI5	Fall	55	56	Thursday	101%	1%	Lane	Lane	Minor Arterial	41
24thWestAdams	Summer	129	126	Tuesday	98%	2%	Lane	Lane	Major Collector	89
GatewayStreetEastI5	Winter	82	84	Thursday	102%	2%	Lane	Lane	Minor Arterial	44
13thWestAlder	Fall	2602	2534	Tuesday	97%	3%	Lane	Lane	Major Collector	21
15thEastAgate	Winter	814	784	Tuesday	96%	4%	Blvd	Blvd	Local	24
16thWestAlder	Summer	167	161	Thursday	96%	4%	NoFacility	NoFacility	Local	70
32ndSouthOregon	Winter	36	35	Thursday	96%	4%	Lane	Lane	Minor Arterial	36
PolkNorth24th	Summer	88	91	Tuesday	104%	4%	NoFacility	NoFacility	Local	90
WillametteNorth15th	Winter	311	322	Tuesday	104%	4%	Lane	Lane	Minor Arterial	13
16thWestAlder	Summer	140	147	Tuesday	105%	5%	NoFacility	NoFacility	Local	70
HighNorth13th	Fall	299	315	Tuesday	105%	5%	Lane	Lane	Minor Arterial	30
HighSouth4th	Winter	331	308	Thursday	93%	7%	NoFacility	NoFacility	Major Collector	48
12thEastLawrence	Winter	495	546	Tuesday	110%	10%	Blvd	Blvd	Major Collector	96
18thWestAlder	Summer	349	385	Tuesday	110%	10%	Lane	Lane	Minor Arterial	46
24thEastFilmore	Summer	101	91	Tuesday	90%	10%	Lane	Lane	Minor Arterial	88
AlderSouthFranklin	Summer	299	329	Tuesday	110%	10%	Blvd	Blvd	Major Collector	27
WillametteNorth15th	Fall	330	364	Tuesday	110%	10%	Lane	Lane	Minor Arterial	13
12thEastLincoln	Summer	513	567	Thursday	111%	11%	Blvd	Blvd	Local	28
13thWestAlder	Winter	1631	1428	Tuesday	88%	12%	Lane	Lane	Major Collector	21
15thEastAgate	Fall	1021	896	Thursday	88%	12%	Blvd	Blvd	Local	24
15thWestAlder	Summer	477	546	Tuesday	114%	14%	Blvd	Blvd	Local	26
13thWestAlder	Summer	1392	1176	Thursday	84%	16%	Lane	Lane	Major Collector	21
AlderNorth27th	Winter	476	553	Thursday	116%	16%	Blvd	Blvd	Local	18

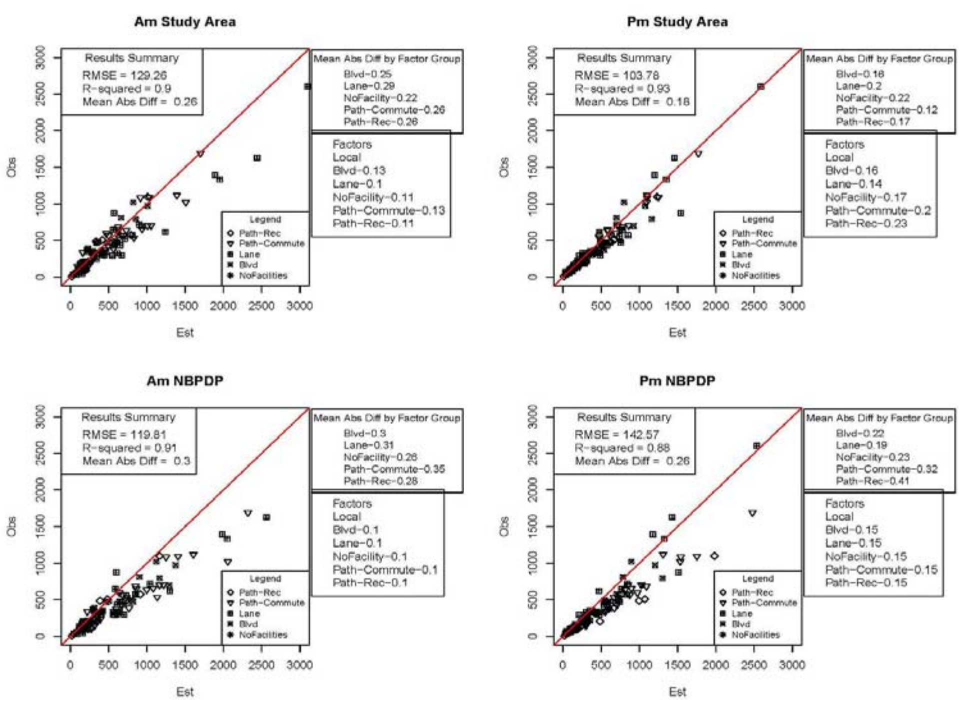
HighSouth4th	Fall	718	840	Thursday	117%	17%	NoFacility	NoFacility	Major Collector	48
OnyxNorthFranklin	Fall	1121	1309	Tuesday	117%	17%	NoFacility	NoFacility	Major Collector	22
ThurstonEast58th	Winter	36	42	Thursday	117%	17%	Lane	Lane	Minor Arterial	37
12thEastLincoln	Summer	492	581	Tuesday	118%	18%	Blvd	Blvd	Local	28
18thWestAlder	Fall	646	763	Thursday	118%	18%	Lane	Lane	Minor Arterial	46
GoodpastureEastDeltaHwy	Fall	149	175	Thursday	118%	18%	Lane	Lane	Major Collector	1
15thEastAgate	Summer	327	392	Tuesday	120%	20%	Blvd	Blvd	Local	24
15thWestAlder	Winter	579	700	Tuesday	121%	21%	Blvd	Blvd	Local	26
FernRidgeWestChambers	Winter	497	602	Thursday	121%	21%	Path	Path-Commute	Path	95
ThurstonEast58th	Fall	44	35	Thursday	79%	21%	Lane	Lane	Minor Arterial	37
AlderSouthFranklin	Summer	345	420	Thursday	122%	22%	Blvd	Blvd	Major Collector	27
OnyxNorthFranklin	Summer	702	854	Thursday	122%	22%	NoFacility	NoFacility	Major Collector	22
15thEastAgate	Summer	340	420	Thursday	124%	24%	Blvd	Blvd	Local	24
15thWestAlder	Fall	974	1204	Tuesday	124%	24%	Blvd	Blvd	Local	26
AgateSouthFranklin	Winter	329	406	Thursday	124%	24%	Lane	Lane	Minor Arterial	23
AmazonPathNorth24th	Winter	538	665	Thursday	124%	24%	Path	Path-Commute	Path	8
HarlowEastI5	Winter	434	539	Thursday	124%	24%	Lane	Lane	Minor Arterial	41
PearlSouth19th	Fall	119	147	Thursday	124%	24%	Lane	Lane	Major Collector	17
13thEastHigh	Fall	623	469	Thursday	75%	25%	Lane	Lane	Major Collector	52
15thWestAlder	Summer	469	588	Thursday	125%	25%	Blvd	Blvd	Local	26
DefazioSouthRiverEastBridge	Winter	230	287	Thursday	125%	25%	Path	Path-Commute	Path	5
HeronBridgeSouthFernRidge	Winter	342	427	Tuesday	125%	25%	Path	Path-Commute	Path	10
UniversitySouth18th	Summer	213	266	Tuesday	125%	25%	NoFacility	NoFacility	Local	71
DefazioSouthRiverEastBridge	Summer	650	819	Thursday	126%	26%	Path	Path-Commute	Path	5
UniversityNorth24th	Winter	184	231	Thursday	126%	26%	NoFacility	NoFacility	Local	15
FrohnmayerSouthRiver	Winter	637	812	Thursday	127%	27%	Path	Path-Commute	Path	6
24thEastFilmore	Summer	93	119	Thursday	128%	28%	Lane	Lane	Minor Arterial	88
EWEBPathEast5th	Fall	76	98	Tuesday	128%	28%	Path	Path-Rec	Path	34
HarrisSouth18th	Summer	121	154	Thursday	128%	28%	NoFacility	NoFacility	Major Collector	73
HighNorth13th	Winter	292	210	Tuesday	72%	28%	Lane	Lane	Minor Arterial	30
42ndNorthCommercial	Winter	189	245	Thursday	129%	29%	Lane	Lane	Minor Arterial	45
AgateSouth18th	Summer	438	567	Thursday	129%	29%	Lane	Lane	Minor Arterial	25
AgateSouthFranklin	Fall	563	728	Tuesday	129%	29%	Lane	Lane	Minor Arterial	23

MonroeSouth8th	Fall	478	616	Thursday	129%	29%	Blvd	Blvd	Major Collector	11
FirEastRiverRd	Fall	319	420	Thursday	132%	32%	NoFacility	NoFacility	Local	19
GWestMohawk	Winter	63	42	Thursday	67%	33%	NoFacility	NoFacility	Major Collector	35
SouthbankSouthGreenwayBr	Winter	576	763	Thursday	133%	33%	Path	Path-Rec	Path	4
DefazioNorthRiverWestBridge	Winter	104	140	Thursday	134%	34%	Path	Path-Commute	Path	47
FriendlySouth18th	Winter	192	259	Tuesday	135%	35%	Blvd	Blvd	Major Collector	14
FirEastRiverRd	Winter	175	238	Thursday	136%	36%	NoFacility	NoFacility	Local	19
OnyxNorthFranklin	Summer	658	896	Tuesday	136%	36%	NoFacility	NoFacility	Major Collector	22
11thWestAlder	Summer	209	287	Tuesday	137%	37%	Lane	Lane	Minor Arterial	72
PioneerPkwySouthQ	Fall	190	259	Tuesday	137%	37%	Path	Path-Rec	Path	39
AgateSouthFranklin	Summer	527	728	Tuesday	138%	38%	Lane	Lane	Minor Arterial	23
NorthbankWestDeltaHwy	Winter	147	203	Tuesday	138%	38%	Path	Path-Commute	Path	16
UniversitySouth24th	Summer	68	42	Thursday	62%	38%	NoFacility	NoFacility	Major Collector	65
UniversitySouth18th	Summer	203	287	Thursday	141%	41%	NoFacility	NoFacility	Local	71
FrohnmayerSouthRiver	Summer	1084	1540	Tuesday	142%	42%	Path	Path-Commute	Path	6
MonroeSouth8th	Winter	304	434	Tuesday	143%	43%	Blvd	Blvd	Major Collector	11
PioneerPkwySouthQ	Winter	123	175	Tuesday	143%	43%	Path	Path-Rec	Path	39
12thWestHigh	Summer	344	497	Tuesday	144%	44%	Blvd	Blvd	Local	12
24thWestAdams	Summer	117	168	Thursday	144%	44%	Lane	Lane	Major Collector	89
OnyxNorthFranklin	Winter	707	1022	Tuesday	145%	45%	NoFacility	NoFacility	Major Collector	22
AgateSouthFranklin	Summer	570	833	Thursday	146%	46%	Lane	Lane	Minor Arterial	23
FernRidgeWestChambers	Winter	537	791	Tuesday	147%	47%	Path	Path-Commute	Path	95
FrohnmayerSouthRiver	Fall	1691	2478	Tuesday	147%	47%	Path	Path-Commute	Path	6
UniversityNorth24th	Fall	220	322	Thursday	147%	47%	NoFacility	NoFacility	Local	15
AlderNorth27th	Fall	702	1036	Thursday	148%	48%	Blvd	Blvd	Local	18
12thWestHigh	Fall	466	693	Tuesday	149%	49%	Blvd	Blvd	Local	12
12thWestHigh	Winter	393	588	Tuesday	150%	50%	Blvd	Blvd	Local	12
AmazonPathNorth24th	Fall	1023	1533	Thursday	150%	50%	Path	Path-Commute	Path	8
DeltaBPBridgeEastGoodPasture	Winter	61	91	Tuesday	150%	50%	Path	Path-Rec	Path	31
11thWestAlder	Summer	180	273	Thursday	152%	52%	Lane	Lane	Minor Arterial	72
15thWestJefferson	Winter	348	539	Thursday	155%	55%	Blvd	Blvd	Local	29
DefazioSouthRiverEastBridge	Fall	566	875	Thursday	155%	55%	Path	Path-Commute	Path	5

GatewayBPBridgeEastI5	Winter	120	189	Thursday	157%	57%	Path	Path-Rec	Path	40
AgateSouth18th	Summer	471	742	Tuesday	158%	58%	Lane	Lane	Minor Arterial	25
DefazioSouthRiverEastBridge	Summer	685	1092	Tuesday	159%	59%	Path	Path-Commute	Path	5
DEastPioneerPkwyPath	Winter	74	119	Tuesday	160%	60%	NoFacility	NoFacility	Local	38
FrohnmayerSouthRiver	Summer	1094	1750	Thursday	160%	60%	Path	Path-Commute	Path	6
HeronBridgeSouthFernRidge	Fall	372	595	Tuesday	160%	60%	Path	Path-Commute	Path	10
AgateSouth18th	Winter	295	476	Thursday	161%	61%	Lane	Lane	Minor Arterial	25
12thWestHigh	Summer	372	602	Thursday	162%	62%	Blvd	Blvd	Local	12
15thWestJefferson	Fall	798	1302	Tuesday	163%	63%	Blvd	Blvd	Local	29
NorthbankEastKnickerbocker	Fall	596	973	Thursday	163%	63%	Path	Path-Commute	Path	97
NorthbankWestDeltaHwy	Fall	338	553	Thursday	164%	64%	Path	Path-Commute	Path	16
FriendlySouth18th	Fall	217	357	Tuesday	165%	65%	Blvd	Blvd	Major Collector	14
RichardsonBridge	Fall	427	707	Tuesday	165%	65%	Path	Path-Commute	Path	32
GatewayStreetEastI5	Fall	42	14	Thursday	32%	68%	Lane	Lane	Minor Arterial	44
FernRidgeEastDanebo	Fall	178	301	Tuesday	169%	69%	Path	Path-Commute	Path	9
EastbankSouthOwossoBr	Winter	136	231	Tuesday	170%	70%	Path	Path-Rec	Path	2
32ndSouthOregon	Fall	878	1512	Thursday	172%	72%	Lane	Lane	Minor Arterial	36
RichardsonBridge	Winter	387	672	Tuesday	174%	74%	Path	Path-Commute	Path	32
DEastPioneerPkwyPath	Fall	75	133	Thursday	178%	78%	NoFacility	NoFacility	Local	38
EWEBPathEastPioneerPkwy	Fall	47	84	Tuesday	179%	79%	Path	Path-Rec	Path	33
SouthbankSouthGreenwayBr	Fall	1098	1981	Tuesday	180%	80%	Path	Path-Rec	Path	4
NorthbankSouthGreenwayBr	Winter	158	294	Tuesday	186%	86%	Path	Path-Rec	Path	3
UniversitySouth24th	Summer	77	147	Tuesday	191%	91%	NoFacility	NoFacility	Major Collector	65
GatewayBPBridgeEastI5	Fall	95	189	Thursday	199%	99%	Path	Path-Rec	Path	40
EastbankSouthOwossoBr	Fall	488	994	Thursday	204%	104%	Path	Path-Rec	Path	2
FernRidgeEastDanebo	Winter	144	301	Tuesday	209%	109%	Path	Path-Commute	Path	9
ClearwaterPath	Winter	10	21	Thursday	210%	110%	Path	Path-Rec	Path	98
NorthbankSouthGreenwayBr	Fall	509	1071	Tuesday	210%	110%	Path	Path-Rec	Path	3
DeltaBPBridgeEastGoodPasture	Fall	207	483	Thursday	233%	133%	Path	Path-Rec	Path	31
ThurstonEast58th	Fall	44	158	Thursday	358%	258%	Lane	Lane	Minor Arterial	37

These results indicate that error in estimating total daily bicycle traffic from 2-hour time-of-day factors can be reduced with more refined factors. Figure 3.16 demonstrates graphically the results presented in the tables above. The results using time-of-day factors based on study area data are featured in the top two plots with the results from the NBPDP factors application are presented in the bottom two plots. Each of these factors' results are presented using both an AM and PM period sample and respective factor. This plot also summarizes the R-squared and RMSE the average absolute percentage difference while also describing the mean absolute percent difference by factor group.

Figure 3.16 – Results for Scenario 2 Study Area Factors Compared to NBPDP Factors



Points in the plots in Figure 3.16 that appear above the line indicate an under estimate while points on the plot below the red line indicate an over estimation. Table 3.23 sums all of the estimates for each factor application and compares with the sum of observed counts to better understand the relative levels of over versus under estimation. Each of the factor application s result in an over estimate but the study area PM factors appear to over estimate by the least amount when reviewed in this way.

Table 3.23– Relative Levels of Over-estimation

Factors	Sum of All Estimates	Observed	Percent Difference
Study Area AM	56,214	48,617	116%
Study Area PM	53,608	48,617	110%
NBPDP AM	67,777	48,617	139%
NBPDP PM	63,474	48,617	131%

Table 3.24 reviews the results by removing count locations that could be considered outliers because of low overall daily traffic. Locations with less than 100 daily cyclists could have substantial variation in hourly traffic which could result in daily estimates with much more error. Removing these locations does improve the average absolute percentage difference for all factor implementations.however slightly.

Table 3.24– Exploring Effect of *Outliers*- Average Absolute % Difference Results Comparison

Factor Set Used	Average Absolute % Difference	Average Absolute % Difference for locations *less than* 100 Daily Bicyclists	Average Absolute % Difference for locations *more than* 100 Daily Bicyclists	Period
Study Area	24%	31%	23%	AM
Study Area	16%	26%	14%	PM
NBPDP	48%	77%	43%	AM
NBPDP	37%	45%	36%	PM
Observations	123	18	105	

Detailed in Table 3.23 below is the average absolute percentage difference by factor group type.

Table 3.25– Average Absolute Percentage Difference by Factor Group

Factors	Blvd	Lane	No Facility	Path-Commute	Path-Recreation	Average
Study Area AM	20%	28%	18%	26%	28%	24%
Study Area PM	14%	19%	19%	11%	16%	16%
NBPDP AM	46%	50%	39%	55%	50%	48%
NBPDP PM	30%	24%	30%	49%	75%	37%

Additional breakdowns of the Scenario 2 results are presented in tables below. Table 3.26 presents the results broken out by the season in which the counts were collected to examine any differences in performance of the estimation. For the AM study area factors result in estimates with less error for the summer results while the study area PM results are identical across seasons. The summer results have slightly less error for both the AM and PM NBPDP factors compared to the average.

Table 3.26 – Average Absolute Percentage Difference by Season

Average Absolute Percentage Difference by Season				
Factors	**Summer**	**Fall**	**Winter**	**Average**
Study Area AM	19%	28%	25%	24%
Study Area PM	16%	16%	16%	16%
NBPDP AM	43%	48%	53%	48%
NBPDP PM	28%	47%	35%	37%
Observations	39	41	43	123

Since some of the factors were applied to data collected on Tuesday and some of Thursday a breakdown of the error is presented in Table 3.27. For the results using study area factors there are slight differences of 2% and 5% between the Tuesday and Thursday results for the AM and PM factors respectively while there is no real difference between the Tuesday and Thursday results for either period for the NBPDP factors.

Table 3.27 – Average Absolute Percentage Difference by Tuesday/Thursday

Average Absolute Percentage Difference by Tuesday/Thursday		
Factors	**Thursday**	**Tuesday**
Study Area AM	27%	22%
Study Area PM	17%	15%
NBPDP AM	48%	49%
NBPDP PM	37%	37%
Observations	63	60

The above tables and plots summarize the results from the application of the Scenario 2 factors derived from study area data and compared with NBPDP factors. A review of these results, as well as the results from the Scenario 1 application will follow in the next section, including discussion on how the factors tested above compare with factors from other data sources including the NHTS and OHAS surveys.

3.5.3 – Comparison of Scenario 1 and Scenario 2 Factor Results

To further the understanding of how well the factors from Scenario 1 and 2 compare, an evaluation of the estimates for the 32 count locations analyzed in Section 3.5.1 (and detailed in Figure 3.14 above) will be presented. Tables 3.26 through 3.29 detail the comparisons of estimates and their measures of absolute percentage difference. The Scenario 2 results presented above were done for 123 locations available for application, including the 32 previously tested in the Scenario 1 application of factors.

Table 3.28 – Comparison of Scenario 1 and Scenario 2 AM Study Area Factors

Comparison of Scenario 1 and Scenario 2 AM Study Area Factors					
Location	Observed	Scenario 1 Estimate	Scenario 2 Estimate	Scenario 1 Absolute % Difference	Scenario 2 Absolute % Difference
15thWestJefferson	798	867	740	9%	7%
AlderNorth27th	702	961	820	37%	17%
AmazonPathNorth24th	1023	1782	1508	74%	47%
DEastPioneerPkwyPath	75	69	69	8%	8%
DefazioSouthRiverEastBridge	566	591	500	4%	12%
DeltaBPBridgeEastGoodPasture	207	227	167	10%	19%
EastbankSouthOwossoBr	488	336	247	31%	49%
EWEBPathEast5th	76	136	100	79%	32%
EWEBPathEastPioneerPkwy	47	82	60	74%	28%
FernRidgeEastDanebo	178	236	200	33%	12%
FirEastRiverRd	319	231	231	28%	28%
FriendlySouth18th	217	266	227	23%	5%
GatewayBPBridgeEastI5	95	200	147	111%	55%
GatewayStreetEastI5	42	39	33	7%	21%
GoodpastureEastDeltaHwy	149	148	127	1%	15%
GWestMohawk	112	108	108	4%	4%
HarlowEastI5	55	62	53	13%	4%
HeronBridgeSouthFernRidge	372	518	438	39%	18%
HighNorth13th	299	523	447	75%	49%
HighSouth4th	718	762	762	6%	6%
MonroeSouth8th	478	375	320	22%	33%

NorthbankEastKnickerbocker	596	555	469	7%	21%
NorthbankSouthGreenwayBr	509	418	307	18%	40%
NorthbankWestDeltaHwy	338	191	162	43%	52%
PearlSouth19th	119	86	73	28%	39%
PioneerPkwySouthQ	190	136	100	28%	47%
RichardsonBridge	427	582	492	36%	15%
SouthbankSouthGreenwayBr	1098	1009	740	8%	33%
ThurstonEast58th	44	117	100	166%	127%
UniversityNorth24th	220	215	215	2%	2%
WillametteNorth15th	330	203	173	38%	48%

Table 3.29 – Comparison of Scenario 1 and Scenario 2 PM Study Area Factors

Comparison of Scenario 1 and Scenario 2 PM Study Area Factors					
Location	**Observed**	**Scenario 1 Estimate**	**Scenario 2 Estimate**	**Scenario 1 Absolute % Difference**	**Scenario 2 Absolute % Difference**
15thWestJefferson	798	1022	979	28%	23%
AlderNorth27th	702	813	779	16%	11%
AmazonPathNorth24th	1023	1043	1043	2%	2%
DEastPioneerPkwyPath	75	113	100	51%	33%
DefazioSouthRiverEastBridge	566	595	595	5%	5%
DeltaBPBridgeEastGoodPasture	207	329	276	59%	33%
EastbankSouthOwossoBr	488	676	568	39%	16%
EWEBPathEast5th	76	67	56	12%	26%
EWEBPathEastPioneerPkwy	47	57	48	21%	2%
FernRidgeEastDanebo	178	205	205	15%	15%
FirEastRiverRd	319	356	316	12%	1%
FriendlySouth18th	217	280	268	29%	24%
GatewayBPBridgeEastI5	95	129	108	36%	14%
GatewayStreetEastI5	42	12	12	71%	71%
GoodpastureEastDeltaHwy	149	154	147	3%	1%
GWestMohawk	112	95	84	15%	25%
HarlowEastI5	55	49	47	11%	15%
HeronBridgeSouthFernRidge	372	405	405	9%	9%

HighNorth13th	299	278	265	7%	11%
HighSouth4th	718	713	632	1%	12%
MonroeSouth8th	478	484	463	1%	3%
NorthbankEastKnickerbocker	596	662	662	11%	11%
NorthbankSouthGreenwayBr	509	729	612	43%	20%
NorthbankWestDeltaHwy	338	376	376	11%	11%
PearlSouth19th	119	130	124	9%	4%
PioneerPkwySouthQ	190	176	148	7%	22%
RichardsonBridge	427	481	481	13%	13%
SouthbankSouthGreenwayBr	1098	1348	1132	23%	3%
ThurstonEast58th	44	31	29	30%	34%
UniversityNorth24th	220	273	242	24%	10%
WillametteNorth15th	330	321	306	3%	7%

Table 3.30 – Comparison of Scenario 1 and Scenario 2 AM NBPDP Factors

Comparison of Scenario 1 and Scenario 2 AM NBPDP Factors					
Location	**Observed**	**Scenario 1 Estimate**	**Scenario 2 Estimate**	**Scenario 1 Absolute % Difference**	**Scenario 2 Absolute % Difference**
15thWestJefferson	798	1166	1166	46%	46%
AlderNorth27th	702	1292	1292	84%	84%
AmazonPathNorth24th	1023	2058	2058	101%	101%
DEastPioneerPkwyPath	75	94	95	25%	26%
DefazioSouthRiverEastBridge	566	682	683	20%	21%
DeltaBPBridgeEastGoodPasture	207	262	263	27%	27%
EastbankSouthOwossoBr	488	388	389	20%	20%
EWEBPathEast5th	76	158	158	108%	107%
EWEBPathEastPioneerPkwy	47	94	95	100%	101%
FernRidgeEastDanebo	178	273	273	53%	53%
FirEastRiverRd	319	315	315	1%	1%
FriendlySouth18th	217	357	357	65%	65%
GatewayBPBridgeEastI5	95	231	231	143%	143%
GatewayStreetEastI5	42	52	53	24%	25%
GoodpastureEastDeltaHwy	149	200	200	34%	34%
GWestMohawk	112	147	147	31%	31%
HarlowEastI5	55	84	84	53%	53%
HeronBridgeSouthFernRidge	372	598	599	61%	61%
HighNorth13th	299	704	704	135%	135%
HighSouth4th	718	1040	1040	45%	45%
MonroeSouth8th	478	504	504	5%	5%

NorthbankEastKnickerbocker	596	640	641	7%	7%
NorthbankSouthGreenwayBr	509	483	483	5%	5%
NorthbankWestDeltaHwy	338	220	221	35%	35%
PearlSouth19th	119	116	116	3%	3%
PioneerPkwySouthQ	190	158	158	17%	17%
RichardsonBridge	427	672	672	57%	57%
SouthbankSouthGreenwayBr	1098	1166	1166	6%	6%
ThurstonEast58th	44	158	158	259%	258%
UniversityNorth24th	220	294	294	34%	34%
WillametteNorth15th	330	273	273	17%	17%

Table 3.31 – Comparison of Scenario 1 and Scenario 2 PM NBPDP Factors

Comparison of Scenario 1 and Scenario 2 PM NBPDP Factors					
Location	Observed	Scenario 1 Estimate	Scenario 2 Estimate	Scenario 1 Absolute % Difference	Scenario 2 Absolute % Difference
15thWestJefferson	798	1302	1302	63%	63%
AlderNorth27th	702	1036	1036	48%	48%
AmazonPathNorth24th	1023	1533	1533	50%	50%
DEastPioneerPkwyPath	75	133	133	77%	78%
DefazioSouthRiverEastBridge	566	875	875	55%	55%
DeltaBPBridgeEastGoodPasture	207	483	483	133%	133%
EastbankSouthOwossoBr	488	994	994	104%	104%
EWEBPathEast5th	76	98	98	29%	28%
EWEBPathEastPioneerPkwy	47	84	84	79%	79%
FernRidgeEastDanebo	178	301	301	69%	69%
FirEastRiverRd	319	420	420	32%	32%
FriendlySouth18th	217	357	357	65%	65%
GatewayBPBridgeEastI5	95	189	189	99%	99%
GatewayStreetEastI5	42	14	14	67%	68%
GoodpastureEastDeltaHwy	149	175	175	17%	18%
GWestMohawk	112	112	112	0%	0%
HarlowEastI5	55	56	56	2%	1%
HeronBridgeSouthFernRidge	372	595	595	60%	60%
HighNorth13th	299	315	315	5%	5%
HighSouth4th	718	840	840	17%	17%
MonroeSouth8th	478	616	616	29%	29%

NorthbankEastKnickerbocker	596	973	973	63%	63%
NorthbankSouthGreenwayBr	509	1071	1071	110%	110%
NorthbankWestDeltaHwy	338	553	553	64%	64%
PearlSouth19th	119	147	147	24%	24%
PioneerPkwySouthQ	190	259	259	36%	37%
RichardsonBridge	427	707	707	66%	65%
SouthbankSouthGreenwayBr	1098	1981	1981	80%	80%
ThurstonEast58th	44	35	35	20%	21%
UniversityNorth24th	220	322	322	46%	47%
WillametteNorth15th	330	364	364	10%	10%

A comparison of the average absolute percentage difference is presented in Table 3.30 to help understand the overall outcomes and the differences between the different estimation scenarios. The table demonstrates that Scenario 2 factors produced estimates with less error on average compared to Scenario 1 factors for locations tested in the initial Scenario 1 factor implementation. The results for the NBPDP did not change since those factors were not altered for either scenario nor id the locations where factors were applied. The study area PM factors again produced the least amount of error. The results from the 32 locations resulted in slightly higher error with 16% compared to the full set of 123 locations that Scenario 2 factors were applied to above which resulted in average absolute error of 15%.

Table 3.32 – Comparison of Scenario 1 and Scenario 2 Average Absolute Percentage Difference

Comparison of Scenario 1 and Scenario 2 Average Absolute Percentage Difference		
Factors	**Scenario 1**	**Scenario 2**
Study Area AM	34%	29%
Study Area PM	20%	16%
NBPDP AM	52%	52%
NBPDP PM	53%	53%

4. Discussion and Conclusion

4.1 – Introduction

Applying time-of-day factors to expand two-hour counts to estimated full day counts can be an effective way to make bicycle count programs with limited resources produce more meaningful bicycle traffic counts provided those estimates are reliable. The examinations completed for this research tested different time-of-day factors created from study area data and compared them to NBPDP factors in order to demonstrate the possible error from each application. Estimates from study area factors continuously out performed estimates derived from NBPDP factors. Factors from the NHTS and OHAS travel surveys would likely produce poor results since they do not conform to either Scenario 1 or Scenario 2 factors and factor groupings are impossible to form from the survey data available. Evaluation of the study area data and the revelation of a university travel pattern is interesting but does not help with time-of-day factoring since the peak period factors do not compare well for locations with a possible university travel designation.

4.2 – NHTS and OHAS Derived Factors

The factors based on NHTS and OHAS travel surveys do not appear capable of producing reliable results in all cases when applied in an extrapolation exercise. Though no test of their application was performed, a review of the factor values compared to those in Scenario 1 and Scenario 2 reveal that the NHTS and OHAS values are different in many instances. For the NHTS factors, the AM factor is identical to the Scenario 1 path factor group but since the rest of the factor group factors vary estimates would result in some error. The OHAS factors also result in some overlap with some of the study area scenario factors. The OHAS AM factors are all much higher compared with AM study area factors but the OHAS-Eugene PM factor is identical to the study area scenario 2 Blvd and No Facility factors. Some testing could be done applying these factors but without bicycle facility specific groupings estimates are likely to contain high levels of error. Based on the review of NHTS and OHAS factors for this research, it is not recommended they be used as time-of-day factors.

4.3 – Review of the University Bicycle Travel Pattern

Using study area data a university travel patterns is suggested with proposed characteristics to identify this pattern. Identification of this travel pattern would be useful to planners looking to understand users of a particular facility but would not be helpful in constructing factors or factor groupings since no trend revealed itself in the AM or PM peak factors for locations characterized as exhibiting university travel patterns. Understanding user types by identifying bicycle travel patterns is important when considering how bicyclists may be interacting with motorized travel which could inform how future improvements might occur. For instance, knowing that bicycle travel around a university is more or less steady throughout the day instead of being diurnal like many transportation facilities with commute patterns could help make the case for completely separated bicycle infrastructure. The identification of this travel pattern is important but there is a need to develop additional attributes like weekday and weekend daily volumes to characterize this traffic pattern.

4.4 – Study Area Time-of-Day Factors Application

The results from study area time-of-day factors consistently outperformed NBPDP factors, especially the estimates derived from PM factor application. This outcome is important to those looking to apply the NBPDP to locally collected two-hour manual counts. It was not known how well the NBPDP factors performed in a given area as no test was previously done with observed 24-hour bicycle counts. An important take-away is that NBPDP factors have the potential for significant error in a given application.

Factors from Scenario 2 produced results with less error compared to Scenario 1 but required more data to create. As described above, an iterative process was created that tested various factors by factor group to determine the best factors to apply. Creating factors from this method would require interested parties to collect a larger number of 24-hour counts that would then be fed into an iterative testing process in order to determine the factors that produce the least amount of error. This research used 123 24-hour observations of data from 40+ locations which is a great deal of data to collect. This process is conceivable if private contractors made such services (collecting 24-hour bicycle counts) available but might be too difficult for other agencies without a lot of resources for their non-morotized traffic data collection programs. The same approach could be taken with factors derived in Scenario 1, though with less data feeding the factor creation process more error is likely.

Basing factor groups on bicycle facility type helped to minimize error and is a convenient way to classify factors. Interestingly, the AM study area factors for both Scenario 1 and Scenario 2 exhibit less variation between groups compared to those in the PM factors. The AM factors also produce more error than the PM factors however. The Scenario 2 study area factor application saw the addition of separate off-street path factor groups, one for paths with more commute users and another for recreational users. This additional factor grouping produced better results for path facilities. For this research the designation was done based on observations of 24-hour distributions which requires some kind of automated counter up front though its possible to make such a characterization based on minimal manual observations.

The results and discussion have described the error associated with each set of factors and their application in terms relative to one another, but how much error is reasonable? Lindsey et al. (2007) reported results for error in estimating monthly and annual figures at between -6.2% to -31.6% and -20.2% to -36.4% respectively. Nordback et al. (2012) suggest acceptable error from using short term counts to estimate annual average daily traffic may be around 15%-30%. Both of these studies used short-term counts to estimate an annual traffic counts. The best estimates this research was able to generate resulted in error of between 0-71% with an average of 16%. Some of the less accurate estimates come from locations where low daily traffic was observed and could very well be removed from the results for the reason described above regarding hourly variability (though a few fairly reliable estimates came form locations with less than 100 daily bicyclists). Removing these outliers, the average absolute percentage difference is 14% for the Scenario 2 PM study area factors. Is this level of error acceptable?

The level of acceptable error might differ depending on the application of the results. If the results are used to describe a daily estimate of traffic perhaps they are acceptable. What if they are used in additional extrapolation procedure to estimate annual traffic? A rough calculation using some test day-of-week and monthly factors can give an idea as to how much error might accumulate for an annual estimate using a daily estimate with some initial error. Annual estimates will be compared based on the method for estimating their daily traffic.

Even though the NBPDP factors have proven themselves as unreliable for the study region, for the purposes of estimating annual bicycle traffic, the NBPDP day-of-week and monthly factors will be applied to a small number of time-of-day estimates to determine how daily estimate error might compound for annual traffic estimates. The NBPDP recommends using 0.13 and 0.12 day-of week factors for Tuesday and Thursday respectively. They also recommend using 0.06 as a monthly factor for counts collected in October and November. Therefore the annual estimation equation will be as follows:

Figure 4.1 – Annual Bicycle Traffic Estimation Equation

$$AnnualTraffic_i = \left(\; DailyEstimate / WeeklyFactor / MonthlyFactor) \; \right)$$

where *AnnualTraffic* is the total yearly bicycle traffic estimate, *DailyEstimate* is the estimate from the time-of-day factor application, *WeeklyFactor* is the day-of-week factor from NBPDP described above and the *MonthlyFactor* is the monthly factor from NBPDP described above. Applying this equation to just one location where the daily estimate varied between study area factors and NBPDP factors, the difference of yearly bicycle traffic will be presented. This quick examination will use a daily estimate from the Frohnmayer South River location which when using the study area Scenario 2 PM factors resulted in almost no error but when applying the NBPDP factors results in 47% error. The results from this annual extrapolation are presented below.

Table 4.1 – Annual Estimate pf Bicycle Traffic Results

Location	Daily Estimate	Observed	Absolute Percent Difference(Time-of-Day Factor Estimate)	Annual Estimate	Factor Type
FrohnmayerSouthRiver	1686	1691	0%	23,417	Study Area PM Scenario 2
FrohnmayerSouthRiver	2478	1691	47%	34,417	NBPDP PM

The annual result error does not necessary compound the daily estimate result using the above day-of-week and monthly factors as the NBPDP derived daily estimate results in a 47% higher annual estimate which is identical to the original time-of-day factor derived result. However, the total bicyclist difference is 11,000 which would have some major implications in any analysis that used these figures as their basis for bicycle travel. Any kind of public health or green house gas analysis using these numbers would vastly over estimate the benefits from bicycle travel using the NBPDP derived estimate. The implications would be similar for a safety analysis where bicyclist's crash data were used in conjunction to this annualized estimate. More work needs to be done to compare how estimates derived from factoring affect the uses of those estimates. Minimizing error should be the goal in all factor development and application of factors whether they are time-of-day, day-of-week, or monthly.

It is possible that additional factor groups are needed to further refine the estimation results. One issue is how to best describe the factor group without count data to support the classification. Bike facility makes for an easy factor group because it only requires that the facility type is known but this may not get at the user differences adequately, as was seen in the off-street path factor group between Scenario 1 and 2. More testing could be done using attributes of urban form in and around the count location to establish more factor groups though that does take more data which might not be available to all users.

4.5 – Research Limitations

It is important to restate that the study area factors were constructed using only Tuesday and Thursday data. Tuesday and Thursday average daily volumes and hourly distributions are similar and remove some of the variation that would likely cause more error if different days of the week were used. Some counts from the summer had multiple days of the week but because of the structure of the count program from which this data was collected, Tuesday and Thursdays are the only days collected for nearly all the locations. The factors presented above then are AM and PM peak period factors for Tuesday and Thursday and would likely be different for other days of the week, especially weekends when bicycle travel is primarily recreational. This would imply that hourly patterns would probably change for all factor groups.

Another limitation to this research is the application of NBPDP for all types of bicycle facilities. The NBPDP factors are only designed to be applied to either a pedestrian district or an off-street path facility, though no explicit guidance against doing so is found on in the NBPDP documentation. Additionally, of the reports that applied NBDPD factors, many counts came from non-path facility types.

The product of using short-term two-hour counts to estimate 24-hour volumes is not the most useful result. As the NBPDP factoring methodology does provide factors to extrapolate short-term counts to weekly, and ultimately monthly, and yearly volumes, any factors developed from local data should also look to maintain the capability to estimate longer term, ideally, annual, traffic counts. Some analysis tools like the World Health Organization's Health Economic Assessment Tools (HEAT) instrument prefer longer term counts that represent average traffic levels (WHO 2011). Additionally, annual volumes tell a more compelling story to the public and to policy makers that are looking at how best to spend scarce public dollars. Though daily estimates from short-term counts are not the most compelling, they may still be an important metric for traffic if more agencies continue to only collect two-hour counts.

This research did attempt to refine the time-of-day estimation process by splitting the typical practice of summing both directions of travel and estimating each direction separately. This led to some improvement in locations that were one-way but overall did not significantly improve estimation results.

4.6 – Conclusion

Having the ability to use short-term two-hour bicycle counts to reliably estimate full day 24-hour counts allows transportation analysts and planners the ability to use fewer resources to get more information they may need for both short-term and long-term planning goals. Having reliable time-of-day factors to estimate daily traffic would reduce error in any analysis where daily traffic estimates are employed. This research tested time-of-day factors developed from study area bicycle counts and compares the results from applying factors from the NBPDP, and found that study area factors consistently out perform NBPDP factors. Factors developed in Scenario 2 from study area data produced results with the least amount of error though it would be up to those wishing to apply factors in a similar way to determine how much error is acceptable. NBPDP factors do not appear to be deployable in the study area without acceptance of levels of error that might mis-characterize the location's level of bicycle traffic. Other areas looking to augment their own two-hour counts by applying the NBPDP factors should do so with caution and this research recommends some kind of validation of the factors similar to what was done for this research. Creating factor groupings on bicycle facility and users is a convenient way to refine factors that help reduce error from 24-hour estimates.

Reliability of estimates was reduced when counts with less than 100 daily riders were observed. This finding would suggest that hourly distributions for these kinds of locations are highly variable and that when locations with low daily traffic are are counted using manual data, multiple 2-hour counts should be collected and averaged in order to reduce some of the variation. This recommendation is supported in the NBPDP documentation where they suggest averaging multiple 2-hour manual counts and report the average.

This work establishes the university travel activity pattern using study area data which may help other areas when they think about how to classify behavior on bicycle facilities. Though not useful for time-of-day factoring, the university travel pattern might be useful for monthly or annual factoring processes. More work should be done in this area. This research also examined available data sets including national and statewide travel survey data in order to assess the ability of those data sources to determine usable time-of-day factors, finding these data sources do not produce usable factors.

For practitionaers and others thinking about how to start a count program, the NBPDP offers good guidance on how to begin data collection but the use of their factors should be limited. If manual counts do not provide enough information and automatic technology can be acquired, a great deal more about bicycle traffic can be learned. Using 24-hour count data collected from automatic devices, time-of-day factors can be derived based on factor groupings that are easily constructed which can then be used to augment any on going or future manual count program. Even without applying factors, so much more information can be acquired with a limited number of automatic movable counting devices. The CLMPO was able to collect all of the data used in this research with just four movable tube counters.

As the funding sources increase for non-motorized traffic, it should become easier to justify spending money on tracking bicycle traffic changes. Two-hour counts provide some useful information about traffic levels but they do not supplant the resolution of full day or week counts. The ultimate goal should be permanent counters that detail each hour of each day over the course of an entire year. As bicycle traffic counting become more common and the investments in bicycle infrastructure can be demonstrated, more investment can be substantiated, which wouldcreate a feedback loop that will help supply the many benefits of bicycling to a growing number of people. Bicycle count programs have begun all over the country, and some, like those in Boulder, Colorado, Minneapolis, Minnesota, and San Diego California, have also installed a large number of permanent continuous automatic counters. As these programs mature and more like them come online, factoring methodologies should catch up to their motorized traffic counter parts, though likely not soon enough. Whether counts are used as supplemental inputs into safety planning or health impact assessments or simply as a performance measure to determine how well a particular areas' investment in bicycle infrastructure is performing, bike count data are vital in telling the story that U.S. Census data like journey to work is unable to tell. Some agencies and practitioners will be unable to afford counting equipment and will rely on manual counts collected by volunteers long into the future which will make reliable extrapolation factors increasingly important. As efforts such as the NPBPD develop, state departments of transportation and metropolitan planning organizations will hopefully gain a greater understanding of these estimation processes and will seek to provide locally relevant bicycle traffic count factors as many of them currently do for motorized traffic.

The benefits from increased bicycling, whether it is for utilitarian purposes like commuting to work or recreational trips, are becoming increasingly apparent with growing body of evidence. The public health, economic development and environmental benefits as well as energy savings from increased walking and biking are demonstratable. Funding bicycle and active transportation improvements in general will likely grow as they have over the last 20 years. According to the bicycle and walking advocacy group Advocacy Advance, federal funding for bicycle and pedestrian related projects has increase from less than $50 million per year to over $600 million a year not accounting for America Reinvestment and Recovery Act funding which would add over a billion dollars to this amount. (Advocacy Advance 2011) If the level of funding for active modes remains stable or continues to grow, planning agencies will need to better measure and understand travel demand for active transportation. Counting users is a necessary next step but updated travel demand models and other analystical tools is also necessary so that policy makers, planners, and the public have the right information to make good decisions about the transportation system.

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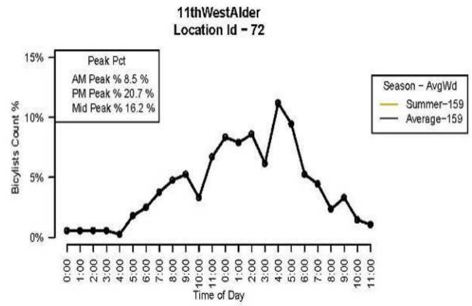
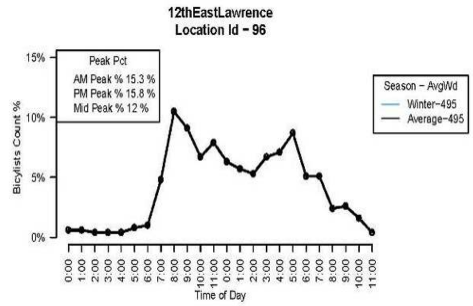
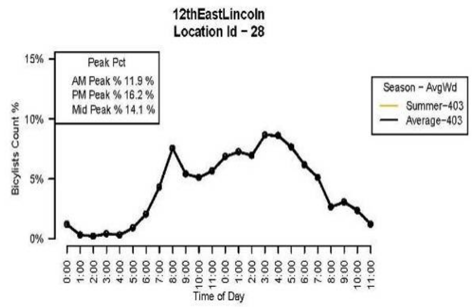
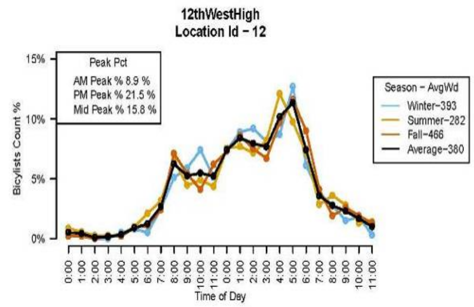
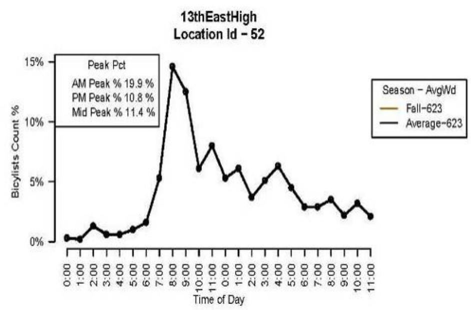
Appendix A - Seasonal Comparison of Hourly Distributions

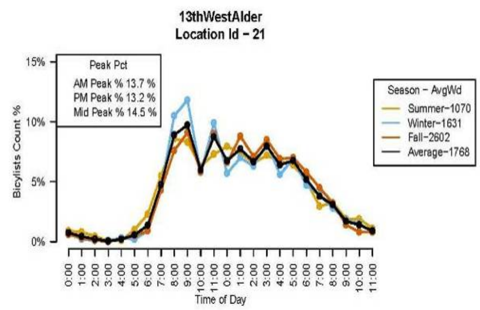


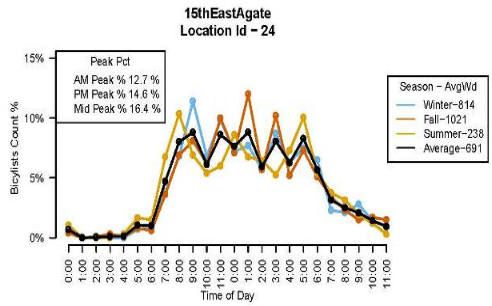


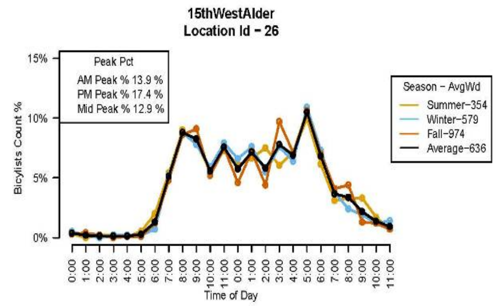









15thEastAgate
Location Id = 24
Peak Pct
AM Peak % 12.7 %
PM Peak % 14.6 %
Mid Peak % 16.4 %
Season – AvgWd
Winter–814
Fall–1021
Summer–238
Average–691
Bicylists Count %
Time of Day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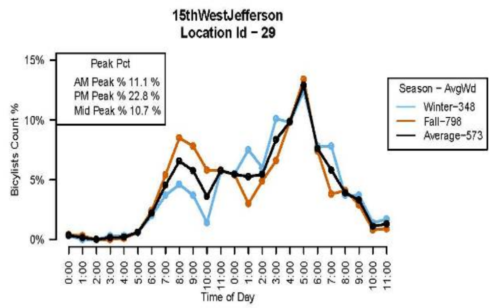
Location Id = 26
Peak Pct
AM Peak % 13.9 %
PM Peak % 17.4 %
Mid Peak % 12.9 %
Season – AvgWd
Summer–354
Winter–579
Fall–974
Average–636
Bicylists Count %
Time of Day


15thWestJefferson
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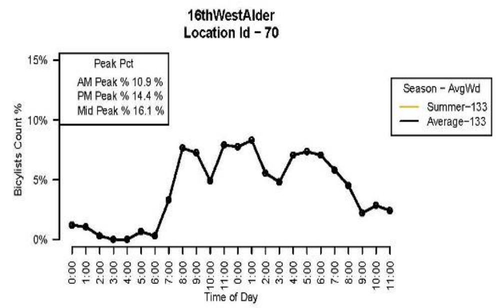
Peak Pct
AM Peak % 11.1 %
PM Peak % 22.8 %
Mid Peak % 10.7 %
Season – AvgWd
Winter–348
Fall–798
Average–573
Bicylists Count %
Time of Day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Location Id = 70
Peak Pct
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PM Peak % 14.4 %
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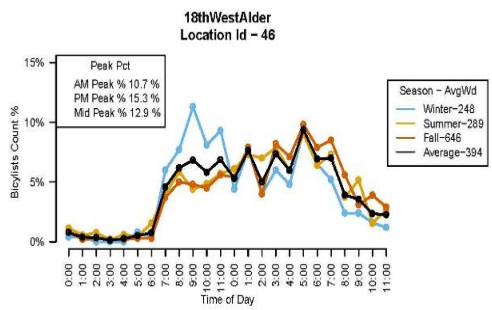
Season – AvgWd
Summer–133
Average–133
Bicylists Count %
Time of Day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Location Id = 46
Peak Pct
AM Peak % 10.7 %
PM Peak % 15.3 %
Mid Peak % 12.9 %
Season – AvgWd
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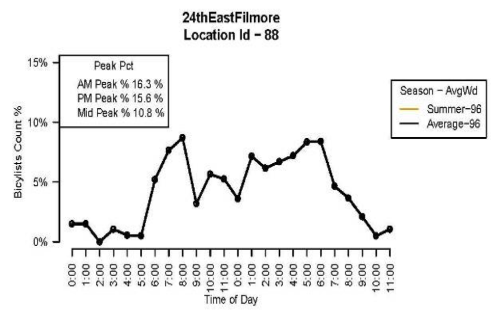
Summer–289
Fall–646
Average–394
Bicylists Count %
Time of Day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Location Id = 88
Peak Pct
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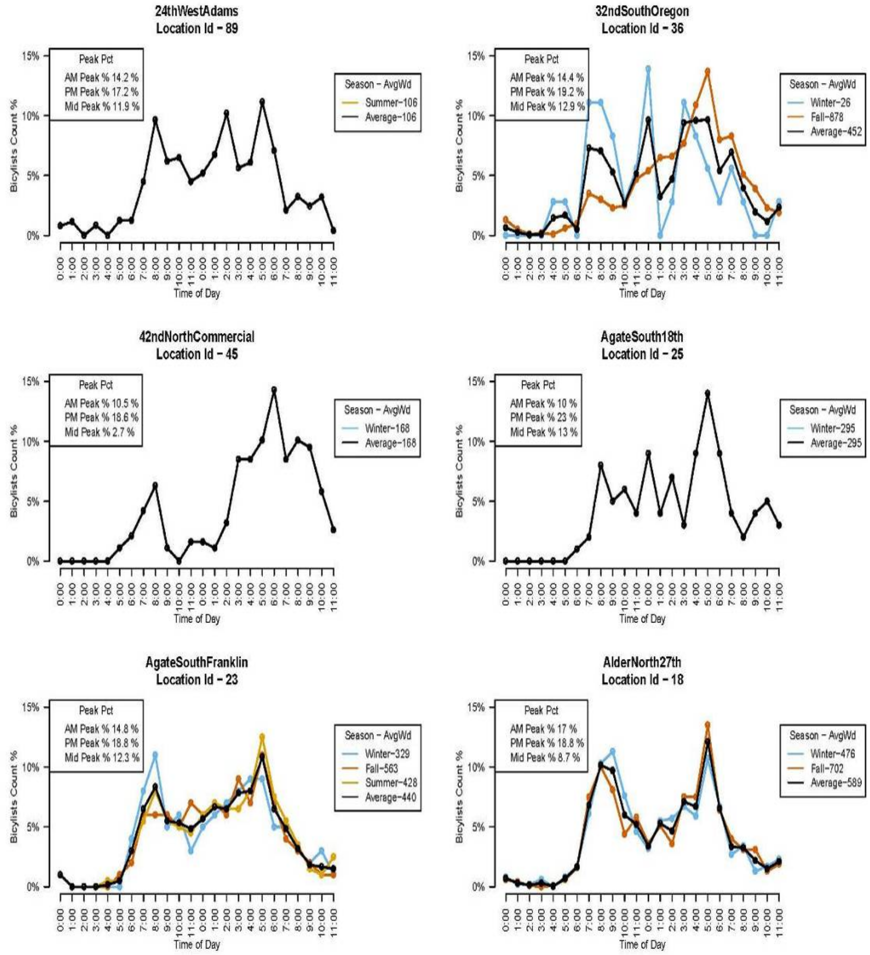
Mid Peak % 10.8 %
Season – AvgWd
Summer–96
Average–96
Bicylists Count %
Time of Day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Peak Pct
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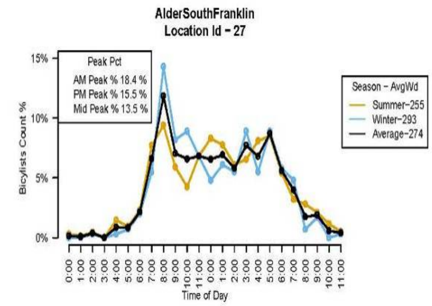
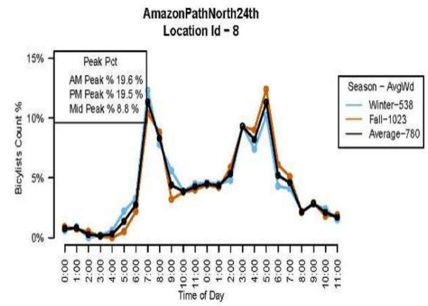
PM Peak % 17.2 %
Mid Peak % 11.9 %
Season - AvgWd
Summer-106
Average-106
Bicylists Count %
Time of Day
32ndSouthOregon
Location Id - 36
Peak Pct
AM Peak % 14.4 %
PM Peak % 19.2 %
Mid Peak % 12.9 %
Season - AvgWd
Winter-26
Fall-678
Average-452
42ndNorthCommercial
Location Id - 45
Peak Pct
AM Peak % 10.5 %
PM Peak % 18.6 %
Mid Peak % 2.7 %
Season - AvgWd
Winter-168
Average-168
AgateSouth18th
Location Id - 25
Peak Pct
AM Peak % 10 %
PM Peak % 23 %
Mid Peak % 13 %
Season - AvgWd
Winter-295
Average-295
AgateSouthFranklin
Location Id - 23
Peak Pct
AM Peak % 14.8 %
PM Peak % 18.8 %
Mid Peak % 12.3 %
Season - AvgWd
Winter-329
Fall-563
Summer-428
Average-440
AlderNorth27th
Location Id - 18
Peak Pct
AM Peak % 17 %
PM Peak % 18.8 %
Mid Peak % 8.7 %
Season - AvgWd
Winter-476
Fall-702
Average-589


AlderSouthFranklin
Location Id - 27
Peak Pct
AM Peak % 18.4 %
PM Peak % 15.5 %
Mid Peak % 13.5 %
Season - AvgWd
Summer-255
Winter-293
Average-274
Bicylists Count %
Time of Day


AmazonPathNorth24th
Location Id - 8
Peak Pct
AM Peak % 19.6 %
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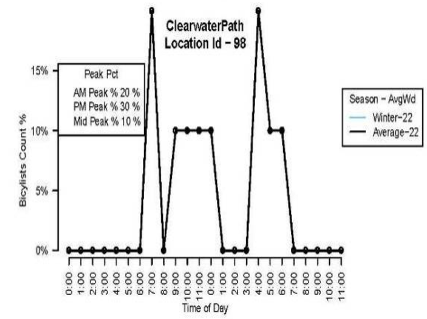
Mid Peak % 8.8 %
Season - AvgWd
Winter-538
Fall-1023
Average-780
Bicylists Count %
Time of Day


ClearwaterPath
Location Id - 98
Peak Pct
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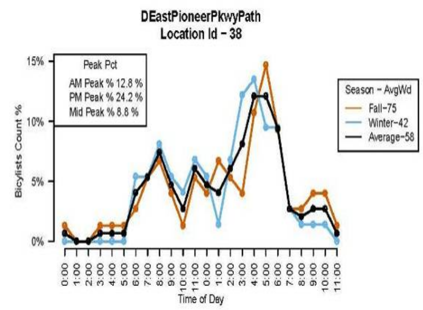
PM Peak % 30 %
Mid Peak % 10 %
Season - AvgWd
Winter-22
Average-22
Bicylists Count %
Time of Day


DEastPioneerPkwyPath
Location Id - 38
Peak Pct
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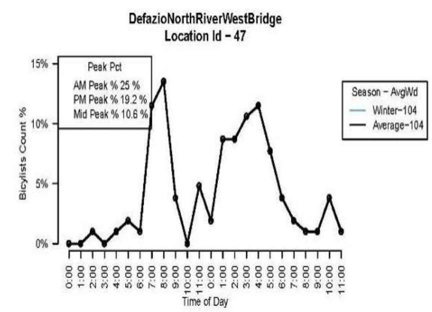
PM Peak % 24.2 %
Mid Peak % 8.8 %
Season - AvgWd
Fall-75
Winter-42
Average-58
Bicylists Count %
Time of Day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Location Id - 47
Peak Pct
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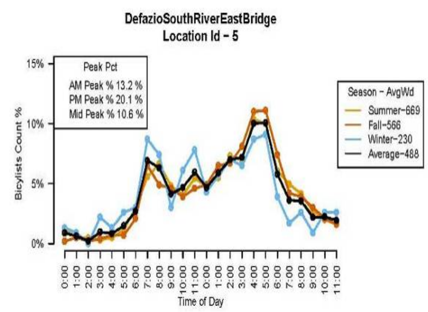
PM Peak % 19.2 %
Mid Peak % 10.6 %
Season - AvgWd
Winter-104
Average-104
Bicylists Count %
Time of Day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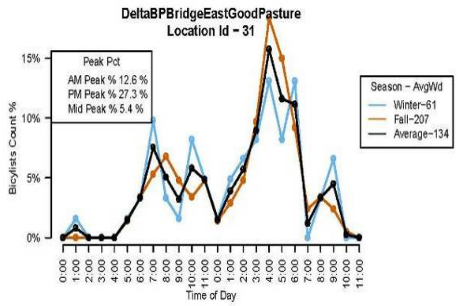
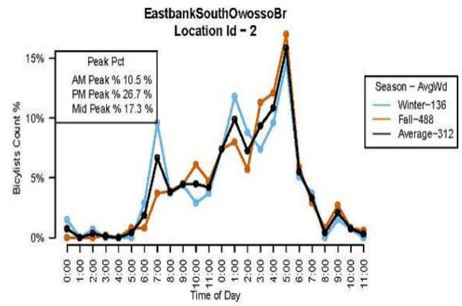
Location Id - 5
Peak Pct
AM Peak % 13.2 %
PM Peak % 20.1 %
Mid Peak % 10.6 %
Season - AvgWd
Summer-669
Fall-566
Winter-230
Average-488
Bicylists Count %
Time of Day


DeltaBPBridgeEastGoodPasture
Location Id - 31
Peak Pct
AM Peak % 12.6 %
PM Peak % 27.3 %
Mid Peak % 5.4 %
Season - AvgWd
Winter-61
Fall-207
Average-134
Bicylists Count %
Time of Day


EastbankSouthOwossoBr
Location Id - 2
Peak Pct
AM Peak % 10.5 %
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Season - AvgWd
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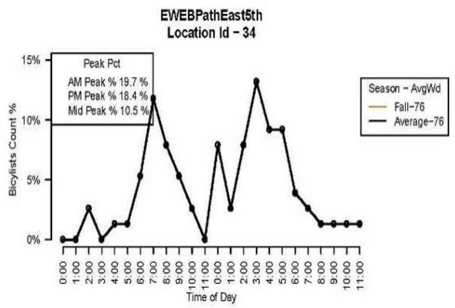
Fall-488
Average-312
Bicylists Count %
Time of Day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Season - AvgWd
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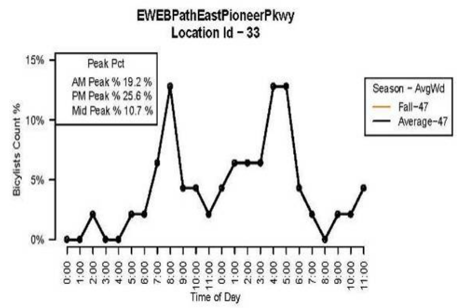
Average-76
Bicylists Count %
Time of Day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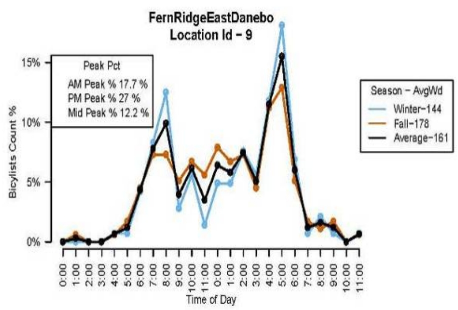
Average-47
Bicylists Count %
Time of Day


FernRidgeEastDanebo
Location Id - 9
Peak Pct
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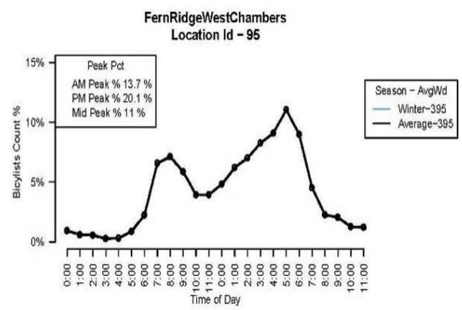
Bicylists Count %
Time of Day


FernRidgeWestChambers
Location Id - 95
Peak Pct
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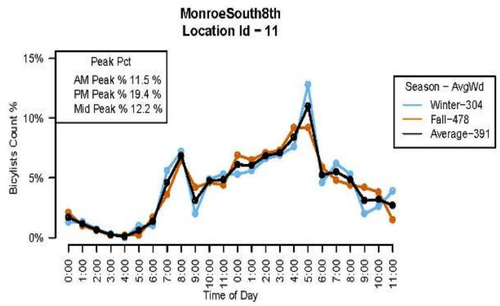
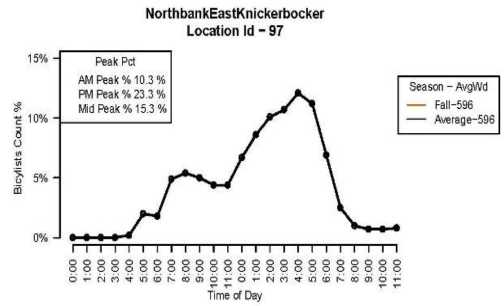
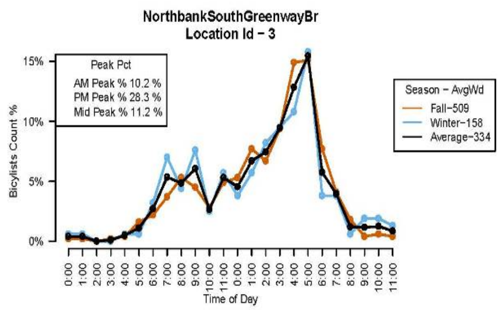
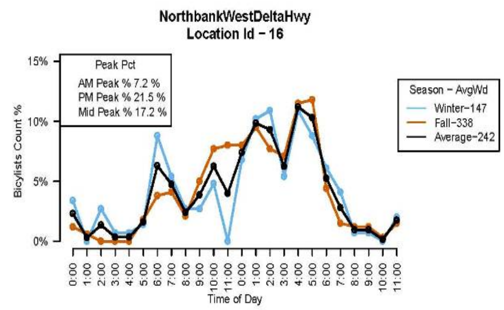
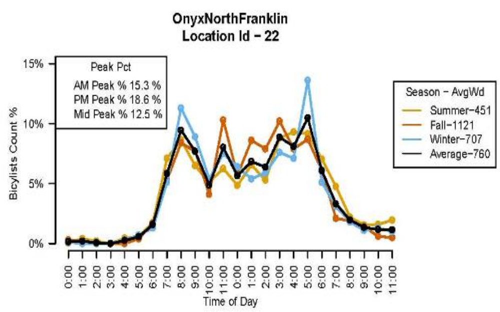
PM Peak % 20.1 %
Mid Peak % 11 %
Season - AvgWd
Winter-395
Average-395
Bicylists Count %
Time of Day

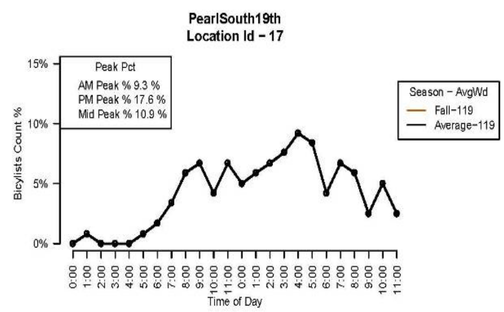

MonroeSouth8th
Location Id - 11
Peak Pct
AM Peak % 11.5 %
PM Peak % 19.4 %
Mid Peak % 12.2 %
Season - AvgWd
Winter-304
Fall-478
Average-391
Bicylists Count %
Time of Day

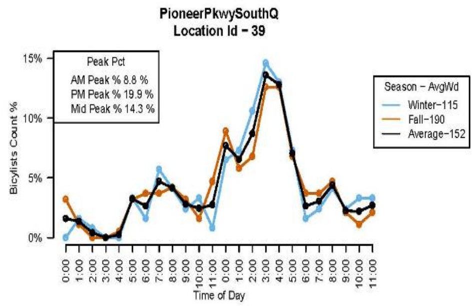

NorthbankEastKnickerbocker
Location Id - 97
Peak Pct
AM Peak % 10.3 %
PM Peak % 23.3 %
Mid Peak % 15.3 %
Season - AvgWd
Fall-596
Average-596
Bicylists Count %
Time of Day

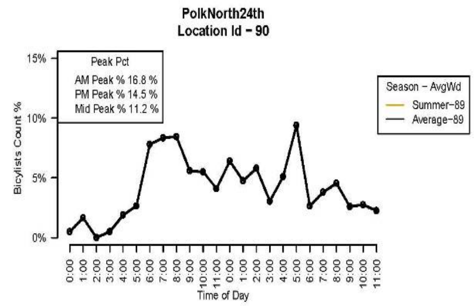

NorthbankSouthGreenwayBr
Location Id - 3
Peak Pct
AM Peak % 10.2 %
PM Peak % 28.3 %
Mid Peak % 11.2 %
Season - AvgWd
Fall-509
Winter-158
Average-334
Bicylists Count %
Time of Day

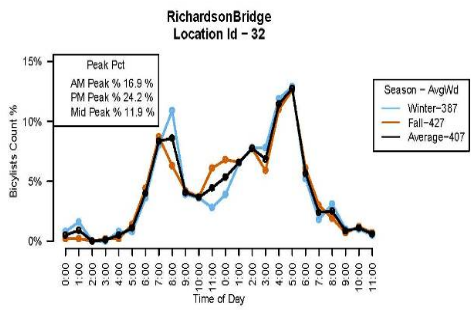

NorthbankWestDeltaHwy
Location Id - 16
Peak Pct
AM Peak % 7.2 %
PM Peak % 21.5 %
Mid Peak % 17.2 %
Season - AvgWd
Winter-147
Fall-338
Average-242
Bicylists Count %
Time of Day

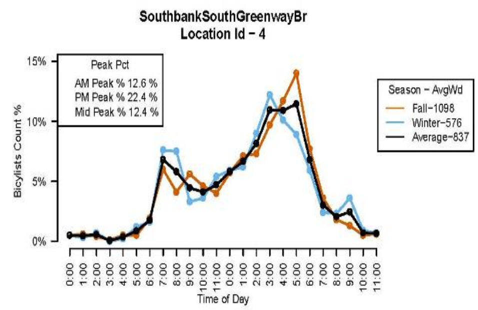

OnyxNorthFranklin
Location Id - 22
Peak Pct
AM Peak % 15.3 %
PM Peak % 18.6 %
Mid Peak % 12.5 %
Season - AvgWd
Summer-451
Fall-1121
Winter-707
Average-760
Bicylists Count %
Time of Day

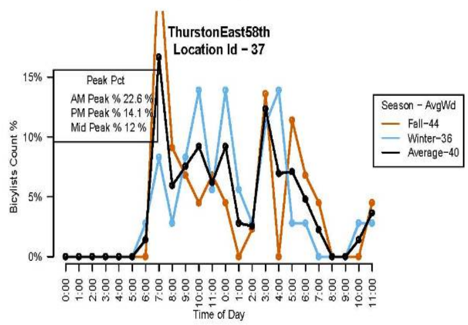

PearlSouth19th
Location Id - 17
Peak Pct
AM Peak % 9.3 %
PM Peak % 17.6 %
Mid Peak % 10.9 %
Season - AvgWd
Fall-119
Average-119
Bicylists Count %
Time of Day

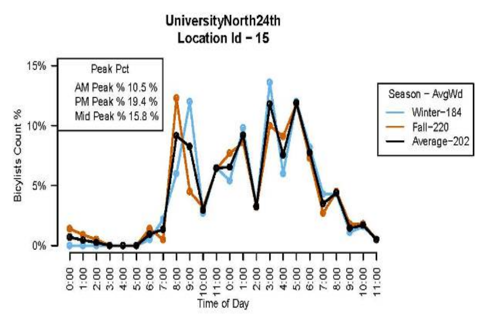

PioneerPkwySouthQ
Location Id - 39
Peak Pct
AM Peak % 8.8 %
PM Peak % 19.9 %
Mid Peak % 14.3 %
Season - AvgWd
Winter-115
Fall-190
Average-152
Bicylists Count %
Time of Day


PolkNorth24th
Location Id - 90
Peak Pct
AM Peak % 16.8 %
PM Peak % 14.5 %
Mid Peak % 11.2 %
Season - AvgWd
Summer-89
Average-89
Bicylists Count %
Time of Day

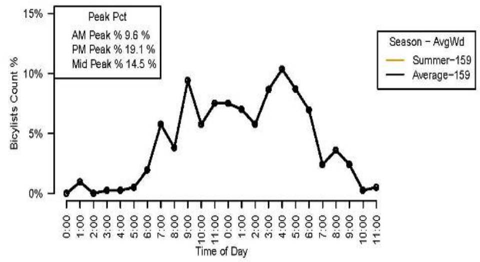

RichardsonBridge
Location Id - 32
Peak Pct
AM Peak % 16.9 %
PM Peak % 24.2 %
Mid Peak % 11.9 %
Season - AvgWd
Winter-387
Fall-427
Average-407
Bicylists Count %
Time of Day


SouthbankSouthGreenwayBr
Location Id - 4
Peak Pct
AM Peak % 12.6 %
PM Peak % 22.4 %
Mid Peak % 12.4 %
Season - AvgWd
Fall-1098
Winter-576
Average-837
Bicylists Count %
Time of Day

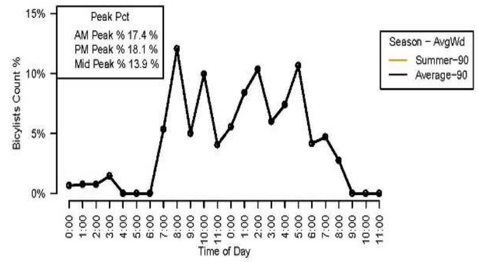

ThurstonEast58th
Location Id - 37
Peak Pct
AM Peak % 22.6 %
PM Peak % 14.1 %
Mid Peak % 12 %
Season - AvgWd
Fall-44
Winter-36
Average-40
Bicylists Count %
Time of Day


UniversityNorth24th
Location Id - 15
Peak Pct
AM Peak % 10.5 %
PM Peak % 19.4 %
Mid Peak % 15.8 %
Season - AvgWd
Winter-184
Fall-220
Average-202
Bicylists Count %
Time of Day

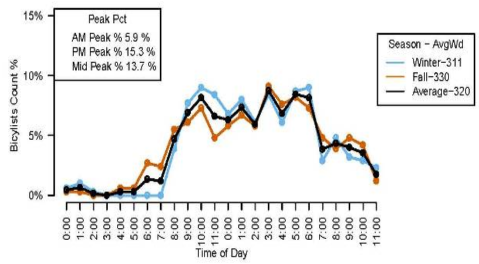
UniversitySouth18th
Location Id = 71

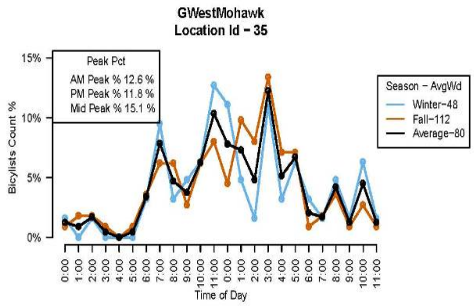


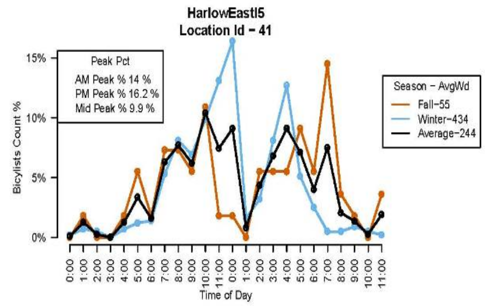
UniversitySouth24th
Location Id = 65

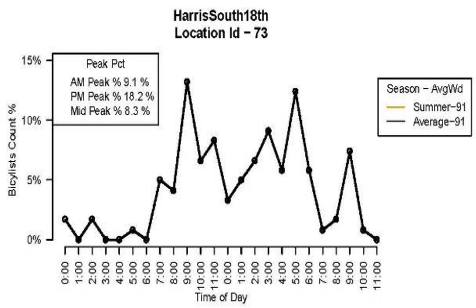


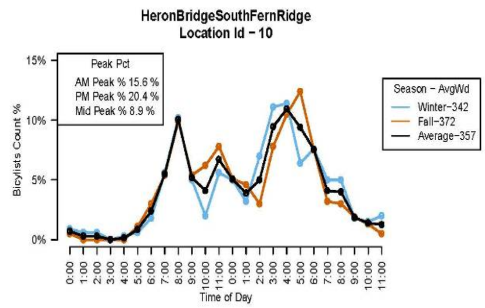
WillametteNorth15th
Location Id = 13

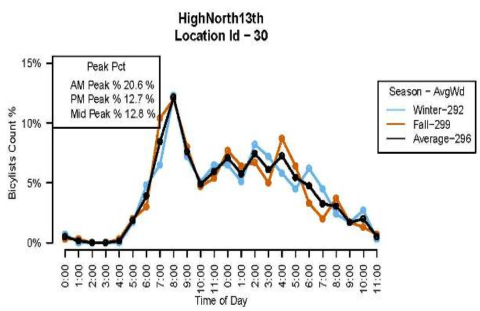


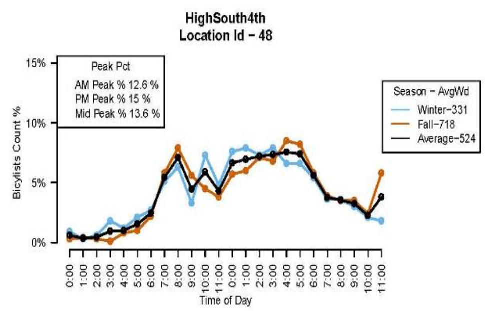

GWestMohawk
Location Id - 35
Peak Pct
AM Peak % 12.6 %
PM Peak % 11.8 %
Mid Peak % 15.1 %
Season - AvgWd
Winter-48
Fall-112
Average-80
Bicylists Count %
Time of Day


HarlowEastI5
Location Id - 41
Peak Pct
AM Peak % 14 %
PM Peak % 16.2 %
Mid Peak % 9.9 %
Season - AvgWd
Fall-55
Winter-434
Average-244
Bicylists Count %
Time of Day

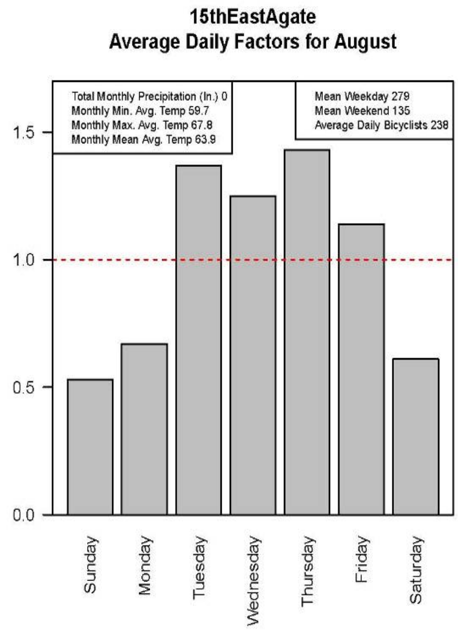

HarrisSouth18th
Location Id - 73
Peak Pct
AM Peak % 9.1 %
PM Peak % 18.2 %
Mid Peak % 8.3 %
Season - AvgWd
Summer-91
Average-91
Bicylists Count %
Time of Day

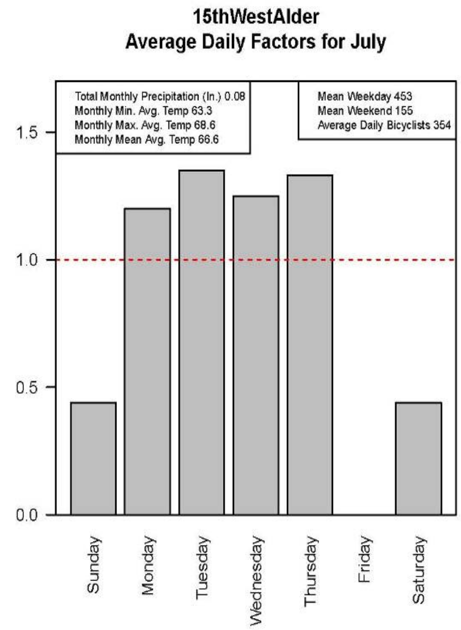

HeronBridgeSouthFernRidge
Location Id - 10
Peak Pct
AM Peak % 15.6 %
PM Peak % 20.4 %
Mid Peak % 8.9 %
Season - AvgWd
Winter-342
Fall-372
Average-357
Bicylists Count %
Time of Day

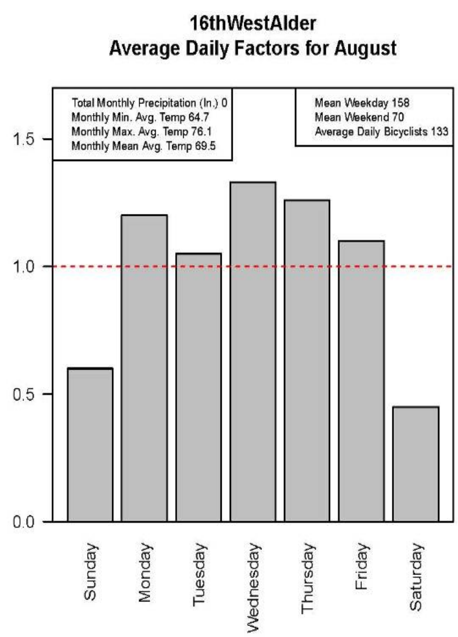

HighNorth13th
Location Id - 30
Peak Pct
AM Peak % 20.6 %
PM Peak % 12.7 %
Mid Peak % 12.8 %
Season - AvgWd
Winter-292
Fall-299
Average-296
Bicylists Count %
Time of Day

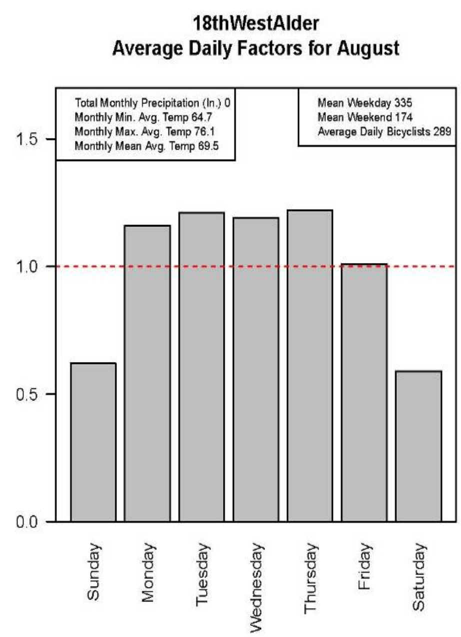

HighSouth4th
Location Id - 48
Peak Pct
AM Peak % 12.6 %
PM Peak % 15 %
Mid Peak % 13.6 %
Season - AvgWd
Winter-331
Fall-718
Average-524
Bicylists Count %
Time of Day

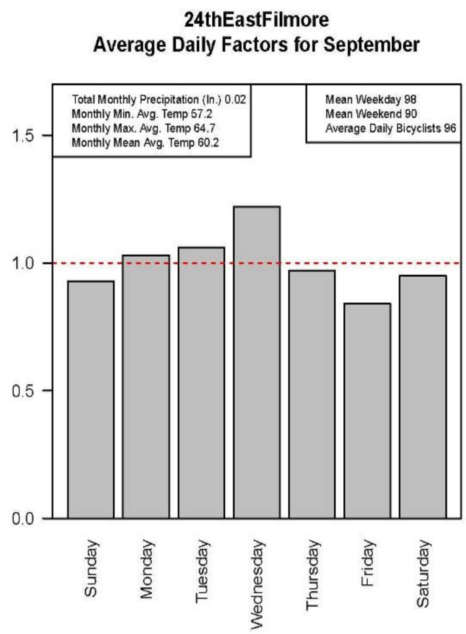
Appendix B - Proportion of Weekly Travel by Day of Week

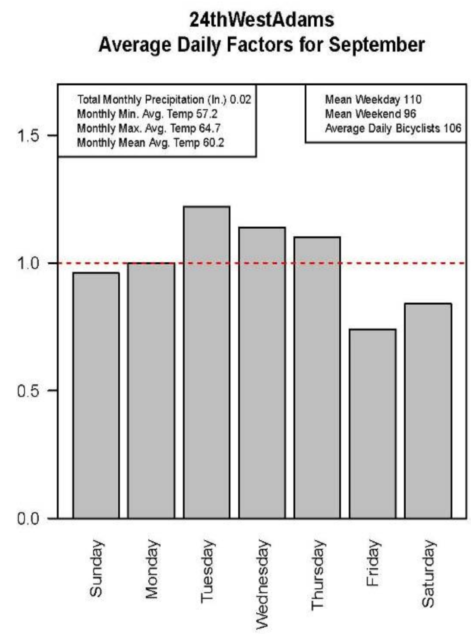


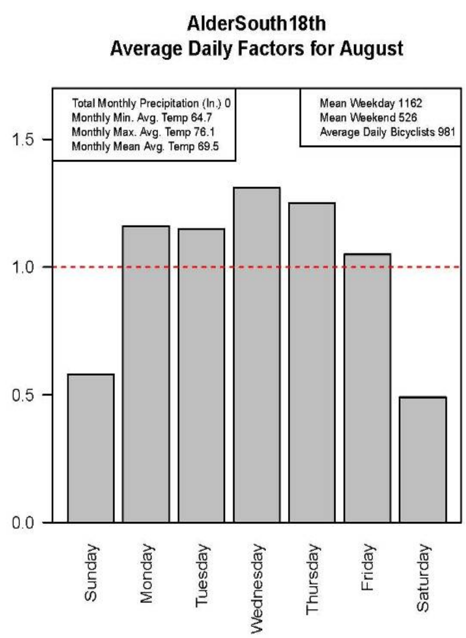


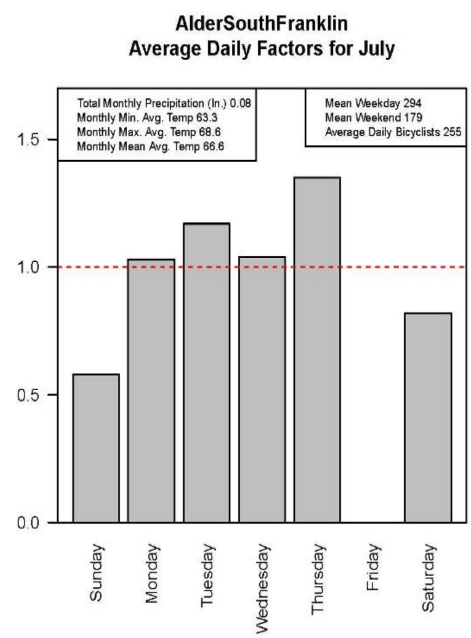


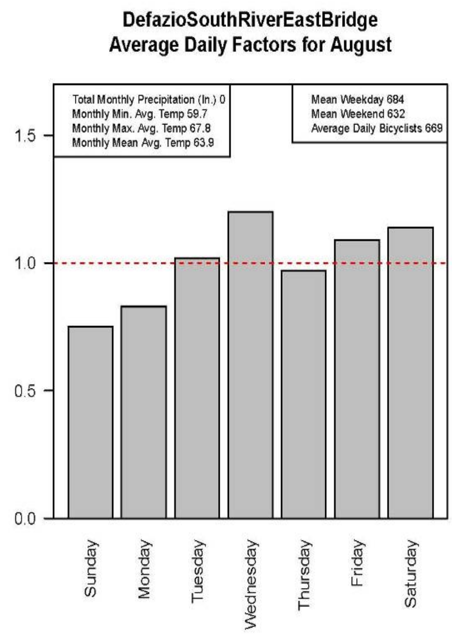


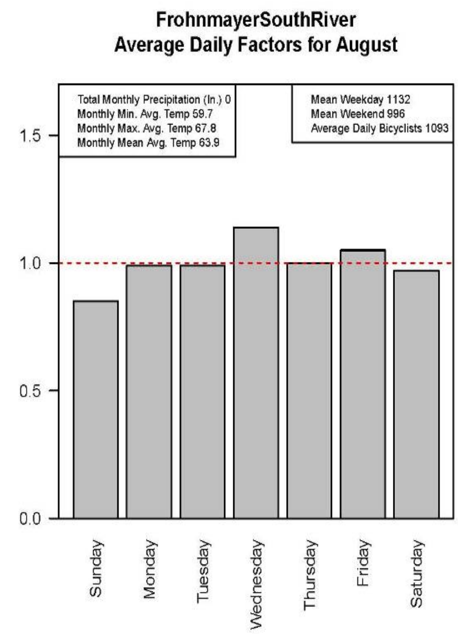

24thEastFilmore
Average Daily Factors for September
Total Monthly Precipitation (In.) 0.02
Monthly Min. Avg. Temp 57.2
Monthly Max. Avg. Temp 64.7
Monthly Mean Avg. Temp 60.2
Mean Weekday 98
Mean Weekend 90
Average Daily Bicyclists 96
1.5
1.0
0.5
0.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday

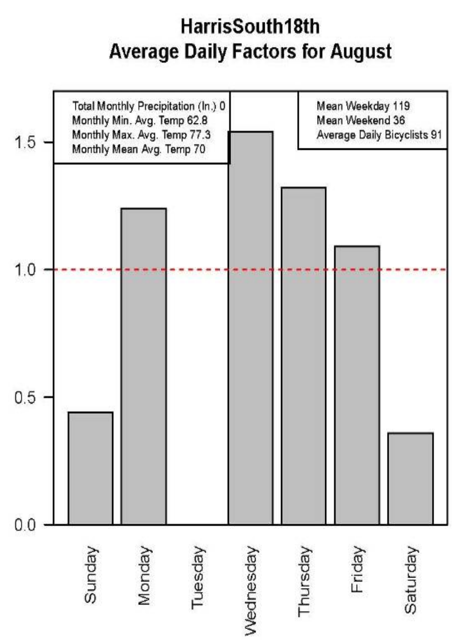

24thWestAdams
Average Daily Factors for September
Total Monthly Precipitation (In.) 0.02
Monthly Min. Avg. Temp 57.2
Monthly Max. Avg. Temp 64.7
Monthly Mean Avg. Temp 60.2
Mean Weekday 110
Mean Weekend 96
Average Daily Bicyclists 106
1.5
1.0
0.5
0.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday

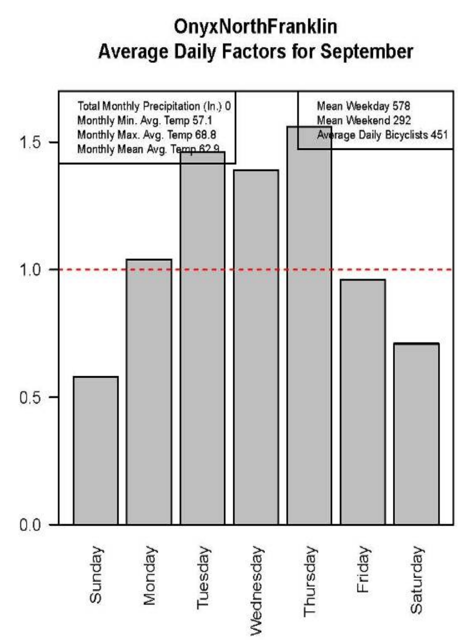

AlderSouth18th
Average Daily Factors for August
Total Monthly Precipitation (In.) 0
Monthly Min. Avg. Temp 64.7
Monthly Max. Avg. Temp 76.1
Monthly Mean Avg. Temp 69.5
Mean Weekday 1162
Mean Weekend 526
Average Daily Bicyclists 981
1.5
1.0
0.5
0.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday

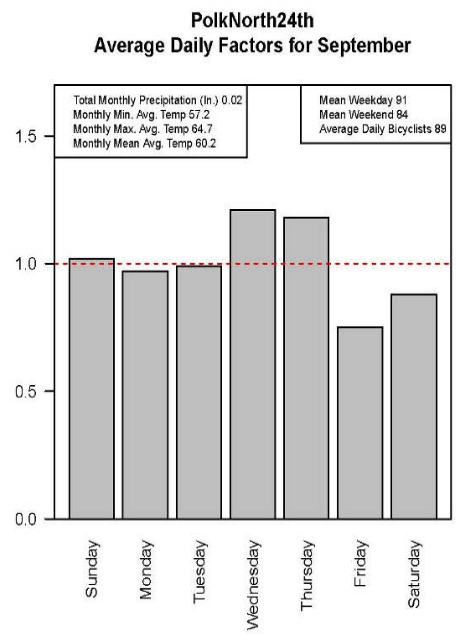

AlderSouthFranklin
Average Daily Factors for July
Total Monthly Precipitation (In.) 0.08
Monthly Min. Avg. Temp 63.3
Monthly Max. Avg. Temp 68.6
Monthly Mean Avg. Temp 66.6
Mean Weekday 294
Mean Weekend 179
Average Daily Bicyclists 255
1.5
1.0
0.5
0.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday

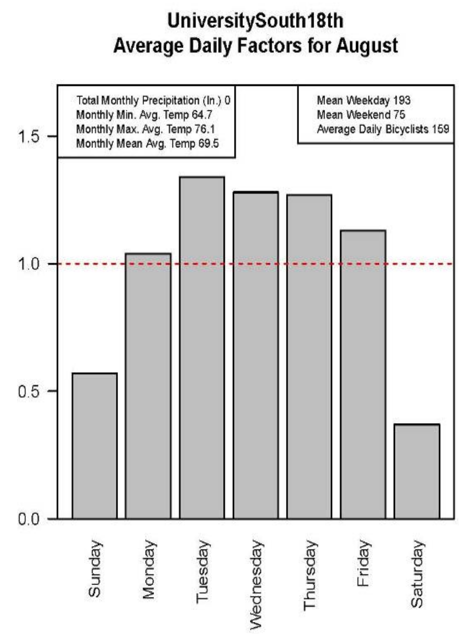

DefazioSouthRiverEastBridge
Average Daily Factors for August
Total Monthly Precipitation (In.) 0
Monthly Min. Avg. Temp 59.7
Monthly Max. Avg. Temp 67.8
Monthly Mean Avg. Temp 63.9
Mean Weekday 684
Mean Weekend 632
Average Daily Bicyclists 669
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday


FrohnmayerSouthRiver
Average Daily Factors for August
Total Monthly Precipitation (In.) 0
Monthly Min. Avg. Temp 59.7
Monthly Max. Avg. Temp 67.8
Monthly Mean Avg. Temp 63.9
Mean Weekday 1132
Mean Weekend 996
Average Daily Bicyclists 1093
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday


HarrisSouth18th
Average Daily Factors for August
Total Monthly Precipitation (In.) 0
Monthly Min. Avg. Temp 62.8
Monthly Max. Avg. Temp 77.3
Monthly Mean Avg. Temp 70
Mean Weekday 119
Mean Weekend 36
Average Daily Bicyclists 91
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday


OnyxNorthFranklin
Average Daily Factors for September
Total Monthly Precipitation (In.) 0
Monthly Min. Avg. Temp 57.1
Monthly Max. Avg. Temp 68.8
Monthly Mean Avg. Temp 62.9
Mean Weekday 578
Mean Weekend 292
Average Daily Bicyclists 451
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday


PolkNorth24th
Average Daily Factors for September
Total Monthly Precipitation (In.) 0.02
Monthly Min. Avg. Temp 57.2
Monthly Max. Avg. Temp 64.7
Monthly Mean Avg. Temp 60.2
Mean Weekday 91
Mean Weekend 84
Average Daily Bicyclists 89
1.5
1.0
0.5
0.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday


UniversitySouth18th
Average Daily Factors for August
Total Monthly Precipitation (In.) 0
Monthly Min. Avg. Temp 64.7
Monthly Max. Avg. Temp 76.1
Monthly Mean Avg. Temp 69.5
Mean Weekday 193
Mean Weekend 75
Average Daily Bicyclists 159
1.5
1.0
0.5
0.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday

Appendix C

All Daily Counts Data

Download the data in .csv format

All Hourly Counts Data

Download the data in .csv format

Appendix D
R Code

```
#########################################################################
###################################
    #        Bicycle Traffic Count Factoring: An Examination of National and Locally
Derived Daily                    #
    #                        Extrapolation Factors Bicycle Traffic Count
     #
    #########################################################################
######################################

    #Author : Josh Roll (MAsters of Urban Studies Candidate)
    #Date: 4/12/13
    #Masters Thesis Bicycle Traffic Factoring Analysis



    #.....................................................
    #Load and prepare data for analysis
    #..........................................................
    #Create script defaults
    #------------------------------------
    #Create 24-hours vector
    Hours. <- as.character(seq(0,2300,100))
    Hours. <- paste(c(0:23),"00",sep=":")

    #Load Data
    #-----------------
    HourlyPct.. <- read.csv("SummaryTables/HourlyPct.csv",stringsAsFactors =FALSE )
    Hourly.. <- read.csv("SummaryTables/Hourly.csv",stringsAsFactors =FALSE )
    Daily.. <- read.csv("SummaryTables/Daily.csv",stringsAsFactors =FALSE )

    #Load reference data
    CountLocationInformation.. <-
read.csv("SupportingData/CountLocationInformation.csv", as.is =TRUE)

    #Prepare Data
    #----------------------
    #Rename column headers
    colnames(HourlyPct..)[1:24] <- Hours.
    colnames(Hourly..)[1:24] <- Hours.

    #Clean out locations and time periods where data is bad or anomalis
```

```
HourlyPct..  <- HourlyPct.. [HourlyPct..$Location != "AlderSouth18th" ,]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "Total-13thWestAlder-11-28-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "Total-13thWestAlder-11-29-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "Total-13thWestAlder-11-30-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "East-13thWestAlder-11-28-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "East-13thWestAlder-11-29-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "East-13thWestAlder-11-30-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "West-13thWestAlder-11-28-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "West-13thWestAlder-11-29-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "West-13thWestAlder-11-30-2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "Total-11.28.2012-11.30.2012-13thWestAlder",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $Location != "13thEastKincaid",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $Location != "13thEastLincoln",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "Total-DefazioNorthRiverWestBridge-10.03.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "Total-DefazioNorthRiverWestBridge-10.04.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "Total-DefazioNorthRiverWestBridge-10.05.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "North-DefazioNorthRiverWestBridge-10.03.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "North-DefazioNorthRiverWestBridge-10.04.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "North-DefazioNorthRiverWestBridge-10.05.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "South-DefazioNorthRiverWestBridge-10.03.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "South-DefazioNorthRiverWestBridge-10.04.2012",]
HourlyPct..  <- HourlyPct.. [HourlyPct.. $UniqueId != "South-DefazioNorthRiverWestBridge-10.05.2012",]
Hourly..  <- Hourly.. [Hourly.. $Location != "AlderSouth18th",]
```

```
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "Total-13thWestAlder-11-28-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "Total-13thWestAlder-11-29-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "Total-13thWestAlder-11-30-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "East-13thWestAlder-11-28-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "East-13thWestAlder-11-29-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "East-13thWestAlder-11-30-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "West-13thWestAlder-11-28-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "West-13thWestAlder-11-29-2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "West-13thWestAlder-11-30-2012",]
Hourly..  <- Hourly.. [Hourly.. $Location != "13thEastKincaid",]
Hourly..  <- Hourly.. [Hourly.. $Location != "13thEastLincoln",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "Total-DefazioNorthRiverWestBridge-
10.03.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "Total-DefazioNorthRiverWestBridge-
10.04.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "Total-DefazioNorthRiverWestBridge-
10.05.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "North-DefazioNorthRiverWestBridge-
10.03.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "North-DefazioNorthRiverWestBridge-
10.04.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "North-DefazioNorthRiverWestBridge-
10.05.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "South-DefazioNorthRiverWestBridge-
10.03.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "South-DefazioNorthRiverWestBridge-
10.04.2012",]
Hourly..  <- Hourly.. [Hourly.. $UniqueId != "South-DefazioNorthRiverWestBridge-
10.05.2012",]
Hourly.. <- Hourly..[Hourly..$Location != "AgateSouth18thSB" && Hourly..$Period !=
"08.22.2012-08.30.2012",]
Hourly.. <- Hourly..[Hourly..$Location != "AgateSouth18thNB" && Hourly..$Period !=
"08.22.2012-08.30.2012",]

#Clean out all data not having 24 hours worth of data
Hourly..  <-  Hourly..[Hourly..$ObsHours == 24,]
HourlyPct..  <-  HourlyPct..[HourlyPct..$ObsHours == 24,]
#Clean out data without an observed daily total
Hourly.. <- Hourly..[Hourly..$DailyCounts > 0,]
HourlyPct.. <- HourlyPct..[HourlyPct..$DailyCounts > 0,]

#Remove Tuesday Thursday
```

```
    Hourly.. <- Hourly..[Hourly..$Weekday%in%c("Tuesday","Thursday"),]
    HourlyPct.. <- HourlyPct..[HourlyPct..$Weekday%in%c("Tuesday","Thursday"),]

    #Add Factor Groups
    Hourly..$FactorGroup <-
CountLocationInformation..$FactorGroup[match(Hourly..$Location,
CountLocationInformation..$Location)]
    HourlyPct..$FactorGroup <-
CountLocationInformation..$FactorGroup[match(HourlyPct..$Location,
CountLocationInformation..$Location)]




    #.......................................................................
    #Scenario 1 Application of Factors
    #.......................................................................

    #Load saved factor values
    load(file =
"T:/Data/COUNTS/BicycleCounts/LCOG/ExtrapolationValidationProject/Data/Factors_.R
Data")


    #Specify season to analyze
    SeasonToAnalyze <- "Fall"

    Factors_[["NoFacility"]] <- Factors_[["Local"]]
    Result_ <- list()
    Result2_ <- list()
    Labels_ <- list()
    AmPeak_ <- list()
    PmPeak_ <- list()


#Iterate through each time period
for(period in c("Am","Pm")){
    TempHourly.. <- Hourly..

    #Create lists to store results
    Result_ <- list()
    Result2_ <- list()
```

```
    Labels_ <- list()

    #Create a counter to project plot results
    PlotLocation <- 0
    #iterate through each hour
    #for(hours in c(1:12)){
        #Each city
        for(city in c("Eugene","Springfield","BothJurisdictions")){
            #Each facility type
            for(type in c("All","Path","Lane","Blvd","NoFacility")){

                if(type == "Blvd" && city == "Springfield"){
                } else {

                    #Use factors to estimate data held out
                    #================================================
                    #Determine data to predict using factors
                    LocationsToPredict.. <-
TempHourly..[TempHourly..$Season==SeasonToAnalyze,]

                    #Use factors to estimate data held out
                    #================================================
                    #Do AM
                    #--------------------------------
                    #Determine data to predict using factors
                    #Create dim names for matrix
                    DM3 <- unique(LocationsToPredict..$Location)

                    #Create matrix
                    AmResultsComparison.. <- matrix(0,nrow = length(DM3),ncol = 4,
                        dimnames =
list(DM3,c("Directional","LocalTotal","NBPD","Actual")))

                    #Add actual column
                    AmResultsComparison..[,"Actual"] <-
rowSums(LocationsToPredict..[1:24])[LocationsToPredict..$Direction == "Total"]

                    #for(clcp in rownames(LocationsToPredict..)){
                    for(clcp in DM3){

                        #Calculate Local Estimate
                        #---------------------------
```

```
                    #Grab data for direction and location
                    DataTotal. <- LocationsToPredict..[LocationsToPredict..$Direction
== "Total" & LocationsToPredict..$Location == clcp,][1:24]
                    #2 hours
                    AmPeakHours. <- 8:9

                    #Determine is location is oneway
                    IsOneway <-
CountLocationInformation..$IsOneway[CountLocationInformation..$Location%in%clcp]

                    #Do if data exists
                    if(length(rownames(DataTotal. )) != 0) {
                      #Determine PM "sample"
                      AmSample. <-  DataTotal.[AmPeakHours.]
                      #Grab location
                      Location <- unlist(strsplit(clcp,split="-"))[4]
                      Location <- clcp
                      #To estimate using Total factors
                      #++++++++++++++++++++++++++++++++
                      #DirectionalAverage. <- FinalTotalAvg.
                      DirectionalAverage. <- Factors_[[type]][["Total"]]
                      #Determine aggregate AM percentage
                      AMPercentage.dr <- sum(DirectionalAverage.[AmPeakHours.])
                      #Calculate value of single percentage 1% = x)
                      Xpct <- sum(AmSample.) / (AMPercentage.dr  * 100)
                      #Multiply by directional average percentages to estimate
"sample" data
                      LocalSum <- round(sum( Xpct * 100),0)
                      #Store Local results
                      AmResultsComparison..[clcp,"LocalTotal"] <- LocalSum

                      #To estimate using Inbound factors
                      #++++++++++++++++++++++++++++++++
                      #Determine Inbound direction
                      InboundDirection <-
CountLocationInformation..$Inbound[CountLocationInformation..$Location%in%clcp]
                      #Assign oneway
                      names(InboundDirection) <-
CountLocationInformation..$OnewayDirection[CountLocationInformation..$Location%in
%clcp]

                      #Select inbound data
```

```
                              DataInbound. <-
LocationsToPredict..[LocationsToPredict..$Inbound == TRUE &
LocationsToPredict..$Location == clcp,][1:24]
                              DirectionalAverage. <- Factors_[[type]][["Inbound"]]
                              AmSample. <-  sum(DataInbound.[AmPeakHours.]    )
                              #Determine aggregate APM percentage
                              AMPercentage.dr <- sum(DirectionalAverage.[AmPeakHours.])
                              #Multiply by directional average percentages to estimate
"sample" data
                              InboundSum <- round(AmSample. / AMPercentage.dr,0)

                              #To estimate using Outbound factors
                              #++++++++++++++++++++++++++++++++
                              #Determine Inbound direction
                              OutboundDirection <-
CountLocationInformation..$Outbound[CountLocationInformation..$Location%in%clcp]
                              #Assign oneway
                              names(OutboundDirection) <-
CountLocationInformation..$OnewayDirection[CountLocationInformation..$Location%in
%clcp]

                              #Select inbound data
                              DataOutbound. <-
LocationsToPredict..[LocationsToPredict..$Outbound == TRUE &
LocationsToPredict..$Location == clcp,][1:24]
                              DirectionalAverage. <- Factors_[[type]][["Outbound"]]
                              AmSample. <- sum(DataOutbound.[AmPeakHours.] )
                              #Determine aggregate AM percentage
                              AMPercentage.dr <- sum(DirectionalAverage.[AmPeakHours.])
                              #Multiply by directional average percentages to estimate
"sample" data
                              OutboundSum <- round(AmSample. / AMPercentage.dr,0)

                              #Store Directional Results
                              #Consider if location is oneway - only count one direction
                              if(IsOneway){
                                   if(InboundDirection  == names(InboundDirection )){
                                        AmResultsComparison..[clcp,"Directional"] <-
InboundSum
                                   }
                                   if(OutboundDirection  == names(OutboundDirection )){
```

```
                                AmResultsComparison..[clcp,"Directional"] <-
OutboundSum
                            }

                        } else {
                            #Store both directions if not a oneway
                            AmResultsComparison..[clcp,"Directional"] <- InboundSum
+ OutboundSum
                        }

                        #Calculate NBPD estimate
                        #--------------------------------
                        AmSample. <-  DataTotal.[AmPeakHours.]
                        #2 hours
                        AMPercentage.dr <- .10
                        #Calculate value of singe percentage 1% = x)
                        Xpct <- sum(AmSample.) / (AMPercentage.dr  * 100)
                        #Multiply by directional average percentages to estimate
"sample" data

                        NBPDSum <- round(sum( Xpct * 100) * 1.05,0)

                        #Store Local results
                        AmResultsComparison..[clcp,"NBPD"] <- NBPDSum

                    }
                }

                #Convert to dataframe
                AmResultsFinal.. <- as.data.frame(AmResultsComparison..)
                AmResultsFinal..$Location <- rownames(AmResultsFinal..)
                #Remove long rownames
                rownames(AmResultsFinal..) <- 1:length(rownames(AmResultsFinal..))
                #Add season
                AmResultsFinal..$Season <- SeasonToAnalyze
                #Add facility type
                AmResultsFinal..$Type <-
CountLocationInformation..$Type[match(AmResultsFinal..$Location,CountLocationInfor
mation..$Location)]


                #Use factors to estimate data held out
                #==============================================
```

```
#Do PM
#--------------------------------
#Determine data to predict using factors
#Create dim names for matrix
DM3 <- unique(LocationsToPredict..$Location)

#Create matrix
PmResultsComparison.. <- matrix(0,nrow = length(DM3),ncol = 4,
    dimnames =
list(DM3,c("Directional","LocalTotal","NBPD","Actual")))

#Add actual column
PmResultsComparison..[,"Actual"] <-
rowSums(LocationsToPredict..[1:24])[LocationsToPredict..$Direction == "Total"]

#for(clcp in rownames(LocationsToPredict..)){
for(clcp in DM3){

    #Calculate Local Estimate
    #---------------------------
    #Grab data for direction and location
    DataTotal. <- LocationsToPredict..[LocationsToPredict..$Direction
== "Total" & LocationsToPredict..$Location == clcp,][1:24]
    #2 hours
    PmPeakHours. <- 17:18

    #Determine is location is oneway
    IsOneway <-
CountLocationInformation..$IsOneway[CountLocationInformation..$Location%in%clcp]

    #Do if data exists
    if(length(rownames(DataTotal. )) != 0) {
        #Determine PM "sample"
        PmSample. <-  DataTotal.[PmPeakHours.]
        #Grab location
        Location <- clcp
        #To estimate using Total factors
        #++++++++++++++++++++++++++++++++++
        #DirectionalAverage. <- FinalTotalAvg.
        DirectionalAverage. <- Factors_[[type]][["Total"]]
        #Determine aggregate AM percentage
        PMPercentage.dr <- sum(DirectionalAverage.[PmPeakHours.])
```

```
#Calculate value of single percentage 1% = x)
Xpct <- sum(PmSample.) / (PMPercentage.dr  * 100)
#Multiply by directional average percentages to estimate
"sample" data
LocalSum <- round(sum( Xpct * 100),0)
#Store Local results
PmResultsComparison..[clcp,"LocalTotal"] <- LocalSum

#To estimate using Inbound factors
#++++++++++++++++++++++++++++++++
#Determine Inbound direction
InboundDirection <-
CountLocationInformation..$Inbound[CountLocationInformation..$Location%in%clcp]
#Assign oneway
names(InboundDirection) <-
CountLocationInformation..$OnewayDirection[CountLocationInformation..$Location%in
%clcp]

#Select inbound data
DataInbound. <-
LocationsToPredict..[LocationsToPredict..$Inbound == TRUE &
LocationsToPredict..$Location == clcp,][1:24]
DirectionalAverage. <- Factors_[[type]][["Inbound"]]
PmSample. <-  sum(DataInbound.[PmPeakHours.]    )
#Determine aggregate APM percentage
PMPercentage.dr <- sum(DirectionalAverage.[PmPeakHours.])
#Multiply by directional average percentages to estimate
"sample" data
InboundSum <- round(PmSample. / PMPercentage.dr,0)

#To estimate using Outbound factors
#++++++++++++++++++++++++++++++++
#Determine Inbound direction
OutboundDirection <-
CountLocationInformation..$Outbound[CountLocationInformation..$Location%in%clcp]
#Assign oneway
names(OutboundDirection) <-
CountLocationInformation..$OnewayDirection[CountLocationInformation..$Location%in
%clcp]

#Select outbound data
```

```
                    DataOutbound. <-
LocationsToPredict..[LocationsToPredict..$Outbound == TRUE &
LocationsToPredict..$Location == clcp,][1:24]
                    DirectionalAverage. <- Factors_[[type]][["Outbound"]]
                    PmSample. <- sum(DataOutbound.[PmPeakHours.] )
                    #Determine aggregate AM percentage
                    PMPercentage.dr <- sum(DirectionalAverage.[PmPeakHours.])
                    #Multiply by directional average percentages to estimate
"sample" data
                    OutboundSum <- round(PmSample. / PMPercentage.dr,0)


                    #Store Directional Results
                    #Consider if location is oneway - only count one direction
                    if(IsOneway){
                        if(InboundDirection  == names(InboundDirection )){
                            PmResultsComparison..[clcp,"Directional"] <-
InboundSum
                        }
                        if(OutboundDirection  == names(OutboundDirection )){
                            PmResultsComparison..[clcp,"Directional"] <-
OutboundSum
                        }

                    } else {
                        #Store both directions if not a oneway
                        PmResultsComparison..[clcp,"Directional"] <- InboundSum
+ OutboundSum
                    }

                    #Calculate NBPD estimate
                    #---------------------------------
                    #Determine PM "sample"
                    PmSample. <-  DataTotal.[PmPeakHours.]
                    #2 hours
                    PMPercentage.dr <- .15
                    #Calculate value of singe percentage 1% = x)
                    Xpct <- sum(PmSample.) / (PMPercentage.dr  * 100)
                    #Multiply by directional average percentages to estimate
"sample" data
                    NBPDSum <- round(sum( Xpct * 100) * 1.05,0)
```

```
#Store Local results
PmResultsComparison..[clcp,"NBPD"] <- NBPDSum

}
}


#Convert to dataframe
PmResultsFinal.. <- as.data.frame(PmResultsComparison..)
PmResultsFinal..$Location <- rownames(PmResultsFinal..)
#Remove long rownames
rownames(PmResultsFinal..) <- 1:length(rownames(PmResultsFinal..))
#Add season
PmResultsFinal..$Season <- SeasonToAnalyze
#Add facility type
PmResultsFinal..$Type <-
CountLocationInformation..$Type[match(PmResultsFinal..$Location,CountLocationInfor
mation..$Location)]

#Select locations to check results
#Never counted in Estimation data
if(city == "Eugene"){
ToPlot. <-
c("15thWestJefferson","AlderNorth27th","AmazonPathNorth24th",

"DefazioSouthRiverEastBridge","DeltaBPBridgeEastGoodPasture","FernRidgeEastDaneb
o","FernRidgeEastSeneca","FernRidgeSouthWestMoeBr",
"FirEastRiverRd"
,"FriendlySouth18th","HighNorth13th","HighSouth4th","MonroeSouth8th",
"NorthbankSouthGreenwayBr",
"NorthbankSouthOwossaBr","NorthbankWestDeltaHwy/","NorthbankEastKnickerbocker
",
"PearlSouth19th",
"SouthbankSouthGreenwayBr","UniversityNorth24th/", "WillametteNorth15th")


}
if(city == "Springfield"){
#Springfield
ToPlot. <-
c("32ndSouthOregon","EWEBPathEast5th","EWEBPathEastPioneerPkwy","DEastPioneer
PkwyPath",
```

```
"GWestMohawk","GoodpastureEastDeltaHwy","GatewayBPBridgeEastI5","Gateway
StreetEastI5" ,"HarlowEastI5","PioneerPkwySouthQ","ThurstonEast58th")
			}

			if(city == "BothJurisdictions"){
				ToPlot. <-
c("15thWestJefferson","AlderNorth27th","AmazonPathNorth24th",

"DefazioSouthRiverEastBridge","DeltaBPBridgeEastGoodPasture","FernRidgeEastDaneb
o","RichardsonBridge","HeronBridgeSouthFernRidge",
				 "FirEastRiverRd"
,"FriendlySouth18th","GoodpastureEastDeltaHwy","GWestMohawk","HighNorth13th","
HighSouth4th","MonroeSouth8th",
				 "NorthbankSouthGreenwayBr",
"EastbankSouthOwossoBr","NorthbankWestDeltaHwy","NorthbankEastKnickerbocker",
				 "PearlSouth19th",
"SouthbankSouthGreenwayBr","UniversityNorth24th", "WillametteNorth15th",

"32ndSouthOregon","EWEBPathEast5th","EWEBPathEastPioneerPkwy","DEastPioneerP
kwyPath",
				"GatewayBPBridgeEastI5","GatewayStreetEastI5"
,"HarlowEastI5","PioneerPkwySouthQ","ThurstonEast58th")
			}

			#Select location of interest
			AmResultsFinalPlot.. <-
AmResultsFinal..[AmResultsFinal..$Location%in%ToPlot.,]
			PmResultsFinalPlot.. <-
PmResultsFinal..[PmResultsFinal..$Location%in%ToPlot.,]

			#Select facility type
			if(type != "All"){
				AmResultsFinalPlot.. <-
AmResultsFinalPlot..[AmResultsFinalPlot..$Type == type,]
				PmResultsFinalPlot.. <-
PmResultsFinalPlot..[PmResultsFinalPlot..$Type == type,]
			}


			# #Create table for output
			#------------------------------
```

```
                        AmResultsFinalPlot..$Period <- "AM"
                        PmResultsFinalPlot..$Period <- "PM"



                        Result_[[city]][[type]] <- rbind( AmResultsFinalPlot..,
PmResultsFinalPlot..)
                        #Result2_[[city]][[type]] <- list(colMeans(AmResultsFinalPlot..[,8:10]),
    colMeans(PmResultsFinalPlot..[,8:10]),
                        #
    colMeans(AmResultsFinalPlot..[,11:13]),colMeans(PmResultsFinalPlot..[,11:13]))


                        #write.csv(Result.., file =
paste("SummaryTables/FactorResults/",type,"_HourExtrapolationResultsByType_",city,"
.csv",sep=""))


                    #Springfield if loop
                    }

                #Facility type loop
                }

            #Jurisdiction loop
            }


#period loop
}



#Format data for easier symbolizing
#>.......................................

    #Create data frame to store results.
    ResultsFormatted.. <- data.frame()


    for(type in c("Path","Lane","Blvd","NoFacility")){
```

```
        #Create data frame
        TempResults.. <- as.data.frame(Result_[["BothJurisdictions"]][[type]])

        if(nrow(TempResults..) > 0 ){

            #Select only columns of interest
            TempResults.. <-
TempResults..[,c("LocalTotal","Directional","NBPD","Actual","Location","Period","Type")
]

            #Add city
            #TempResults..$City <- cities

            #Add to master results dataframe
            ResultsFormatted.. <- rbind(ResultsFormatted..,TempResults..)

        }
    }


    #Change row names
    rownames(ResultsFormatted..) <- 1:nrow(ResultsFormatted..)

    #Reformat factors for display
    FinalFactors_ <- list()
    for(period in c("AM","PM")){
        Am. <- NULL
        Pm. <- NULL
        Period. <- NULL
        for(type in c("Path","Lane","Blvd","NoFacility")){
            if(period == "AM"){
                Period <- round(sum(Factors_[[type]][["Total"]][8:9]),2)
                names(Period) <- type
                Period. <- c(Period.,Period)
            }
            if(period == "PM"){
                Period <- round(sum(Factors_[[type]][["Total"]][17:18]),2)
                names(Period) <- type
                Period. <- c(Period.,Period)
            }

        }
```

```
        FinalFactors_[["LocalTotal"]][[period]] <- list(Period.)
    }

    #Add NBPDP
    NBPDPAmFactors. <-  c(0.10,0.10,0.10,0.10)
    names(NBPDPAmFactors.) <- c("Path","Lane","Blvd","NoFacility")
    FinalFactors_[["NBPD"]][["AM"]] <- NBPDPAmFactors.
    NBPDPPmFactors. <- c(.15,.15,.15,.15)
    names(NBPDPPmFactors.) <-  c("Path","Lane","Blvd","NoFacility")
    FinalFactors_[["NBPD"]][["PM"]] <- NBPDPPmFactors.

    #Plot the results
    #----------------------------

    #Create a list to tore all final results
    FinalResults_ <- list()

    #open pdf
    pdf(paste("Reports/FactorReports/FallSummerFactors_ComarisonTotal_and_NBPDP
.pdf",sep=""),width = 11.5, height = 9)
    #Set pdf parameters
    par(mfrow = c(2,2),xpd = TRUE,mar=par()$mar+c(0,2,0,9))

    Xlim <- c(0,3000)
    Ylim <- c(0,3000)
    Obs_ <- list()
    Est_ <- list()

    #Local Total AM
    #++++++++++++++++++++++
    TestLocations. <- unique(ResultsFormatted..$Location)

    for(result in c("LocalTotal","NBPD")){
        for(period in c("AM","PM")){
            Obs_ <- list()
            Est_ <- list()
            for(tl in TestLocations. ){
                ###
                Obs <- ResultsFormatted..$Actual[(ResultsFormatted..$Location == tl &
ResultsFormatted..$Period == period)]
                Est <- ResultsFormatted..[,result][ResultsFormatted..$Location == tl &
ResultsFormatted..$Period == period]
```

```
			#Determine symbol for plot
			#BikeFac <- CountLocationInformation..$FactorGroup[match(tl,
CountLocationInformation..$Location)]
			BikeFac <- CountLocationInformation..$Type[match(tl,
CountLocationInformation..$Location)]
			if(BikeFac == "Path"){Pch <- 5}
			if(BikeFac == "Lane"){Pch <- 10}
			if(BikeFac == "Blvd"){Pch <- 18}
			if(BikeFac == "NoFacility"){Pch <- 8}

			#Plot is available
			if(!(is.na(Obs))){
				plot(Obs~Est, main = paste("Results for",result, period, sep=" "),xlim =
Xlim, ylim = Ylim, pch = Pch, col = "black")
				par(new = TRUE)
				#Store
				Obs_[[tl]] <- Obs
				Est_[[tl]] <- Est
			}
		}


	par(xpd = FALSE)
	#Add 45 reference line
	abline(a = 0, b = 1, col = "red")
	par(xpd = TRUE)
	#Develop summary
	Location. <- as.character(do.call("rbind",strsplit(names(Obs_),"-"))[,1])
	#Season <- as.character(do.call("rbind",strsplit(names(Obs_),"-"))[,2])
	BestResult.. <- data.frame(Location = Location., Obs = unlist(Obs_,F,F), Est =
unlist(Est_,F,F))
	#BestResult..$PctDiff <- round(BestResult..$Obs / BestResult..$Est,2)
	#BestResult..$AbsPctDiff <- round( abs(1-(BestResult..$Obs / BestResult..$Est)),2)
	BestResult..$PctDiff <- round(BestResult..$Est / BestResult..$Obs,2)
	BestResult..$AbsPctDiff <- round( abs(1-(BestResult..$Est / BestResult..$Obs)),2)
	BestResult..$Type <-
CountLocationInformation..$Type[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult..$FedClass <-
CountLocationInformation..$FedClass[match(BestResult..$Location,
CountLocationInformation..$Location)]
```

```
	BestResult..$FactorGroup <-
CountLocationInformation..$FactorGroup[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult..$LocationId <-
CountLocationInformation..$LocationId[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult.. <- BestResult..[order(BestResult..$AbsPctDiff),]
	#BestResult.. <- BestResult..[order(BestResult..$Type),]
	#Store final results data frame
	FinalResults_[[paste(result, period, sep="-")]] <- BestResult..

	#Add legend
	RMSE <- round(summary(lm(unlist(Obs_)~unlist(Est_)))$sigma,2)
	RMSE <-	paste("RMSE = ",RMSE,sep="")
	RSquared <- round(summary(lm(unlist(Obs_)~unlist(Est_)))$r.squared,2)
	RSquared <- paste("R-squared = ", RSquared, sep= "")
	MeanAbsDiff <- round(mean(BestResult..$AbsPctDiff),2)
	MeanAbsDiff <- paste("Mean Abs Diff = ", MeanAbsDiff)
	#MeanAbsDiff.Fg <-
round(tapply(BestResult..$AbsPctDiff,BestResult..$FactorGroup,mean),2)
	MeanAbsDiff.Fg <-
round(tapply(BestResult..$AbsPctDiff,BestResult..$Type,mean),2)


	#Add legend 1
	legend("topleft",title = "Results Summary", legend =c(RMSE, RSquared,
MeanAbsDiff) )

	#Add legend 2
	legend(3150,3100,title = "Mean Abs Diff by Factor Group", legend
=c(paste(names(MeanAbsDiff.Fg[1]),MeanAbsDiff.Fg[1],sep="-"),
		paste(names(MeanAbsDiff.Fg[2]),MeanAbsDiff.Fg[2],sep="-
"),paste(names(MeanAbsDiff.Fg[3]),MeanAbsDiff.Fg[3],sep="-"),
		paste(names(MeanAbsDiff.Fg[4]),MeanAbsDiff.Fg[4],sep="-")),cex = .9)

	#Add legend 3
	Factors. <-  unlist(FinalFactors_[[result]][[period]])
	Factors. <- paste(names(Factors.),Factors.,sep="-")
	#legend("bottomright", legend = c("Factors","Local",AmTotalFactors.))
	legend(3150,2000, legend = c("Factors",result,Factors.))

	#Add legend 4
```

```
          legend("bottomright",title = "Legend", legend =
c("Path","Lane","Blvd","NoFacilities"),
          pch = c(5,10,18,8), cex = .8,pt.cex = 1.2)
          par(xpd = FALSE)

          }
     }

     dev.off()



     #.....................................................................
     #Process for determining Scenario 2 factors
     #.....................................................................
     #Create list ot store results
     Result2_ <- list()

     #Define vector or factors to work through
     SampleFactors. <- seq(.05,.30,.02)

for(samplefactor in SampleFactors.){

     TotalPmFactors. <- rep(samplefactor, 5)
     names(TotalPmFactors.) <-  c("Blvd","Lane","NoFacility","Path-Commute","Path-
Rec")
     TotalAmFactors. <- rep(samplefactor, 5)
     names(TotalAmFactors.) <-  c("Blvd","Lane","NoFacility","Path-Commute","Path-
Rec")


     #Apply Factors to count stations not selected for factor creation
     #..........................................................
     #Determine count stations to apply factors too
     TestData.. <-  Hourly..
     #Create vector of test locations
     TestLocations. <- unique(TestData..$Location)
     #Remove All days but Tuesday and Thursday
     TestData.. <- TestData..[TestData..$Weekday%in%c("Tuesday","Thursday"),]
     #Remove Spring
     TestData.. <- TestData..[TestData..$Season != "Spring",]
     #Append factor Groups
```

```
    TestData..$FactorGroup <-
CountLocationInformation..$FactorGroup[match(TestData..$Location,
CountLocationInformation..$Location)]

    #Create an observed array
    #-----------------------------------
    #Create an array to store observed counts
    ObservedCounts..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))

    #Populate array with observed values
    for(tl in TestLocations.){
        #Select data
        TempTestData.. <- TestData..[TestData..$Location == tl,]
        #Do Total
        #+++++++++++++++++++++++++++++
        TempTestData.. <- TempTestData..[TempTestData..$Direction == "Total",]
        #Do each day
        for(day in TempTestData..$Date){
            #Establish day
            Weekday <-  TempTestData..$Weekday[TempTestData..$Date%in%day]
            #Establish season
            season <- TempTestData..$Season[TempTestData..$Date%in%day]
            #Do Am
            ObservedCount <-
sum(TempTestData..[TempTestData..$Date%in%day,][1:24])
            #Store result
            ObservedCounts..DayClSe [tl,season,Weekday] <- ObservedCount
        }
    }

    #Estimate using factors
    #------------------------------------
    #Create Array to store raw results

    #Total
    AmTotalResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))
    PmTotalResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
```

```
        c("Tuesday","Thursday")))
    #NBPDP
    AmNBPDPResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))
    PmNBPDPResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))



    #Apply Factors
    #.......................................
    #Total
    for(tl in TestLocations.){
        #Select data
        TempTestData.. <- TestData..[TestData..$Location == tl,]
        #Establish facility type
        #type <- unique(TempTestData..$Type)
        type <- unique(TempTestData..$FactorGroup)
        #Do Total
        #+++++++++++++++++++++++++++++
        TempTestData.. <- TempTestData..[TempTestData..$Direction == "Total",]

        #Do each day
        for(day in TempTestData..$Date){
            #Local Total
            #+++++++++++++++++++++++++++++++++++
            #Establish day
            Weekday <-  TempTestData..$Weekday[TempTestData..$Date%in%day]
            #Establish season
            season <- TempTestData..$Season[TempTestData..$Date%in%day]
            #Raw
            #Do Am
            AmResult <-
round(sum(TempTestData..[TempTestData..$Date%in%day,][8:9]) /
TotalAmFactors.[type],0)

            AmTotalResults..DayClSe[tl,season,Weekday] <- AmResult
            #Do Pm
```

```
            PmResult <-
round(sum(TempTestData..[TempTestData..$Date%in%day,][17:18]) /
TotalPmFactors.[type],0)

            PmTotalResults..DayClSe[tl,season,Weekday] <- PmResult


        }
    }

    #Plot results
    #====================================
    #====================================

    #Create vector of ll result matrices
    Results. <- c("Am Study Area","Pm Study Area")


    for(result in Results.){
        if(result == "Am Study Area"){Data.. <- AmTotalResults..DayClSe}
        if(result == "Pm Study Area"){Data.. <- PmTotalResults..DayClSe}
        if(result == "Am NBPDP"){Data.. <- AmNBPDPResults..DayClSe}
        if(result == "Pm NBPDP"){Data.. <- PmNBPDPResults..DayClSe}

        Obs_ <- list()
        Est_ <- list()

        #Local Total AM
        #++++++++++++++++++++++
        for(tl in TestLocations. ){
            for(season in c("Summer","Fall","Winter")){
                for(weekday in c("Tuesday","Thursday")){

                    #Determine symbol for plot
                    BikeFac <- CountLocationInformation..$FactorGroup[match(tl,
CountLocationInformation..$Location)]
                    if(BikeFac == "Path-Rec"){Pch <- 5}
                    if(BikeFac == "Path-Commute"){Pch <- 25}
                    if(BikeFac == "Lane"){Pch <- 12}
                    if(BikeFac == "Blvd"){Pch <- 13}
                    if(BikeFac == "NoFacilities"){Pch <- 8}
```

```
#Tuesday
if(weekday == "Tuesday"){
	#Grab observed and estimated data
	Obs <- ObservedCounts..DayClSe[tl,season,"Tuesday"]
	Est <- Data..[tl,season,"Tuesday"]
	if(!(is.na(Obs))){
		#Store
		Obs_[[paste(tl,season,weekday,sep="-")]] <- Obs
		Est_[[paste(tl,season,weekday,sep="-")]] <- Est
	}
}

#Thursday
if(weekday == "Thursday"){
	Obs <- ObservedCounts..DayClSe[tl,season,"Thursday"]
	Est <- Data..[tl,season,"Thursday"]
	#Grab observed and estimated data  #Plot is available
	if(!(is.na(Obs))){

		#Store
		Obs_[[paste(tl,season,weekday,sep="-")]] <- Obs
		Est_[[paste(tl,season,weekday,sep="-")]] <- Est

	}
}
}
}
}


Location. <- as.character(do.call("rbind",strsplit(names(Obs_),"-"))[,1])
Season <- as.character(do.call("rbind",strsplit(names(Obs_),"-"))[,2])
BestResult.. <- data.frame(Location = Location., Season = Season, Obs =
unlist(Obs_,F,F), Est = unlist(Est_,F,F),
	Weekday = do.call("rbind",strsplit( names(Obs_),"-"))[,3] )
BestResult..$PctDiff <- round(BestResult..$Est /BestResult..$Obs ,2)
BestResult..$AbsPctDiff <- round( abs(1-( BestResult..$Est / BestResult..$Obs )),2)
BestResult..$Type <-
CountLocationInformation..$Type[match(BestResult..$Location,
CountLocationInformation..$Location)]
```

```
	BestResult..$FactorGroup <-
CountLocationInformation..$FactorGroup[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult..$FedClass <-
CountLocationInformation..$FedClass[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult..$LocationId <-
CountLocationInformation..$LocationId[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult.. <- BestResult..[order(BestResult..$AbsPctDiff),]

	#Result_[[result]] <- BestResult..

	#Add legend
	RMSE <- round(summary(lm(unlist(Obs_)~unlist(Est_)))$sigma,2)
	RMSE <-    paste("RMSE = ",RMSE,sep="")
	RSquared <- round(summary(lm(unlist(Obs_)~unlist(Est_)))$r.squared,2)
	RSquared <- paste("R-squared = ", RSquared, sep= "")
	MeanAbsDiff <- round(mean(BestResult..$AbsPctDiff),2)
	MeanAbsDiff <- paste("Mean Abs Diff = ", MeanAbsDiff)
	MeanAbsDiff.Fg <-
round(tapply(BestResult..$AbsPctDiff,BestResult..$FactorGroup,mean),2)

	if(result != "Am Study Area"){
		if(any(MeanAbsDiff.Fg < .30)){
			ToSave <- MeanAbsDiff.Fg[MeanAbsDiff.Fg < .30]
			Result2_[[paste(as.character(samplefactor),result,sep="-")]] <- ToSave
		}
	}


   #End result loop
   }

}



   #.....................................................................
   #Apply Scenario 2 factors - analysis and comparison with NBPDP
   #.....................................................................
   #Create data to apply data
```

```
    TestData.. <-  Hourly..
    #Define factors derived froim iterative process
    TotalAmFactors. <-  c(0.15,0.15,0.13,0.13,0.15)
    names(TotalAmFactors.) <-  c("Blvd","Lane","NoFacility","Path-Commute","Path-
Rec")
    TotalPmFactors. <-  c(0.19,0.17,0.19,0.21,0.25)
    names(TotalPmFactors.) <-  c("Blvd","Lane","NoFacility","Path-Commute","Path-
Rec")

    #define NPBDP factors
    NBPDPAmFactors. <-  c(0.10,0.10,0.10,0.10,0.10)
    names(NBPDPAmFactors.) <-  c("Blvd","Lane","NoFacility","Path-Commute","Path-
Rec")
    NBPDPPmFactors. <-  c(.15,.15,.15,.15,.15)
    names(NBPDPPmFactors.) <-  c("Blvd","Lane","NoFacility","Path-Commute","Path-
Rec")


    #Apply Factors to count stations not selected for factor creation
    #..........................................................
    #Determine count stations to apply factors too
    #TestData.. <- Hourly..[!(Hourly..$Location%in%SampleIds.),]
    #Create vector of test locations
    TestLocations. <- unique(TestData..$Location)
    #Remove All days but Tuesday and Thursday
    TestData.. <- TestData..[TestData..$Weekday%in%c("Tuesday","Thursday"),]
    #Remove Spring
    TestData.. <- TestData..[TestData..$Season != "Spring",]
    #Append factor Groups
    TestData..$FactorGroup <-
CountLocationInformation..$FactorGroup[match(TestData..$Location,
CountLocationInformation..$Location)]


    #Create an observed counts array
    #----------------------------------
    #Create an array to store observed counts
    ObservedCounts..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))

    #Populate array with observed values
```

```
    for(tl in TestLocations.){
        #Select data
        TempTestData.. <- TestData..[TestData..$Location == tl,]
        #Do Total
        #++++++++++++++++++++++++++++++
        TempTestData.. <- TempTestData..[TempTestData..$Direction == "Total",]
        #Do each day
        for(day in TempTestData..$Date){
            #Establish day
            Weekday <-  TempTestData..$Weekday[TempTestData..$Date%in%day]
            #Establish season
            season <- TempTestData..$Season[TempTestData..$Date%in%day]
            #Do Am
            ObservedCount <-
sum(TempTestData..[TempTestData..$Date%in%day,][1:24])
            #Store result
            ObservedCounts..DayClSe [tl,season,Weekday] <- ObservedCount
        }
    }

    #Estimate using factors
    #------------------------------------
    #Create Array to store raw results

    #Total
    AmTotalResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))
    PmTotalResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))
    #NBPDP
    AmNBPDPResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))
    PmNBPDPResults..DayClSe <- array(NA, c(length(TestLocations.), 3, 2), dimnames =
list(TestLocations., c("Summer","Fall","Winter"),
        c("Tuesday","Thursday")))



    #Apply Factors
```

```
#........................................
#Total
for(tl in TestLocations.){
    #Select data
    TempTestData.. <- TestData..[TestData..$Location == tl,]
    #Establish facility type
    #type <- unique(TempTestData..$Type)
    type <- unique(TempTestData..$FactorGroup)
    #Do Total
    #++++++++++++++++++++++++++++++
    TempTestData.. <- TempTestData..[TempTestData..$Direction == "Total",]

    #Do each day
    for(day in TempTestData..$Date){
        #Local Total
        #++++++++++++++++++++++++++++++++++++
        #Establish day
        Weekday <-  TempTestData..$Weekday[TempTestData..$Date%in%day]
        #Establish season
        season <- TempTestData..$Season[TempTestData..$Date%in%day]
        #Raw
        #Do Am
        AmResult <-
round(sum(TempTestData..[TempTestData..$Date%in%day,][8:9]) /
TotalAmFactors.[type],0)
        if(is.na(AmResult)){
            AmResult <-
round(sum(TempTestData..[TempTestData..$Date%in%day,][8:9]) /
mean(TotalAmFactors.),0)
        }
        AmTotalResults..DayClSe[tl,season,Weekday] <- AmResult
        #Do Pm
        PmResult <-
round(sum(TempTestData..[TempTestData..$Date%in%day,][17:18]) /
TotalPmFactors.[type],0)
        if(is.na(PmResult)){
            PmResult <-
round(sum(TempTestData..[TempTestData..$Date%in%day,][17:18]) /
mean(TotalPmFactors.),0)
        }
        PmTotalResults..DayClSe[tl,season,Weekday] <- PmResult
```

```
            #NBPDP
            #+++++++++++++++++++++++++++++++++++
            #Local Total
            #+++++++++++++++++++++++++++++++++++
            #Establish day
            Weekday <-  TempTestData..$Weekday[TempTestData..$Date%in%day]
            #Establish season
            season <- TempTestData..$Season[TempTestData..$Date%in%day]
            #Do Am
            AmResult <- 
round(sum(TempTestData..[TempTestData..$Date%in%day,][8:9]) / 
NBPDPAmFactors.[type],0)
            if(is.na(AmResult)){
                AmResult <- 
round(sum(TempTestData..[TempTestData..$Date%in%day,][8:9]) / 
mean(NBPDPAmFactors.),0)
            }
            #Add NBPDP multiplier
            AmResult <- AmResult * 1.05
            AmNBPDPResults..DayClSe[tl,season,Weekday] <- AmResult
            #Do Pm
            PmResult <- 
round(sum(TempTestData..[TempTestData..$Date%in%day,][17:18]) / 
NBPDPPmFactors.[type],0)
            if(is.na(PmResult)){
                PmResult <- 
round(sum(TempTestData..[TempTestData..$Date%in%day,][17:18]) / 
mean(NBPDPPmFactors.),0)
            }
            PmResult <- PmResult * 1.05
            PmNBPDPResults..DayClSe[tl,season,Weekday] <- PmResult


        }
    }

    #Plot results
    #====================================
    #====================================


    #open pdf
```

```
    pdf(paste("Reports/FactorReports/SelectedFactors_ComarisonTotal_and_NBPDP.pd
f",sep=""),width = 11.5, height = 9)
    #Set pdf parameters
    par(mfrow = c(2,2),xpd = TRUE,mar=par()$mar+c(0,2,0,9))
    Xlim <- c(0,3000)
    Ylim <- c(0,3000)

    #Create vector of ll result matrices
    Results. <- c("Am Study Area","Pm Study Area","Am NBPDP","Pm NBPDP")
    Result_ <- list()

    for(result in Results.){
        if(result == "Am Study Area"){Data.. <- AmTotalResults..DayClSe}
        if(result == "Pm Study Area"){Data.. <- PmTotalResults..DayClSe}
        if(result == "Am NBPDP"){Data.. <- AmNBPDPResults..DayClSe}
        if(result == "Pm NBPDP"){Data.. <- PmNBPDPResults..DayClSe}

        Obs_ <- list()
        Est_ <- list()

        #Local Total AM
        #++++++++++++++++++++++
        for(tl in TestLocations. ){
            for(season in c("Summer","Fall","Winter")){
                for(weekday in c("Tuesday","Thursday")){

                    #Determine symbol for plot
                    BikeFac <- CountLocationInformation..$FactorGroup[match(tl,
CountLocationInformation..$Location)]
                    if(BikeFac == "Path-Rec"){Pch <- 5}
                    if(BikeFac == "Path-Commute"){Pch <- 25}
                    if(BikeFac == "Lane"){Pch <- 12}
                    if(BikeFac == "Blvd"){Pch <- 13}
                    if(BikeFac == "NoFacilities"){Pch <- 8}

                    #Tuesday
                    if(weekday == "Tuesday"){
                        #Grab observed and estimated data
                        Obs <- ObservedCounts..DayClSe[tl,season,"Tuesday"]
                        Est <- Data..[tl,season,"Tuesday"]
                        if(!(is.na(Obs))){
```

```
                              plot(Obs~Est, xlim = Xlim, ylim = Ylim, pch = Pch, col = "black",
main = "")
                              par(new = TRUE)
                              #Store
                              Obs_[[paste(tl,season,weekday,sep="-")]] <- Obs
                              Est_[[paste(tl,season,weekday,sep="-")]] <- Est
                         }
                    }

                    #Thursday
                    if(weekday == "Thursday"){
                         Obs <- ObservedCounts..DayClSe[tl,season,"Thursday"]
                         Est <- Data..[tl,season,"Thursday"]
                         #Grab observed and estimated data  #Plot is available
                         if(!(is.na(Obs))){
                              plot(Obs~Est, xlim = Xlim, ylim = Ylim, pch = Pch, col = "black",
main = result)
                              par(new = TRUE)
                              #Store
                              Obs_[[paste(tl,season,weekday,sep="-")]] <- Obs
                              Est_[[paste(tl,season,weekday,sep="-")]] <- Est

                         }
                    }
               }
          }
     }

     par(xpd = FALSE)
     #Add 45 reference line
     abline(a = 0, b = 1, col = "red")
     par(xpd = TRUE)
     #Develop summary
     Location. <- as.character(do.call("rbind",strsplit(names(Obs_),"-"))[,1])
     Season <- as.character(do.call("rbind",strsplit(names(Obs_),"-"))[,2])
     BestResult.. <- data.frame(Location = Location., Season = Season, Obs =
unlist(Obs_,F,F), Est = unlist(Est_,F,F),
          Weekday = do.call("rbind",strsplit( names(Obs_),"-"))[,3] )
     #BestResult..$PctDiff <- round(BestResult..$Obs / BestResult..$Est,2)
     #BestResult..$AbsPctDiff <- round( abs(1-(BestResult..$Obs / BestResult..$Est)),2)
     BestResult..$PctDiff <- round(BestResult..$Est / BestResult..$Obs,2)
     BestResult..$AbsPctDiff <- round( abs(1-(BestResult..$Est / BestResult..$Obs)),2)
```

```
	BestResult..$Type <-
CountLocationInformation..$Type[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult..$FactorGroup <-
CountLocationInformation..$FactorGroup[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult..$FedClass <-
CountLocationInformation..$FedClass[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult..$LocationId <-
CountLocationInformation..$LocationId[match(BestResult..$Location,
CountLocationInformation..$Location)]
	BestResult.. <- BestResult..[order(BestResult..$AbsPctDiff),]
	Result_[[result]] <- BestResult..

	#Add legend
	RMSE <- round(summary(lm(unlist(Obs_)~unlist(Est_)))$sigma,2)
	RMSE <-	paste("RMSE = ",RMSE,sep="")
	RSquared <- round(summary(lm(unlist(Obs_)~unlist(Est_)))$r.squared,2)
	RSquared <- paste("R-squared = ", RSquared, sep= "")
	MeanAbsDiff <- round(mean(BestResult..$AbsPctDiff),2)
	MeanAbsDiff <- paste("Mean Abs Diff = ", MeanAbsDiff)
	MeanAbsDiff.Fg <-
round(tapply(BestResult..$AbsPctDiff,BestResult..$FactorGroup,mean),2)


	#Add legend 1
	legend("topleft",title = "Results Summary", legend =c(RMSE, RSquared,
MeanAbsDiff) )

	#Add legend 2
	legend(3150,3100,title = "Mean Abs Diff by Factor Group", legend
=c(paste(names(MeanAbsDiff.Fg[1]),MeanAbsDiff.Fg[1],sep="-"),
		paste(names(MeanAbsDiff.Fg[2]),MeanAbsDiff.Fg[2],sep="-
"),paste(names(MeanAbsDiff.Fg[3]),MeanAbsDiff.Fg[3],sep="-"),
		paste(names(MeanAbsDiff.Fg[4]),MeanAbsDiff.Fg[4],sep="-
"),paste(names(MeanAbsDiff.Fg[5]),MeanAbsDiff.Fg[5],sep="-")),cex = .9)


	#Add legend 3
	if(result == "Am Study Area"){AmTotalFactors. <- TotalAmFactors.}
	if(result == "Pm Study Area"){AmTotalFactors. <- TotalPmFactors.}
```

```
        if(result == "Am NBPDP"){AmTotalFactors. <- NBPDPAmFactors.}
        if(result == "Pm NBPDP"){AmTotalFactors. <- NBPDPPmFactors.}
        AmTotalFactors.<-
paste(names(AmTotalFactors.),round(AmTotalFactors.,2),sep="-")
        AmNBPDPFactors. <- NBPDPAmFactors.
        AmNBPDPFactors.<- paste(names(AmNBPDPFactors.),AmNBPDPFactors.,sep="-")
        #legend("bottomright", legend = c("Factors","Local",AmTotalFactors.))
        legend(3150,2000, legend = c("Factors","Local",AmTotalFactors.))

        #Add legend 4
        legend("bottomright",title = "Legend", legend = c("Path-Rec","Path-
Commute","Lane","Blvd","NoFacilities"),
        pch = c(5,25,12,13,8), cex = .8)
        par(xpd = FALSE)

    #End result loop
    }
    #Close pdf
    dev.off()
```