Analyses of Bicycle and Pedestrian Trail Traffic: New Tools for Modeling User Expenditures and Demand

A THESIS
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

Alireza Ermagun

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
MASTER OF URBAN AND REGIONAL PLANNING

Greg Lindsey

August, 2017

Acknowledgements

In the words of Paul Samuelson "Good questions outrank easy answers." Through the course of writing this thesis, and finishing my Master of Urban and Regional Planning, I have come up with many good questions and nary an easy answer. If it were not for the people in my life who helped me up, kept me going, and read my questions and answers time and again, I would not have made it to this day. All my hard work and determination would mean far less if it were not for a strong group of people who helped guide me through this process.

This research thesis was conducted with support from the Rails to Trails Conservancy and the Mid-Ohio Regional Planning Commission. The materials presented in this research thesis have appeared in several academic publications and conference presentations as follows:

- Ermagun, A., and Lindsey, G. (2016). Differences in Spending by Local Trail Users: Two-Part Model of Expenditures. Transportation Research Record: Journal of the Transportation Research Board, (2598), 58-66.
- Ermagun, A., Lindsey, G., and Loh, T. Urban Trails and Demand Response to Weather Variations. 56th Annual Meeting of the Association of Collegiate Schools of Planning (ACSP), Portland, Oregon, November 2016.
- Ermagun, A., Lindsey, G., and Loh, T (2017). Urban Trails and Demand Response to Weather Variations. Transportation Research Part D: Transport and Environment, under revision.
- Ermagun, A., Lindsey, G., and Loh, T (2017). Bicycle, Pedestrian, and Mixed-mode Trail Traffic: A Performance Assessment of Demand Models. Landscape and Urban Planning, under review.

I would like to thank my co-authors on this endeavor, Professor Greg Lindsey and Dr. Tracy Hadden Loh, and acknowledge the intellectual contributions they have made to my research. This work is proof of the dedication and strong devotion of the many people in my life, both in the United States and around the world. This may have never happened without the unwavering support of some individuals who I would like to thank now.

To Professor Greg Lindsey, thank you for always keeping me moving forward. For the last three years you have been my mentor, my father-figure, and most importantly, my friend. From my first day stepping off the plane in Minnesota and meeting you, I knew I had made the right decision. You have shown me how to be a teacher by demonstrating your wisdom and compassion. Now, as our journey together has come to an end, I want to thank you for always being a hand to guide me, both professionally and personally. I hope one day I am able to influence a student the way you have influenced me. There are not words strong enough to express my appreciation, so “thank you” will just have to make due.

To Professor Jason Cao, thank you for all your advice and guidance. Our long chats in your office have helped shape the course of the path I have taken. Thank you for always making time for me. To Professor Yingling Fan, you have been a sounding board for me and my decisions. Your stalwart insistence that I will not only finish this research, but find the job of my dreams, have kept me on track at times when I felt lost. To Tracy Hadden Loh, thank you for all your support and your input into this work. You gave so much of your time and energy to helping this research be the best it could be, and I hope you know how much I appreciate your efforts. To my committee, Professor John Hourdos and Professor Maria Hanratty, thank you for giving me the chance to take the journey. Your support of my final step in this journey is truly humbling.

To Professor David Levinson, there just are not enough words to express the gratitude I have for you. You took a chance on me and it paid off. Your tough love brought out a strength and resigned determination in me to do my best. I feel I have learned more from the short time I was able to study under you than in my many years of schooling. Thank you for all our meetings, our lunches, and our 4:00 AM email exchanges that helped me get all this done. The only reason I would easily do this all over again, is for the privilege of getting to spend time with you.

To Madeline, what more could I say that I have not already said. You have stood by me through the hard times, the long nights, and a job that takes me 400 miles from you.

You have been my rock, my cheerleader, and my, sometimes begrudging, proofreader. Thank you for always being there.

I wanted to save the best for last and thank my family in Iran. While they cannot be here in person, the calls, the emails, the hours spent learning new technology just to cheer me on will never be forgotten. To my father, your words of advice and encouragement kept me going in the days I was ready to turn around and come home. To my sister, thank you for taking care of our mother and in turn giving me a chance to follow my dreams. To my mom, thank you for giving me the strength to have dreams to follow, and never letting me think any desire I had was too big or too bold. You have given me a life I cherish, and I will never sufficiently be able to return to you the gift you have given me. Thank you for your love, with your encouragement, and most of all, for just being the amazing mother you are.

Dedication

To my always encouraging and beloved mother, Shahrbanoo Khaniky, whose words of inspiration and push for tenacity always whisper in the back of my mind.

To my compassionate and courageous father, Cyrus Ermagun, who taught me honesty and strength.

Words are just not expressive enough.

Abstract

Despite the importance of multi-use trails in urban non-motorized transportation networks, transportation planners, engineers, and trail managers lack tools for describing economic activity associated with local trail use and for predicting bicycle and pedestrian demand for trails. New tools are needed to plan and prioritize investments in new facilities and to inform management and maintenance of trail infrastructure. Among other needs, they need tools to predict (1) expenditures by local users to support local economic development initiatives and assess neighborhood effects of proposals for trail development and (2) trail traffic demand for optimizing investments and managing maintenance of systems and facilities. This thesis responds to these needs and augments the burgeoning literature on trail traffic analysis by developing models of trail-related expenditures and mode-specific trail demand models.

From the expenditures by local users side, using the results of intercept surveys completed by 1,282 trail users on the Central Ohio Greenway trail network in 2014, this thesis estimates the probabilities and patterns that different types of trail users will make expenditures. Approximately one-fifth of trail users reported spending between US$15 and US$20 for food, drink, and other incidental items. Across all trail users the average expenditure by individuals is about US$3 per visit. All else equal, cyclists are more than twice as likely than other users to report expenditures. Users visiting trails principally for recreation are 53% more likely to spend, while users visiting trails mainly for exercise were about 19% less likely. Both longer trips to and on the trails are associated with higher spending.

From the trail traffic demand side, this thesis employs trail traffic volumes recorded at 15-minute intervals for 32 multi-use trails located in 13 urban areas across the United States from January 1, 2014 through February 16, 2016. The results of analyses indicate (1) daily trail traffic varies substantially – over three orders of magnitude – across the monitoring stations included in the study; (2) daily trail traffic is highly correlated with weather, and the parabola form of weather parameters works well for modeling variables such as temperature, where trail use is associated with warmer temperatures, but only up to a point at which higher temperatures then decrease use; (3) bicyclists and pedestrians

respond differently to variations in weather, and their responses vary both within and across regions; (4) with only a few exceptions, average daily pedestrians (ADP) and average daily bicyclists (ADB) are correlated with different variables, and the magnitude of effects of variables that are the same varies significantly between the two modes; (5) the mean relative percentage error (MRPE) for bicyclist, pedestrian, and mixed-mode demand models, respectively, are 65.4%, 85.3%, and 45.9%; (6) although using multimodal monitoring networks enables us to juxtapose the bicyclist demand with pedestrian demand, there is not a significant improvement in predicting total demand using multimodal sensors; (7) a new post-validation procedure improves the demand models, reducing the MRPE of bicyclist, pedestrian, and mixed-mode models by 27.2%, 32.1%, and 14.1%.

Transportation planners, engineers, and trail managers can use these results to estimate the effects of weather and climate on trail traffic and to plan and manage facilities more effectively. The developed models also can be used in practical applications such as selection of route corridors and prioritization of investments where order-of-magnitude estimates suffice.

Table of Contents

Acknowledgements **i**

Dedication **iv**

Abstract **v**

List of Tables **ix**

List of Figures **x**

1 Introduction **1**

2 Literature Review **6**

2.1 Introduction 6

2.2 Trails, User Groups, and Expenditures 7

2.3 The Effects of Weather on Bicycling, Walking, and Trail Use 9

2.3.1 Weather and trail use 9

2.3.2 Weather and bicycling 10

2.3.3 Weather and walking 11

2.3.4 Summary 12

2.4 Recent Progress in Non-Motorized Demand Modeling 12

3 Data **16**

3.1 Intercept Survey 16

3.2 The Trail Modeling and Assessment Platform 19

3.3 Weather Data 23

3.4 Smart Location Database 24

4 Differences in Spending by Local Trail Users **25**

4.1 Introduction 25

4.2 Survey Results 26

4.2.1 Patterns of trail use 26

4.2.2 Expenditures by user type 28

4.3 A Two-Part Model of Trail Expenditures 29

4.4 Interpretation of the Two-Part Model 33

4.5 Pseudo-estasticities for the Probability of Spending 34

4.6 Interaction Effects: Some Parsimonious Models 36

4.7 Summary 37

5 Urban Trails and Demand Response to Weather Variations 38

5.1 Introduction 38

5.2 Bicycle and Pedestrian Volumes on Urban Trails 39

5.3 Regional Weather Models 43

5.4 Demand Returns 49

5.4.1 An example: demand response to daily average temperature 50

5.5 Elasticity Analysis 54

5.6 Summary 59

6 A Performance Assessment of Demand Models 60

6.1 Introduction 60

6.2 Trail Traffic Data 62

6.3 Trail Demand Models 65

6.4 Built-Environment, Socioeconomic, and Trail Demand 67

6.5 Cross-validation 69

6.6 Do Mode-specific Models Produce Better Estimates of Total Demand? 71

6.7 Post Validation Analyses: A Step toward Boosting the Accuracy 73

6.8 Summary 77

7 Closing Remarks 79

7.1 A Review of Findings 79

7.2 Implementations and limitations 84

References 88

List of Tables

4.1 Mean expenditures by trail user types 28
4.2 AIC and BIC results to choose the best generalized linear model 30
4.3 Description of variables used in the analysis 31
4.4 The final two-part model of trail expenditures 32
4.5 The results of the two-step analysis for parsimonious models 36
5.1 Descriptive statistics for ADB and ADP for all trail sites by climate regions 41
5.2 Descriptive of data and parameters used in the analysis 45
5.3 Results of negative binomial regression models for bicyclists on trails 46
5.4 Results of negative binomial regression models for pedestrians on trails 47
5.5 Vertex point of weather variables in different climate regions classified by mode . . . 53
5.6 Results of elasticity and marginal effects for bicyclist and pedestrian models 55
6.1 Annual average daily and average daily measures over monitoring stations 63
6.2 Results of two-sample mean- and variance-comparison tests 64
6.3 Descriptive of data and parameters used in the analysis 64
6.4 Results of the AIC measurement for different error distributions 66
6.5 Bicycle, pedestrian, and mixed-mode trail demand models 67

List of Figures

3.1 Maps of the central Ohio trails system 19
3.2 Trail traffic monitoring locations 21
4.1 Time and distance traveled to and on central Ohio trails 27
4.2 Pseudo-elasticity for the probability of expenditure with trail visit 35
5.1 A graphical distribution of ADB and ADP 43
5.2 Elasticity of continuous weather variables in different climate regions 58
6.1 Elasticity analysis of trail traffic demand models 69
6.2 MRPE analysis over all stations 71
6.3 Comparing MRPE of mixed-mode and combined models 72
6.4 Comparing observed and predicted trail traffic demand 75
6.5 Box-plot for absolute percentage error 77

Chapter 1

Introduction

Multi-use trails, or shared-use paths, are off-road facilities that form the backbones of non-motorized transportation networks in many metropolitan areas across the United States (Fabos, 2004; Searns, 1995). They serve cyclists and pedestrians, including walkers, runners, and skaters, for utilitarian, recreational, and other purposes such as health and fitness. They also boost access to valued destinations and serve public purposes such as economic development and public health promotion (Ryan et al., 2006; Gobster, 1995).

Since passage of The Intermodal Surface Transportation Efficiency Act in 1991, the federal government has allocated more than US$13 billion to multi-use trail projects (Rails to Trails Conservancy, 2016). These investments have been supported by hundreds of millions of additional investments by state and local governments, private foundations, and nonprofit organizations. Many jurisdictions have integrated plans for multi-use trails into local and regional transportation infrastructure plans and networks. The Rails to Trails Conservancy (RCT) estimates that 46% of Americans currently live within 3 miles of a multi-use trail that is at least 0.5 miles long. RTC also notes, however, that municipal and regional governments are working with state agencies and trail advocates to expand access to trails in many, if not most, of the 381 Census-designated Metropolitan Statistical Areas (MSAs) in the United States (Rails to Trails Conservancy, 2016).

Despite the importance of multi-use trails in urban non-motorized transportation networks, transportation planners, engineers, and trail managers lack tools for describing economic activity associated with local trail use and for predicting bicycle and pedestrian demand for trails. New tools are needed to plan and prioritize investments in new facilities and to inform management and maintenance of trail infrastructure. Among other needs, they need tools to predict (1) expenditures by local users for planning local economic development initiatives and assessing neighborhood effects of proposals for trail development and (2) trail traffic demand for optimizing investments and managing maintenance of systems and facilities.

Pertaining to expenditures by local users, the characteristics and behavior patterns of trail users generally have been well documented, but expenditures by local users typically have not been analyzed as they represent reallocation of expenditures within regions and not new spending in regional economies. However, local policy-makers and entrepreneurs are interested in who spends money during their visits to trails. Information about expenditures also can inform practical activities ranging from marketing to zoning to gauging demand for new businesses to serve the needs of trail users. To shed new lights on trail-related expenditures, this thesis employs an intercept survey of 1,282 multi-use trail users in the Columbus, Ohio during the summer of 2014.

Pertaining to trail traffic demand analysis, previous efforts to model trail traffic have been hampered by the lack of mode-specific data from automated, continuous monitor and, for the most part, have been limited to models for particular cities or metropolitan regions. This shortcoming has been largely rooted in the absence of continuous traffic counts for non-motorized traffic (Ryus et al., 2014). This thesis overcomes this limitation by analyzing trail traffics at 32 locations on multi-use trails in 13 urban areas across the United States for periods of at least one year at each site.

In particular, this thesis augments the burgeoning literature on trail traffic analysis by developing models of trail-related expenditures and mode-specific trail demand models. The research addresses eight specific questions:

1. Which behavioral and personal factors affect the probability and magnitude of expenditures during a trail visit?
2. How much does the variation in temperature, precipitation, wind speed, dew point, and hours of daylight affect daily bicycle and pedestrian trail traffic volumes?

3. How do multi-use trail users respond to variations in weather in different climate regions across the country?
4. How much do bicyclists and pedestrians in the same climate regions respond differently to variations in weather?
5. How well do built-environment and socio-economic characteristics describe bicyclist and pedestrian trail traffic demand?
6. How accurately can trail traffic models predict demand?
7. Can using multimodal devices predict total (i.e., mixed-mode) travel demand more accurately?
8. How and to what extent are trail traffic models improved by using post-validation techniques?

The remainder of the thesis is organized in six chapters. The content of the chapters is as follows:

Chapter 2 synthesizes three distinct branches of research focusing on multi-use trails. It aims to identify the limitations of the current understanding of spending by local trail users and multi-use trail traffic demand analysis.

Chapter 3 describes the data sets obtained for the analyses. These consist of: (1) the intercept survey of 1,282 multi-use trail users in Columbus, Ohio and surrounding counties during the summer of 2014; (2) trail traffic volumes recorded at 15-minute intervals for 32 multi-use trails located in 13 urban areas across the United States from January 1, 2014 through February 16, 2016; (3) weather variables extracted to examine the correlations between daily trail traffic and weather variables; and (4) the 2014 Smart Location Database obtained from The Environmental Protection Agency to study the relationship between average daily trail traffic and built-environment variables.

Chapter 4 answers the first research question and makes two contributions in the literature on determinants of expenditures by users on multi-use trails. First, it describes the patterns of expenditures by local trail users on different trails in the metropolitan trail network. Second, it uses a two-part model to estimate not only the probabilities that different trail users visiting the trails for different purposes will make expenditures, but also factors that correlate with the amount of expenditures.

Chapter 5 answers research questions two through four, and its contribution to the existing body of knowledge is twofold. First, it presents a set of econometrics models that summarize the effects of variation in temperature, precipitation, wind speed, dew point, and hours of daylight on daily bicycle and pedestrian trail traffic volumes. Many studies assume a linear relationship between weather factors and trail use, and few studies explicitly model this complex relationship to capture the more realistic weather effects. This chapter tests the parabola form of weather factors to explore a more realistic relationship between weather factors and trail use. Under the umbrella of this modeling approach, the chapter introduces the concept of demand returns. This approach better captures the actual response of trail users to weather variations across climate regions. Second, it compares regional elasticities for each weather variable for both bicyclists and pedestrians.

Chapter 6 answers research questions five through eight and contributes fourfold to the practical literature on trail traffic demand analysis. First, it develops a set of econometric models to predict average daily pedestrians (ADP), average daily bicyclists (ADB), and average daily mixed-mode traffic (ADM) using 5 D's of the built environment (Density, Diversity, Design, Distance to Transit, and Destination Accessibility) and socio-economic characteristics. Second, it tests the performance of trail demand models in predicting ADB, ADP, and ADM using the leave-one-out cross-validation technique, and it compares the accuracy of the models against one another. Third, it assesses the performance of separate bicycle and pedestrian demand models in predicting mixed-mode travel demand. This assessment sheds light on whether and to what extent planners and advocates gain in the accuracy of non-motorized total demand prediction when they establish multimodal monitoring networks. Fourth, it introduces a post-validation technique to advance the prediction accuracy of trail traffic demand models.

Chapter 7 concludes by providing an in-depth discussion on research implementations and broaches a number of arguments and suggestions for future studies.

Chapter 2

Literature Review

2.1 Introduction

In places where trail networks have been developed, planners and advocates often have cited economic, health, and social benefits in addition to recreation and transportation benefits as rationales for investing in trails (Fabos, 1995). The need for evidence to justify investments in trails and other infrastructure also has grown, as public funds for investment have become scarcer.

The increasing need to justify investments in trail infrastructure has been accompanied by growth in the literature on trails and their impacts. This literature has grown and spans many fields. In the transportation and recreation literatures, for example, many researchers have described the demographics and activity patterns of trail users (Lindsey, 1999; Shafer et al., 2000; Coutts, 2008; Coutts and Miles, 2011). They have shown that trail users tend to be white, disproportionately well-educated individuals with higher incomes, and that the trails may reflect the characteristics of neighborhoods in which they are located. Mode-mix on trails varies, but user patterns converge: cyclists tend travel further to and spend more time on trails than walkers or skaters, and, the commuters are disproportionately cyclists. Transportation researchers have analyzed hourly, weekly, and seasonal traffic patterns associated with different modes of traffic on trails (Miranda-moreno et al., 2013; Hankey et al., 2014) and estimated both daily and average daily trail demand models (Lindsey et al., 2007; Wang et al., 2013, Wang et al. 2016). Their research shows that methods used in transportation engineering to characterize motorized traffic can be adapted to non-motorized traffic, including bicycling and walking on trails. More recently, researchers have assessed the public health implications of trails (Brownson et al., 2000; Troped et al., 2005). Wang et al. (2005) concluded that every US$1 investment in trails results in direct medical benefits valued at US$2.94.

In consonance with the research questions enumerated in the preceding chapter, this chapter synthesizes three distinct, yet related branches of research focusing on multi-use trails. Despite the differences in approaches and main goals, all three branches emphasize the need for practical tools to ensure existing and proposed trail networks maximize the benefits. First, the literature on multi-use trail user expenditures is reviewed to identify the limitations of the current understanding of spending on local trails. Second, the effects of weather on bicycling, walking, and trail use are elaborated. This shows that the general effects of weather on biking, walking, and trail use are understood, but that most studies have not compared findings across regions or analyzed effects over the range of weather conditions illustrative of those in the continental United States. Third, practical insights are provided into recent progress in non-motorized demand modeling.

2.2 Trails, User Groups, and Expenditures

Although researchers have studied expenditures by recreationists and tourists on destination trails (Moore, 1992), measuring or modeling user expenditures is still in its infancy. Frechtling (2006) reviewed 11 methods for assessing visitor expenditures, differentiated studies of areas and studies of events, and reviewed best practices for administration of surveys required to obtain expenditure data. These survey methods are used in both cost-benefit analysis and regional economic impact analysis. For example, when using the travel cost method to estimate the economic benefits of destination trails, analysts typically survey users about their purchase of goods and services. Their expenditures then are aggregated and (along with other data) used to estimate total willingness to pay, the measure of benefits used to calculate net benefits. In regional economic impact studies expenditure data is used to assess the ripple effect through the economy by non-resident visitors to a region. The notion is that expenditures by non-residents are new and multiply as the money is re-spent by local service providers. Because trail-related expenditures by local residents are not new and would be spent locally on something else if not spent on trail-related goods and services, they are not included in estimates of total regional impact.

These types of studies have shown that expenditures at destination trails may be significant but that non-local visitors and local trail users have considerably different expenditure patterns. The former spends mostly on transportation and lodging while the latter spends mostly on “soft goods” such as food, drink, and incidental items (Toma et al., 2003). The Maine Department of Transportation studied the direct spending of bicycle tourism in 1999 (Maine DOT, 2001). The agency concluded that bicycle tourists injected US$36.3 million into the region in 1999; US$16.2 million was spent for food and groceries. As part of a study of the economic impact of the 150-mile Coastal Georgia Greenway, Toma et al. (2003) surveyed 578 separate households that participated in the 2002 Historic Savannah Bikefest. They reported that daily spending on food, drink, and entertainment while at the Bikefest was US$41 and US$11 for non-local and local trail users, respectively. In a study of expenditures by 2,229 users of the Allegheny Trail Alliance system in Western Pennsylvania, Farber et al., (2003) found that expenditures varied with distance traveled to a trail: users travelling less than 10 miles and more than 60 miles spent, on average, US$4.03 and US$15.44 per day, respectively. Similar findings have been report internationally. Lumsdon et al. (2004) studied the expenditure patterns of cyclists on the North Sea Cycle Route, a long distance trail in England. The mean expenditure per group (each with an average of two persons) was US$21.70 per day. In a study of cycle tourism particularly relevant to this inquiry, Downward et al. (2009) modeled expenditures of cyclists who completed travel diaries. They found that “incomes, group sizes, and durations of activity are integrally linked determinants of expenditure” (p. 25). In a 2010 study of the economic impact of a 106-km greenway in Spain, analyses of a survey of 1,261 non-local users indicate tourists spend, on average, US$14.32 on bars, restaurants, shopping, transport, and accommodation (Mundet and Coenders, 2010).

In sum, the current literature has described local trail users and their patterns of use, and measured trail-related expenditures for use in cost-benefit analyses and regional economic impact analyses. Researchers have noted that non-resident visitors to recreation facilities, including destination trails, travel for different reasons and spend more than local users. Researchers also have explored market segmentation to categorize users into different groups that share recreational and other attitudes and behaviors. Few studies, however, have focused on expenditure patterns by local trail users or modeled how factors such as trip purpose are correlated with local expenditures.

2.3 The Effects of Weather on Bicycling, Walking, and Trail Use

Researchers have published many papers on the effects of weather on bicycling and walking, including some papers specifically about the effects of weather on trail use. These papers have been published in the transportation, health, recreation, geography, planning, and meteorological journals. Not surprisingly, these studies have confirmed casual observations and intuitive hypotheses: people bicycle and walk more when the weather is pleasantly warm and sunny and less when it rains, snows, is very hot or very cold, very humid, and very windy. These findings generally are consistent regardless of the measures of cycling and walking (e.g., traffic counts, travel diaries), trip purpose (e.g., commuting, recreation), season, and geographic region. However, the magnitude of the marginal effects of weather on mode and trips made for different purposes in different seasons in different places varies within and across regions. Variations in weather generally have been shown to have greater effects on cycling than on walking.

2.3.1 Weather and trail use

Studies of the effect of weather on use of multi-use trails or shared-use paths are of greatest relevance to this thesis (Gobster et al. 2017; Wang et al., 2013; Thomas et al., 2013; Maslow et al., 2012; Burchfield et al., 2012; Wolff and Fitzhugh, 2011; Brandenburg et al., 2007; Lindsey et al., 2007; Lindsey et al., 2006; Gobster, 2005). Most of these studies have analyzed traffic counts from automated monitoring devices, either infrared devices that cannot distinguish between cyclists and pedestrians (Wang et al., 2013; Wolff and Fitzhugh, 2011; Lindsey et al., 2007; Lindsey et al., 2006) or pneumatic tubes (Thomas et al., 2013). Some have relied on manual counts from video or field observations (Gobster, 2005) or on survey data (Maslow et al., 2012). Most have used regression analysis to analyze counts; different modeling techniques have included OLS, log-linear models, and negative binomial models. Temperature and precipitation have been analyzed more frequently than wind speed and humidity; daylight has been modeled less frequently. These variables have been operationalized in a variety of ways. For example, temperature has been represented as degrees (Fahrenheit or Celsius), as categorical variables (e.g., days in temperature ranges), or as deviations from long-term or seasonal averages. Similarly, in models of the effects of precipitation, researchers have used both measures of depth and categorical variables (e.g., zero, trace, < 1 inch, etc.) based on depth. Researchers have found that trail use increases with temperature, but only up to a point: trail use levels or drops off at higher temperatures (e.g., above 32℃). Deviations from expected temperature also are correlated with variation in trail use, and this effect may vary seasonally. For example, in cold climates, unexpectedly high temperatures in winter months (e.g., 10℃) may be associated with spikes in use, while the same temperatures in summer may be associated with dips in use. Collectively, studies of trails in Chicago IL (Gobster et al., 2017; Gobster, 2005), Indianapolis IN (Lindsey et al., 2007; Lindsey et al., 2006), Knoxville TN (Wang et al., 2013; Wolff and Fitzhugh, 2011), Spartanburg SC (Maslow et al., 2012), Vienna, Austria (Brandenburg et al., 2007), and cities in the Netherlands (Thomas et al., 2013) show that trail use is positively associated with temperature and hours of sunshine and inversely associated with precipitation and wind speed.

2.3.2 Weather and bicycling

Researchers have used a variety of approaches to analyze the effects of weather on cycling. Some researchers have used survey-based discrete choice modeling to assess the effects of weather on propensity to bicycle or for different trip purposes (Liu et al., 2015; Liu et al., 2014; Fernández-Heredia et al., 2014; Helbich et al., 2014; Saneinejad et al., 2012; Flynn et al., 2012; Bergström and Magnusson, 2003). Other researchers have developed count-based, facility demand models of hourly or daily traffic that control for the effects of weather (Corcoran et al., 2014; Kraemer et al., 2015; Nosal and Miranda-Moreno, 2014; Miranda-Moreno et al., 2013; Tin et al., 2012; Miranda-Moreno and

Nosal, 2011). These models have become increasingly common as new technologies for distinguishing cyclists from vehicles on streets have been developed. Other researchers have used sample surveys to model the effects of weather (Motoaki and Daziano, 2015) or focus groups and interviews to assess why cyclists respond to variations in particular ways (Spencer et al., 2013). Most of these studies have been of general population surveys or counts on public facilities, but some studies have been limited to special facilities or populations of interest including bike share stations, university students, faculty, and staff (Motoaki and Daziano, 2015; Corcoran et al., 2014). Studies have been reported for a variety of facilities, cities, and regions around the world: Ithaca, NY (Motoaki and Daziano, 2015); Vermont (Spencer et al., 2013), Auckland, New Zealand (Tin et al., 2012); Brisbane, Australia (Corcoran et al., 2014), Madrid, Spain (Fernández-Heredia et al., 2014), Melbourne, Australia (Nankervis, 1999), Montreal, Canada (Nosal and Miranda-Moreno, 2014), the Rotterdam region in Netherlands (Helbich et al., 2014), Toronto, Canada (Saneinejad et al., 2012), and in cities and regions of Sweden (Liu et al., 2015; 2014). With few exceptions, the findings are consistent: cyclists are less likely to bicycle on colder, rainier, and windier days or when there is snow accumulation, and these effects are larger for recreational cyclists than for commuters.

2.3.3 Weather and walking

Travel diaries generally show that walking accounts for a larger percentage of trips than bicycling, but fewer studies seem to have explored the effects of weather on walking than on bicycling. Automated counts of pedestrians are less common than counts of bicyclists, partly because devices for monitoring pedestrians on sidewalks are not as widely available as devices for monitoring cyclists on roads, and partly because pedestrian behaviors are more complex. In some cases, researchers have relied on manual field observations or counts of pedestrians from video (e.g., peak-hour, intersection counts (Miranda-Moreno and Fernandes, 2011)). One study focused on Montreal, Quebec; another compared patterns in nine cities across the world (Montiguy et al., 2012). Both discrete choice models of walking estimated from travel diaries and counts of pedestrians indicate: (1) walking fluctuates less seasonally than bicycling and (2) daily variations within seasons are less than for cycling.

2.3.4 Summary

Researchers have produced quantitative information about the marginal effects of specific elements of weather on cycling and walking, including their effects on mixed-mode trail use. In general, bicycling has been shown to be more elastic than walking: both models of propensity to bicycle and models of traffic counts of bicyclists show bicycling generally is characterized by greater seasonality and variation in response to differences in daily weather than walking. While our understanding of these effects has grown, it is not complete. None of the studies cited here has separately analyzed counts of both cyclists and pedestrians taken with automated sensors over long sampling periods in regions with different climates. In addition, although many researchers have shown that trail use increases with higher temperatures, and some analysts have shown that trail use may decrease if temperatures become too high, researchers have not yet presented a general framework for analyzing and describing these types of effects.

2.4 Recent Progress in Non-Motorized Demand Modeling

Researchers have made considerable progress in modeling demand for non-motorized transportation in the past 20 to 25 years, moving from models based on two hour manual counts of bicyclists and pedestrians on roads, sidewalks, and trails to models using continuous counts recorded with automated devices of different types. In general, as researchers have gained access to longer, longitudinal datasets, their use of more sophisticated modeling techniques has increased. Because of the importance of trails in non-motorized networks, the absence of motorized traffic on trails, and a geometry that lends itself to monitoring, better datasets are available for trail traffic than for bicycles on streets and pedestrians on sidewalks. The increased availability of trail datasets is reflected in the modeling literature.

Demand models based on bicycle, pedestrian, or trail counts have been built both to explore theoretical relationships and for practical purposes such as prediction. These models have shown that weather and the built environment exert powerful influences on demand for both cycling and walking. Wang et al. (2016) summarized eight direct bicycle and pedestrian demand models published in the peer reviewed literature since 2007; additional models have been published since then. Using manual, short duration counts (e.g., two hour peak hour counts), researchers have modeled pedestrian traffic at intersections (Liu and Griswold, 2009; Schneider et al., 2009; Haynes and Andrezejewski, 2010; Jones et al., 2010; Schneider et al., 2013) and bicycle and pedestrian traffic along street segments (Hankey et al., 2012). Researchers have used continuous counts from automated infrared monitors to monitor both daily traffic and annual average daily trail traffic (AADTT) on trails (Lindsey et al., 2007; Lindsey et al., 2008; Wang et al., 2013; Wang et al., 2016; Gobster et al., 2017). Researchers also have developed demand models for bike-share programs (e.g., Bachand-Marleau et al. 2012; Buck et al. 2012; Wang et al. 2015). These bike share models are not reviewed here because of the unique characteristics of bike share programs and the locations in which they operate. However, they show generally that bike share demand is correlated with job and population density and, in some cases, proximity or access to trails, on-street bicycle facilities, surface water features, and recreation destinations.

The modeling approaches have included estimation of linear models (Liu and Griswold, 2009; Schneider et al., 2009; Haines and Andrezejewski, 2010; Wang et al., 2013), log-linear models (Lindsey et al., 2007; Lindsey et al., 2008; Jones et al., 2010; Schneider et al., 2013), and negative binomial models (Hankey et al., 2012; Wang et al., 2013; Wang et al., 2016) based on different assumptions about the underlying distributions of the data. Variables found to be significantly associated with bicycling and pedestrian traffic include socio-demographic variables (e.g., education and race); characteristics of the built environment (e.g., population and job density); and location in transportation network (e.g., transit accessibility; street functional class). Daily models have focused on weather or used weather as controls, while models of AADT typically have not included them because the models have been estimated for specific regions and the effects of variations of weather are taken into account by average daily counts.

Several researchers have described efforts to validate the predictive capacity of their models (Schneider et al., 2009; Haines and Andrezejewski, 2010; Hankey et al., 2012; Wang et al., 2013; Wang et al., 2016). Validation analyses have shown that, for daily count data, the negative binomial models perform better. Specifically, for models of daily demand where the dependent variable is a count, negative binomial models outperform OLS models in validation tests: average error of predictions is lower, and predictions of negative values do not occur (Hankey et al. 2012). Almost all of these efforts have relied on in-city validation; only one paper has reported cross-validation across cities that involved transfer of models across cities using comparable datasets (Wang et al., 2016). This experiment involved cross-validation of mixed mode trail demand models developed for 80 trail segments in Minneapolis, MN and 100 trail segments in Columbus, OH. Errors in estimation of AADTs ranged between 100% and 200%, with errors for the networks overall of between 19% and 26% (Wang et al., 2016). Researchers concluded that the models could be used for general planning studies but that the better tools would be needed for site-specific design studies.

More generally, work to develop and apply direct demand models in practical contexts is increasing. In a National Cooperative Highway Research Program (NCHRP) guidebook for estimating bicycle and pedestrian demand, Kuzmyak et al. (2014) describe the limitations of direct demand models relative to individual choice-based models, but note they are useful because of their simplicity and practicality, and that the models will benefit from ongoing efforts to produce better, longitudinal data. As part of its efforts to develop a Non-motorized Travel Analysis Toolkit, the Federal Highway Administration (2017) calibrated and applied the bicycle and pedestrian demand models originally estimated for the City of Minneapolis by Hankey et al. (2012) in Alexandia, Virginia (http://nmtk.pedbikeinfo.org/ui/#/). As part of a master plan for trail development in Prince George's County, Maryland, trail traffic demand models originally estimated for Minneapolis, MN were used to estimated AADTT for both existing and proposed trails (MNCPPC, 2016). Trail planners assessed validity through comparisons to counts that had been taken ad hoc and used the estimates to identify segments likely to have higher counts.

As is evident from this brief review, additional research to develop new trail demand models that can be used as planning tools for practice is needed. None of the studies previously published has reported separate demand models for bicyclists and pedestrians on trails. In addition, most models have been developed with data from a particular city or metropolitan region. Models built using data from multiple locations may help overcome this limitation.

Chapter 3

Data

This chapter represents the data sets used in this thesis, which were obtained from four distinct sources. Two of them are multi-use trail related data sets that form the backbone of the research, while the other two were extracted to augment the data for the purpose of analysis. The first data set is the intercept survey conducted on the central Ohio trails system by the Mid-Ohio Regional Planning Commission (MORPC) in summer 2014. The data encompasses the expenditure information of 1,282 trail users. The second data set collected by the RTC and is a multi-year national data focused on urban trail use in the United States. The third and fourth data sets are complementary weather and built-environment data sets, respectively. They were extracted from national data sources to augment the trail traffic data. The following subsections provide an in-depth discussion over each data.

3.1 Intercept Survey

The central Ohio trails system encompasses 10 trails with 110.8 miles length in total in both Franklin and Delaware Counties (Figure 3.1.a). Trails are located in urban, suburban, and rural neighborhoods, along river and stream corridors or on historic rail lines, and are bordered by land uses ranging from park and residential to commercial and industrial. Access to commercial and retail services along trails varies. The Olentangy Trail, for example, runs from suburban Delaware County, past Ohio State University, to downtown Columbus where it joins the Scioto Trail. The Alum Creek Trail traverses rural to urban neighborhoods, including smaller commercial districts. Many trail access points are located in parks, but users also can access each trail at road crossings.

To collect detailed information about user patterns and expenditures, MORPC, the Central Ohio Greenways and Trails Group (COG) steering committee, and a research team designed and administered an intercept survey. The final intercept survey had 19 questions and required only a few minutes to complete. Most questions were close-ended and required respondents to provide a single answer or response by filling in a circle next to their answer choice. Users were asked about:

- their main activity on the trail,
- their purpose for visiting the trail,
- the time and distance they had or intended to spend on the trail,
- the time and distance they had traveled to use the trail, their mode of transportation to the trail,
- whether they were using the trail alone, with others, or with children,
- whether they had or would make expenditures while on their trail visit,
- how many times they had used the trail in the past seven days,
- how many different trails they had used in the past seven days, and
- their gender, age, education, income, and zip code.

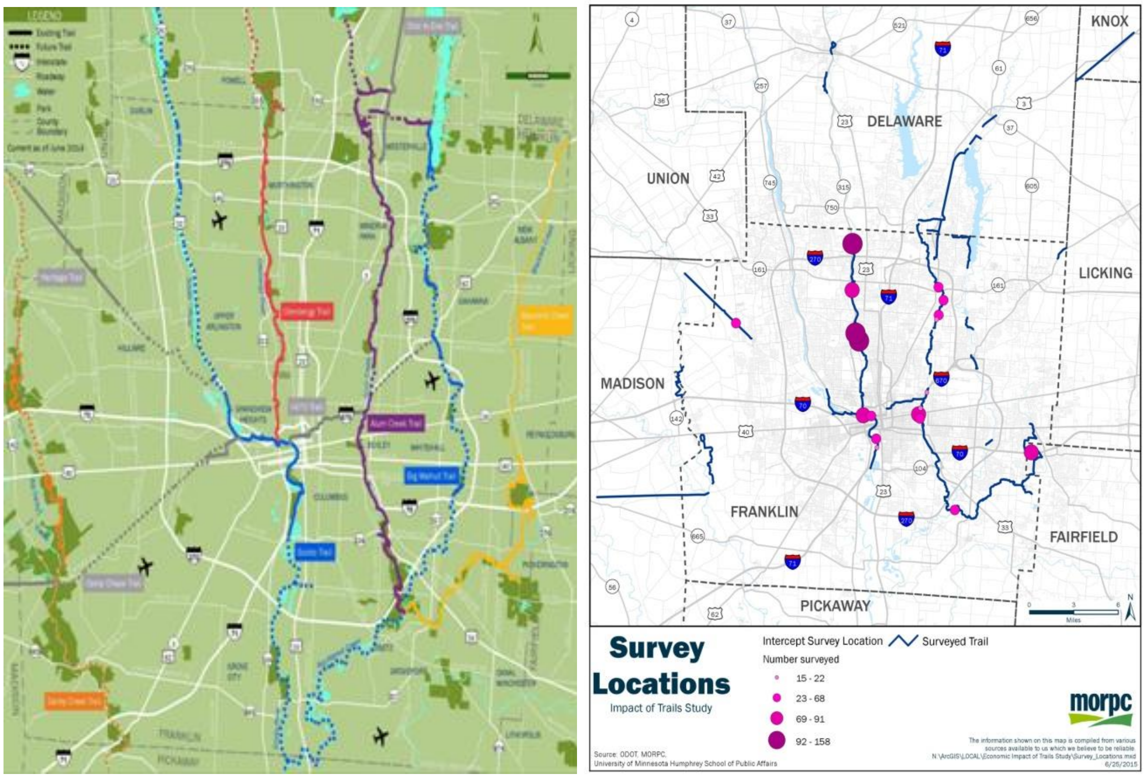
The wording of the expenditure question was:

> *On your visit to this trail today, will/did you make any expenditures for refreshments, meals, or other goods and services?* (No, Yes). *If yes, approximately how much will/did you spend?*

The research team developed a systematic, stratified sampling plan that involved sampling at different times of day on each day of the week at multiple locations on multiple trails. The intercept survey was conducted on 39 days between July 28, 2014 and September 7, 2014. A research assistant sampled users at different locations in three-hour “bouts” one or two times per day between 7:00 AM and 7:00 PM. Users were approached and asked to complete the survey; people who reported they already had completed a survey were not surveyed again. The numbers of and types of users who declined to participate in the survey were not tracked because high volumes of users at some locations precluded accurate monitoring by the individual administering the surveys.

The survey locations were selected in consultation with MORPC staff and trail managers familiar with the trails. Most of the locations were trailheads used by people to access trails. Other considerations in selecting intercept sites included distance from other trailheads on the trail, the availability of space for setting up a table, and safety. The final sampling plan included 19 locations on five different trails: the Alum Creek Trail, the Blacklick Creek Trail, the Heritage Trail, the Olentangy Trail, and the Scioto Trail. The length of these five trails (68.8 miles) is approximately two-thirds of the COG network. Figure 3.1.b shows the distribution of collected data by trail segment. A total of 1,282 trail users completed the intercept survey.

Stratified samples like this one are not random samples but often are used to approximate when random samples cannot be drawn due to the complexity or difficulty of obtaining truly random samples. This approach to the administration of the intercept survey is believed to generate a sample that generally is representative of trail users, but it has several limitations. The sample is likely to include some self-selection bias that may be associated with trail users' activities on the trail. For example, cyclists who accessed the trail riding their bicycles may have been less likely to stop when approached. Similarly, people commuting on trails may be underrepresented because they may have been less likely to stop when approached. Conversely, people using the trail for recreation may have had more flexible schedules and therefore more likely to participate. Other trail user characteristics (e.g., gender, education) also may be associated with an individuals' likelihood of completing the survey. Because these characteristics are not known for entire populations of trail users, the extent to which this sample differs from the "true" population of trail users cannot be determined. Assessing the propensity of users to spend while holding all other factors equal, which is used in Chapter 4, helps to mitigate this limitation of the sample.



a. The central Ohio trails system   b. Distribution of gathered questionnaires

FIGURE 3.1 Maps of the central Ohio trails system

3.2 The Trail Modeling and Assessment Platform

The RTC's Trail Modeling and Assessment Platform (T-MAP) is a multi-year national data collection and research effort focused on urban trail use in the United States. The goal of the project is to understand American trail use in the urban context, establish baseline volumes of trail use and identify correlates of trail use, including weather, which can be used to predict trail use. T-MAP focuses specifically on urban areas, where over 80% of the U.S. population resides, in alignment with RTC's goal of bringing every American within 3 miles of a high quality trail network by 2020. This thesis uses the first results from this initiative, specifically, from a network of 32 trail traffic monitoring stations on trails in 13 urban areas across all climate zones in the continental U.S. These volume data will be complemented in the future with additional geo-spatial data and with measurements from an intercept survey of trail users conducted on a sample of 15 trails from the traffic monitoring network.

The T-MAP study area includes urban areas in seven continental climate zones identified by the U.S. Department of Energy (DOE) (Baechler et al., 2010): very cold, cold, marine, mixed-dry, mixed-humid, hot-dry, and hot-humid. The DOE zones are used to group sites because the zones cross state boundaries and generally are descriptive of climatic factors that affect how people use trails.

The sample includes only larger cities with Census-designated urbanized areas of over 150,000 people. Specific cities were recruited to the study based on RTC staff knowledge of the existence and maturity of an area's trail facilities and the interest and willingness of local trail managers to permit the permanent installation of traffic monitoring equipment on local trails. In each study area, a minimum of two distinct trail facilities were selected by local partners for monitoring. The trail-specific monitoring locations were based on safety, security, suitability, and minimization of proximate features that might affect the performance of the monitoring equipment. Suitability included considerations such as ease of access for checking the equipment and the proximity to access point for trail users. Trail traffic volumes were not a consideration in site selection as the objective was to monitor over a range of volumes. In addition, several locations where traffic monitoring equipment already had been installed as part of a local initiative are included in the sample. However, only stations of the same make and model as the traffic monitoring equipment used elsewhere in this thesis are included. The final sample includes stations in the following cities: Portland, ME; Arlington, VA; Miami, FL; New Orleans, LA; Indianapolis, IN; Minneapolis, MN; Duluth, MN; Fort Worth, TX; Houston, TX; Albuquerque, NM; Colorado Springs, CO; Billings, MT; Seattle, WA; and San Diego, CA (Figure 3.2). A limitation of the dataset is that the number of monitoring locations varies across regions and the information of only one or two stations are available in some regions. I recognize, a priori, that I cannot completely characterize a region with a single station, but my objective is to illustrate variation that does exist across regions, and I believe the selected sample accomplishes this.

All locations were subject to the same data validation protocol. When evaluating the suitability of a site for traffic monitoring, the primary concern was the potential for false readings, or the triggering of the automated counter by anything other than a trail user. When using an infrared sensor, the location must be screened to prevent overlap between the infrared beam and any right of way other than the trail, including other trails/trailheads, streets, sidewalks, transit plazas, and train tracks. Ideally the location is one where trail users are not particularly likely to be tempted to stop or pause, such as a trailhead, viewpoint or trailside amenity location.

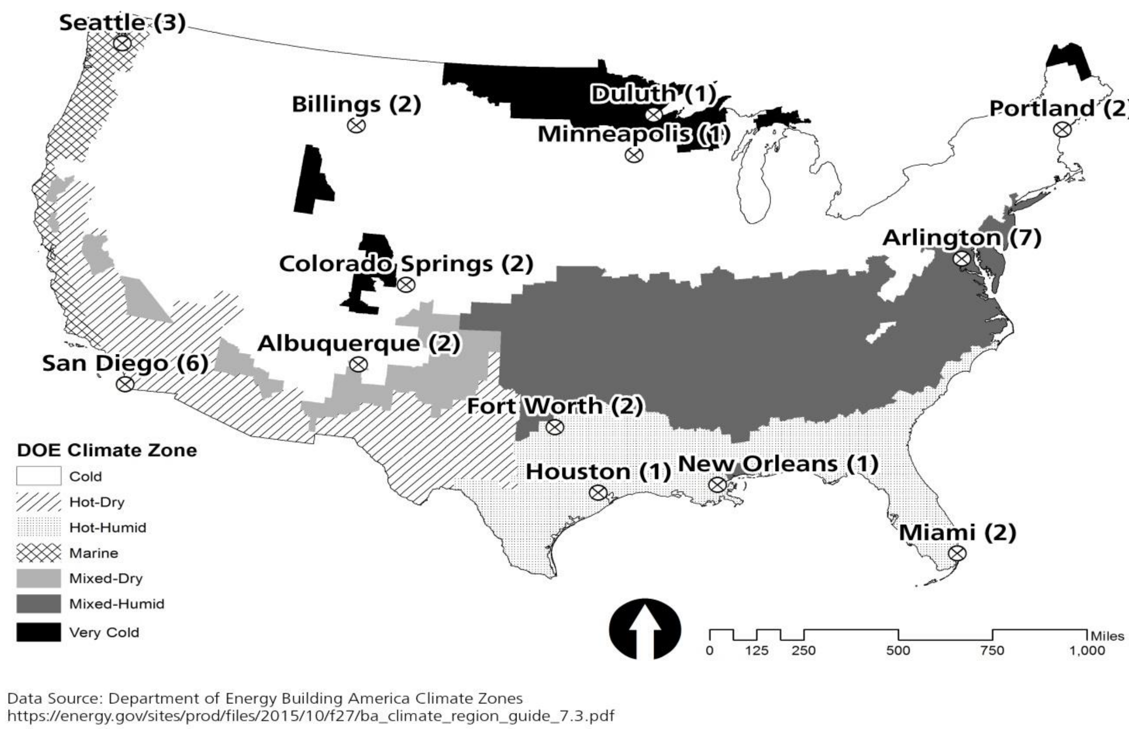


FIGURE 3.2 Trail traffic monitoring locations

The trail monitoring devices measure traffic – the number of users that pass by the monitoring station – not the number of different individual users. Within each city, the monitoring stations are located on distinct trails, such that it is highly unlikely an individual trail user would pass two separate monitoring locations in one trail trip. It is certain, however, that a percentage of trail users completing “loop” trips pass by the same monitoring location on a single trip. Across cities, the locations represent a variety of surrounding land use conditions, covering a full spectrum from ocean views, residential neighborhoods, employment centers, tourism destinations, to interstate highways. Maintenance practices, such as snow removal and night lighting, are similarly diverse across locations. All locations are on paved multi-use trails with the exception of one location in Colorado Springs, CO where the surface is crushed limestone.

Each traffic monitoring station consists of a combination inductive loop and passive infrared sensor. A recent NCHRP Project 07-19 found that inductive loops provide accurate counts of cyclists with less than 1% deviation from true volumes, while passive infrared sensors are accurate, on average, within 10% (Ryus et al., 2014). A principal source of error associated with passive infrared sensors is occlusion – an undercount that occurs because the heat signatures of users who pass the sensor simultaneously cannot be distinguished. Although it is possible to adjust this systematic error (Ryus et al., 2014), the analysis presented in this thesis is based on unadjusted data. It was decided not to adjust measurements for observed error because this is consistent across sites and adjustment mainly is a scaling exercise that should not affect these modeling results significantly. More generally, the problems that prevented inclusion of all data underscore the need for managers launching new monitoring programs to validate counts.

The original T-MAP traffic monitoring network included 50 station locations. Following procedures used in NCHRP Project 07-19 (Ryus et al., 2014), a four-hour manual validation count was conducted at each location. The absolute percentage deviation from true volumes on an hourly basis by mode and in total for each location was estimated, and then any location that had over 40% deviation for any one hour for either mode was extracted from this analysis. This criterion was not applied to hours in which volumes per mode were under 10, because at extremely low volumes, very small errors in absolute volumes produce large percentage deviations that do not reflect the order of magnitude of the significance of the error. Professional judgment was used to make decisions about including sites with low volumes. Factors considered included the magnitude of counts, consistency in the direction of error, and consistency in the four hour samples. With this approach, 18 original station locations were excluded from the study.

Visualizations of all counts were inspected and standard procedures were followed for quality assurance, quality control, eliminating days in the record when no data were recorded or only one sensor was functioning. Both visual inspection and statistical procedures were used to identify and censor outliers. Because events can result in atypical volumes, the web was searched to determine whether events may have occurred on days with high readings.

3.3 Weather Data

Based on findings of previous studies, six weather variables are selected for analysis: temperature, precipitation, snow, dew point, average daily wind speed, and hours of daylight (Wang et al., 2013; Thomas et al., 2013; Maslow et al., 2012; Burchfield et al., 2012; Wolff and Fitzhugh, 2011; Brandenburg et al., 2007; Lindsey et al., 2007; Lindsey et al., 2006). All weather data were downloaded from two electronic archives maintained by the National Oceanic and Atmospheric Administration (2015): the Global Historical Climatology Network (2015) and the Quality Controlled Local Climatological Data (2015). The closest weather station with a complete record of data for the variables of interest was selected for each trail site. This resulted in the selection of one weather station for each urban area. Although it is true that weather may vary within a metropolitan region, data typically are not recorded and in this case were not available for subareas for each trail monitoring location. The distance to each weather station varied, but the weather data are believed to be representative of conditions at the trail. The seasons are defined according to the Northern Hemisphere as the study is conducted in the United States. Therefore, spring covers March, April, and May; summer covers June, July, and August; fall covers September, October, and November; and winter covers December, January and February.

3.4 Smart Location Database

For modeling and estimation purposes, the T-MAP data were augmented by a group of built-environment characteristics extracted from the 2014 Smart Location Database prepared by the U.S. Environmental Protection Agency (Ramsey and Bell, 2014). The database consists of more than 90 land use and urban form variables summarizing conditions for every census block group at the national level. The land use and urban form variables fall into five major categories, the so-called 5D's of built-environment: (1) density, (2) diversity, (3) design, (4) distance to transit, and (5) destination accessibility. This data were selected as it is a national data set, which enables users to calibrate the models for their own communities, and thereby enhances practical application of the models. I refer the reader to Ramsey and Bell (2014) for more information about the data preparation and variable definitions as it is not in the scope of the current thesis.

Chapter 4

Differences in Spending by Local Trail Users

4.1 Introduction

A common justification for trail development is that users spend money and support retail businesses in trail corridors. Information about expenditures by trail users is potentially useful to planners, economic development specialists, business owners and entrepreneurs, and trail advocates.

Most studies of expenditures by trail users focus on the regional economic impacts of destination trails that bring non-residents into regions for recreational purposes. Fewer studies have assessed expenditures by urban trail users who use local trails frequently for exercise, recreation, or commuting. Expenditures by local trail users do not constitute new regional economic impacts because they simply shift spending from one location to another within a region. However, these types of expenditures are important locally to planners, business owners, and others who view trails as mechanisms to stimulate local economic activity. Local officials can use information about trail-related expenditures, for example, to inform entrepreneurs exploring the feasibility of commercial or retail projects near trails, or to assess proposals for bicycle-related enterprises. In addition, owners of cafes, restaurants, and shops near trails may find information about expenditure patterns useful for marketing.

This chapter presents new information about trail-related expenditures by users of multiuse trails in the Columbus, Ohio metropolitan area. Findings are based on the results of an intercept survey of 1,282 trail users in the summer of 2014. A two-part modeling approach is tested to evaluate (1) the relative probabilities that different types of users (e.g., cyclists, walkers) traveling for different purposes (e.g., recreation, commuting) will make expenditures, and (2) behavioral and other factors that affect the magnitude of expenditures.

The remainder of the chapter is structured as follows. First, a descriptive data analysis is represented to give the reader a sense of trail use and expenditure patterns in the sample. Second, the model is provided followed by both descriptive and modeling results. The chapter concludes with summarizing the findings of the analysis.

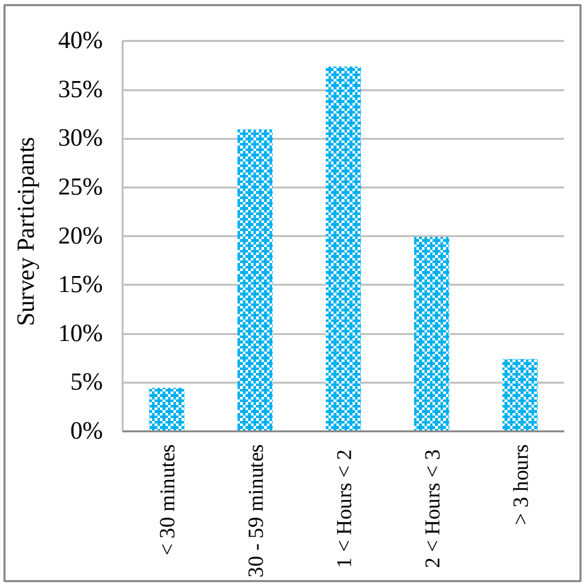
4.2 Survey Results

4.2.1 Patterns of trail use

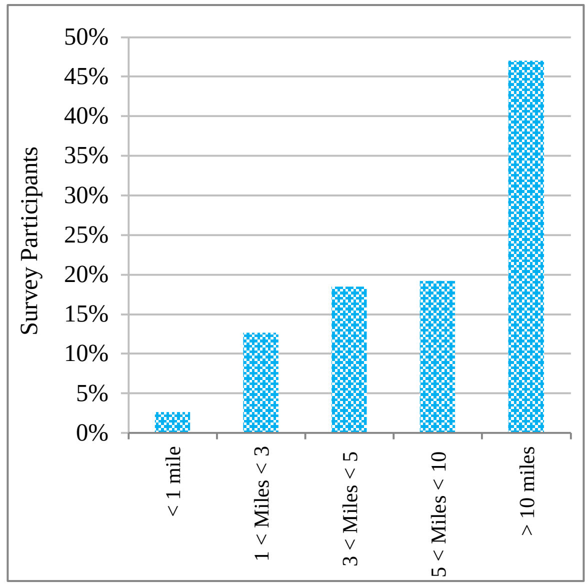
Cyclists accounted for 60% of respondents; the proportions of runners and walkers were 21% and 19%, respectively. The vast majority of respondents (91%) reported their main purpose as recreation, exercise, or both activities. Few reported that their visit was primarily for utilitarian purposes (commuting – 6%; shopping – 1%). The majority of respondents either cycled (44%) or drove to get to the trail (38%). The proportions of respondents who walked (9%t) or ran (8%) were comparable. A slight majority said they were using the trail by themselves, but nearly half said they were visiting with others, including nine percent with children. The results also indicate that most users visit the trail multiple times per week. Two-thirds of respondents said they had visited three or more times per week. Ten percent said they visit daily or more often; 29% said they had visited only once (i.e., the visit when they were surveyed).

A majority of respondents were male (60%). A plurality of respondents (36%) was between the ages of 50 and 64, and an additional 27% were between the ages of 35 and 49. The majority was well educated: 35% reported having at least bachelor's degree, and an even higher percentage (39%), reported having a graduate degree. More than half of the respondents reported annual household incomes greater than US$75,000.

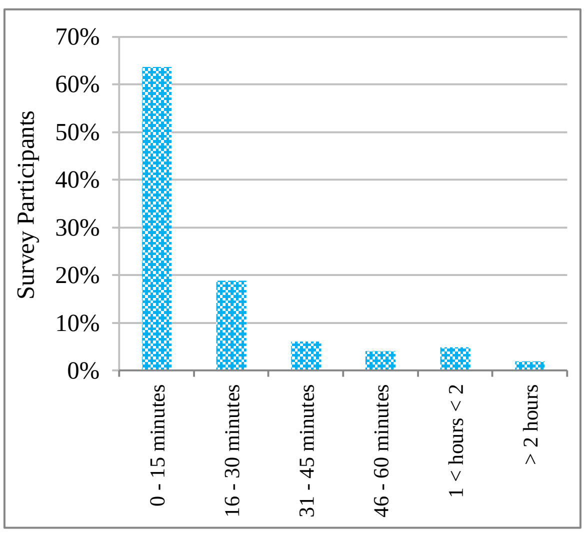
As shown in Figure 4.1, travel time and distance to trail and duration of trail use are particularly important variables in analyses of expenditures. Nearly two-thirds of the respondents took less than 15 minutes to get to the trail. Cumulatively, 83% of users reported accessing the trail within 30 minutes.



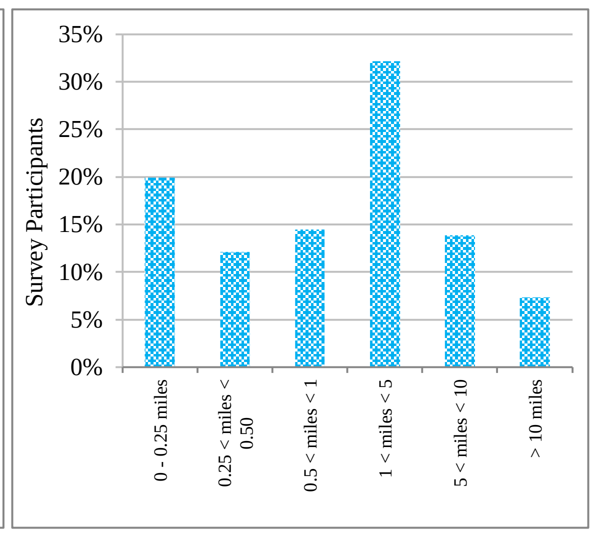
a. Estimated time spent on trail (n=1,277)



b. Estimated distance traveled on trail (n=1,276)



c. Estimated time to get to trail (n=1,276)



d. Estimated distance traveled to trail (n=1,276)

FIGURE 4.1 Time and distance traveled to and on central Ohio trails

Only 7% reported taking more than one-hour to get to the trail. About one-third reported living within one-half mile of the trail. Another one-third, however, said they live between 1 and 5 miles from the trail, while slightly more that 20% said they live five or more miles from the trail. Nearly two-thirds of the respondents said they had or would be using the trail for more than one hour; the most common duration of use reported by respondents was between one and two hours. More than 45% said they had or would travel more than 10 miles during their visit; only about 15% reported traveling less than three miles.

4.2.2 Expenditures by user type

Approximately 20% of trail users reported they had or would make trail-related expenditures during their visit. As shown in Table 4.1, the respondents who said they had or would spend money reported average expenditures of approximately US$17.60. Averaged across all users, the average expenditure by visitors therefore was a little more than US$3.00.

TABLE 4.1 Mean expenditures by trail user types

	Type of User	Number of Trail User			Mean Expenditure		
		All	*Male*	*Female*	*All*	*Male*	*Female*
All	Total	1,282	749	493	3.19	3.42	2.85
	Cyclists	741	487	232	4.98	4.86	5.19
	Walkers	238	98	132	0.75	0.41	1.05
	Runners	267	141	116	0.60	0.69	0.53
	Other	20	14	6	1.50	2.14	0.00
Spenders	Total	231	147	75	17.68	17.40	18.73
	Cyclists	188	125	54	19.63	18.93	22.28
	Walkers	16	5	11	11.13	8.00	12.55
	Runners	22	13	9	7.23	7.46	6.89
	Other	3	3	0	15.00	15.00	0.00

Cyclists were more likely to spend money than other users during their visit and, if they spent, they spent larger amounts. For instance, while cyclists accounted for 59% of respondents in the sample, they accounted for 81% of the respondents who said they would spend money. Twenty-five percent of cyclists reported spending, compared to only seven percent of walkers and eight percent of runners. Cyclists who said they had or would spend money during their visit reported spending an average of nearly US$20; the average amounts spent by walkers and runners were approximately US$11.00 and

US$7.00, respectively. Females who spent tended to spend slightly more than males who spent.

4.3 A Two-Part Model of Trail Expenditures

Modeling of local expenditures for trail use requires different procedures than modeling expenditures by non-residents because the majority of users have no expenditures. The presence of a high proportion of zero values in the distribution of the expenditure variable means that standard approaches such as ordinary least squares regression cannot be used. Throughout the past decade, statisticians and econometricians have introduced a number of methods to account for these types of distributions, and selection of the appropriate model is important to represent the marginal effects of exogenous variables accurately. The Heckit, latent Heckit, and two-part methods are widely used to model distributions of continuous, nonnegative data that include a large proportion of zeroes. The pros and cons of each method have been debated in the literature (Dow and Norton, 2003). The Heckit method is usually used when the zero observations are potential outcome or latent variables that are only partially observed (Dow and Norton, 2003). The two-part method, however, is employed when the zero values are actual, valid outcomes that are fully observed. A two-part model is used in this thesis as the zero expenditures reported by users are valid measures.

The two-part model dates to 1964 when Weiler (1964) presented a significance test for quantitative responses and when, following Weiler, Lachenbruch (1976) introduced a two-part model. A simple two-part model considers a parametric model such as probit or logit for the probability of having expenditure in the first part and a generalized linear model for the positive expenditure in the second part. The model separates the endogenous variable into two parts: (1) $y > 0$ and (2) $y \mid \mathrm{y} > 0$. Equation 1 represents a two-part model formulation with the binary logit model for the first part and the generalized linear model for the second part. In this equation, y and x are endogenous and exogenous variables, respectively. α and β stand for the coefficients of variable of interests in models that are estimated during the modeling procedure.

$$\begin{cases} Part\ 1\text{: } \Pr(\,y > 0) = \frac{\exp(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon)}{1 + \exp(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon)} \\ Part\ 2\text{: } E(\,y \mid \mathrm{y} > 0) = \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_n x_n, \quad \mathrm{y} \sim \mathrm{Gamma} \end{cases} \tag{1}$$

Generalized linear models allow for testing various distributions of the response variable, including Gaussian (normal), binomial, Poisson, Gamma, or inverse-Gaussian (Nelder and Baker, 1972). To choose the appropriate model, the general goodness-of-fit of the developed models are compared by both Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) statistics. Equations 2 and 3 represent the general formulation, respectively, for AIC and BIC in which L is the likelihood at convergence, k presents the number of estimated variables, and n stands for the number of observations.

$$AIC = 2 \times k - 2 \times \ln(L) \tag{2}$$

$$BIC = -2 \times \ln(L) + k \times \ln(n) \tag{3}$$

Lower AIC and BIC statistics indicates better fit to the data. In addition, these tests collapse to a simple likelihood comparison test when models have the same number of exogenous variables. Table 4.2 shows the AIC and BIC results for the models building on the constant variable. According to both criteria, the Gamma distribution performs better than the other examined distributions.

TABLE 4.2 AIC and BIC results to choose the best generalized linear model

Distribution Type	Log-Likelihood	AIC	BIC
Gaussian	-1094.60	9.44	168207
Inverse Gaussian	-1024.30	8.83	-1231.68
Poisson	-2972.04	25.62	3721.03
Negative binomial	-903.90	7.80	-1013.71
Gamma	**-897.44**	**7.74**	**-991.12**
Number of observations:		232	

The explanatory variables used in the models are outlined in Table 4.3, and the final two-part model is summarized in Table 4.4. The final model encompasses a binary logit for the first part and a generalized linear model with Gamma distribution for the second part. The first part of the model predicts the probability of any expenditure. The second part predicts expenditure conditional on nonzero expenditures for trail users.

TABLE 4.3 Description of variables used in the analysis

Variables	Description	Average	Std. Dev.
Cycling	1: If the primary activity on the trail is cycling / 0: Otherwise	0.58	0.49
Running	1: If the primary activity on the trail is running / 0: Otherwise	0.21	0.40
Recreation	1: If the main reason for the trip on the trail is recreation / 0: Otherwise	0.08	0.27
Exercise	1: If the main reason for the trip on the trail is exercise / 0: Otherwise	0.39	0.49
Utilitarian	1: If the main reason for the trip on the trail is commuting/shopping / 0: Otherwise	0.01	0.11
Walk	1: If users got to the trail by walk / 0: Otherwise	0.09	0.29
Bus	1: If users got to the trail by bus / 0: Otherwise	0.00	0.03
S-time-on-trail	1: If the duration on trail is less than 60 minutes / 0: Otherwise	0.35	0.47
M-time-on-trail	1: If the duration on trail is between 60 and 120 minutes / 0: Otherwise	0.37	0.48
L-time-on-trail	1: If the duration on trail is more than 120 minutes / 0: Otherwise	0.27	0.44
S-time-to-trail	1: If the travel time to trail is less than 15 minutes / 0: Otherwise	0.63	0.48
M-time-to-trail	1: If the travel time to trail is between 15 and 60 minutes / 0: Otherwise	0.29	0.45
L-time-to-trail	1: If the travel time to trail is more than 60 minutes / 0: Otherwise	0.06	0.25
S-cyclist Duration	S-time-on-trail × Cycling	0.15	0.35
M-cyclist Duration	M-time-on-trail × Cycling	0.23	0.42
Child	1: If trail user visited the trail with a child/ 0: Otherwise	0.09	0.28
Number of Children	Number of children with trail users on the trail	0.12	0.73
Companion	1: If trail user was accompanied on the trail / 0: Otherwise	0.49	0.50
Number of Companions	Number of persons who accompanied trail user	0.93	1.73
Trail Visit	1: If trail user visited more than 4 trails in the past week / 0: Otherwise	0.05	0.23
Female	1: Female / 0: Male	0.39	0.48
Female Cyclist	= Female × Cycling	0.18	0.39
Age	1: If the age of trail user is more than 50 years old / 0: Otherwise	0.44	0.49
Low-frequent	1: One time visiting the trail in a week/ 0: Otherwise	0.44	0.49
High-frequent	1: More than four times visiting the trail in a week/ 0: Otherwise	0.28	0.45
Low-income	1: Less than 49 thousand dollars household income/ 0: Otherwise	0.19	0.39
High-income	1: More than 75 thousand dollars household income/ 0: Otherwise	0.54	0.49
Weekend	1: If trail user visited the trail on weekend / 0: Otherwise	0.60	0.48
Morning	1: If trail user visited the trail between 7 and 10 AM/ 0: Otherwise	0.20	0.40
Afternoon	1: If trail user visited the trail between 1 and 4 PM / 0: Otherwise	0.31	0.46
Evening	1: If trail user visited the trail between 4 and 7 PM / 0: Otherwise	0.14	0.35
Evening Weekend	$= \text{Evening} \times \text{Weekend}$	0.04	0.20
Y1	1: If trail user spent any money as part of visit / 0: Otherwise	0.20	0.40
Y2	The logarithmic amount of expenditure of users when they spent	3.18	13.35

TABLE 4.4 The final two-part model of trail expenditures

Variable	**First Step:** Who Spent			**Second Step**: How much spent			
	Coefficient	*t-test*	*p-value*	*Coefficient*	*t-test*	*p-value*	*VIF*
Constant	-2.57	-8.88	0.000	0.69	7.00	0.000	-
Cycling	0.94	4.29	0.000	0.13	1.60	0.112	1.44
Recreation	0.55	1.97	0.049	-	-	-	-
Exercise	-0.25	-1.29	0.199	-	-	-	-
Utilitarian	2.25	3.47	0.001	0.39	2.57	0.007	1.17
L-time-on-trail	0.42	2.36	0.018	-0.18	-2.78	0.006	1.52
S-time-on-trail	-	-	-	-0.10	-1.47	0.143	1.56
L-time-to-trail	0.80	2.77	0.006	-	-	-	-
Walk	-1.93	-2.59	0.010	-0.32	-1.14	0.255	1.16
Bike	-	-	-	0.07	1.21	0.227	1.45
Bus	2.25	1.55	0.122	-	-	-	-
Companion	0.73	3.34	0.001	0.34	5.00	0.000	1.61
Number of Companions	0.10	1.87	0.061	-0.03	-1.96	0.051	1.57
Trail Visit	-	-	-	0.51	4.40	0.000	1.22
Age	0.40	2.30	0.022	0.12	2.11	0.036	1.18
Child	0.56	1.99	0.047	0.39	2.86	0.005	2.55
Number of Children	-	-	-	-0.22	-3.50	0.001	2.41
Low-frequent	-0.48	-2.37	0.018	0.07	1.17	0.244	1.62
High-frequent	-0.34	-1.58	0.114	-0.20	-2.37	0.019	1.24
Female	-0.27	-1.46	0.143	-	-	-	-
Low-income	-0.46	-1.94	0.052	-0.13	-1.71	0.090	1.11
Evening Weekend	-1.34	-2.17	0.030	-0.27	-1.18	0.240	1.21
Afternoon	0.14	2.78	0.003	-	-	-	-
Morning	-	-	-	-0.16	-2.13	0.035	1.20
Number of observations:	1,105			201			1.48
Initial log likelihood	-539.79			-			
Log likelihood:	-452.94			-			
Pseudo/Adjusted R^2:	0.16			0.36			

In specification of both parts of the model, it is attempted to include all theoretically relevant exogenous variables, while controlling for multicollinearity. To control for multicollinearity, a step-wise approach is used and Variance Inflation Factor (VIF) is calculated for each independent variable listed in Table 4.3. The VIF has a lower bound of 1, and the larger the value of VIF, the more collinearity (Gujarati, 2012). As a rule of thumb, a variable is highly collinear when VIF exceeds 10 (Gujarati, 2012). A maximum VIF value of 5 (Rogerson, 2010) and 4 (Pan and Jackson, 2008) are also recommended in the literature. For all variables in the final model, the mean VIF is 1.48, with the maximum value of 2.55, indicating there are no issues related to multicollinearity.

The final model was determined based on the model selection criteria that include goodness-of-fit measures and the theoretical and practical relevance of the variables. The student's t-test statistic is used to assess the significance of each explanatory variable. The final explanatory variables are of the right sign in light of the hypotheses and the descriptive analysis. Most of the variables are significant at a 90% confidence interval in both steps. Variables not significant were *Exercise, Bus,* and *High-frequent*, in the first step and *Cycling, S-time-on-trail, Walk, Bike, Low-frequent,* and *Evening Weekend* in the second step.

4.4 Interpretation of the Two-Part Model

Among the main purpose for visiting the trail variables, it is found that recreation and utilitarian travel for shopping are statistically significant at the 95% confidence interval. As hypothesized, trail users visiting a trail for recreation and utilitarian were more likely to spend than those who visited for exercise. None of these purposes for trail use was significantly correlated with the amount of expenditure, although utilitarian travel for shopping has a positive correlation.

The two-part model shows cyclists were more likely to spend than other users. However, in contrast to the descriptive results, and after controlling for other variables, there was not a significant difference with respect to the amount of expenditure at the 95% confidence interval. The *L-time-to-trail* variable shows visitors traveling more than one hour to the trail are more likely to spend money than other travelers. The *L-time-on-trail* variable also indicates that trail visitors who spend more than two hours on the trail are more likely to spend than other users, but the amounts they spend were lower. It is worth noting that this group of visitors forms around 30% of the sample.

The *Companion* and *Number of Companions* variables show that visitors who were accompanied by others were more likely to spend and also that when the number of group members increased, the tendency to spend increased significantly. However, the results show the amount of expenditures among a group of users diminishes significantly by increasing the number of group members. With respect to socio-demographic characteristics of users, it is found that visitors older than 50 years of age are more likely to spend, and if they spend, they will spend more than other age groups. Females were less likely to spend than male visitors, but after controlling for other characteristics, there were not significant differences in spending amounts. As expected, users from low-income families were less likely to spend on the trail. These families further spend fewer amounts on trail significantly. With respect to the effects of frequency of use on spending, the results indicate two groups of users are less likely to spend: (1) users who visited the trail one time in a week and (2) users who visited the trail more than five times in a week. The latter also spends significantly less amounts of money than other users.

Pertaining to the time-of-day and day-of-week of trail visit, it is found when a trail user visited the trail between 1:00 PM and 4:00 PM, they are more likely to spend on the trail than other times of the day. The *Morning* variable also shows trail users who visited the trail between 7:00 AM and 10:00 AM spend significantly less money than other times of the day. The interaction variable *Evening Weekend* indicates that trail users who visited the trail between 4:00 PM and 7:00 PM on weekend are significantly less probable to spend on trail.

4.5 Pseudo-estasticities for the Probability of Spending

To quantify the strength of the association of the exogenous variables with expenditures, I calculated pseudo-elasticity of four significant variables. By definition, the elasticity of continuous variables is the percentage change in the dependent or decision variable when the variable of interest is increased by one percent (Hensher et al., 2005). This concept, however, is not applicable to dichotomous or dummy variables. Instead, pseudo-elasticity is calculated that implies the magnitude of change in the probability of the decision variable when the dummy variable is increased from 0 to 1. To estimate pseudo-elasticity, the value of each continuous variable is set at its average and each discrete variable at its statistical mode. The changing probability of spending is then estimated when the binary variable of interest changes from 0 to 1 while other variables are turned off at their statistical mode. This estimate should only be considered as an approximation, because partial derivatives that are used to calculate elasticities are valid in only a small vicinity of the observation point. The pseudo-elasticities are presented in Figure 4.2.

The probability of spending on trail for cyclists is higher than other trail users – nearly 128%. Trail users who visited for recreation were 53% more likely to spend, while users who traveled more than one hour to visit the trail were 83% more likely to spend. The elasticity of *Companion* variable indicates that if a trail visitor is accompanied with another person, the probability of spending increases by nearly 74%. Further, if the number of group members increases, the probability of spending increases significantly. For instance, by increasing the group size from two to three and two to five, the probability of spending increases 8% and nearly 24%, respectively.

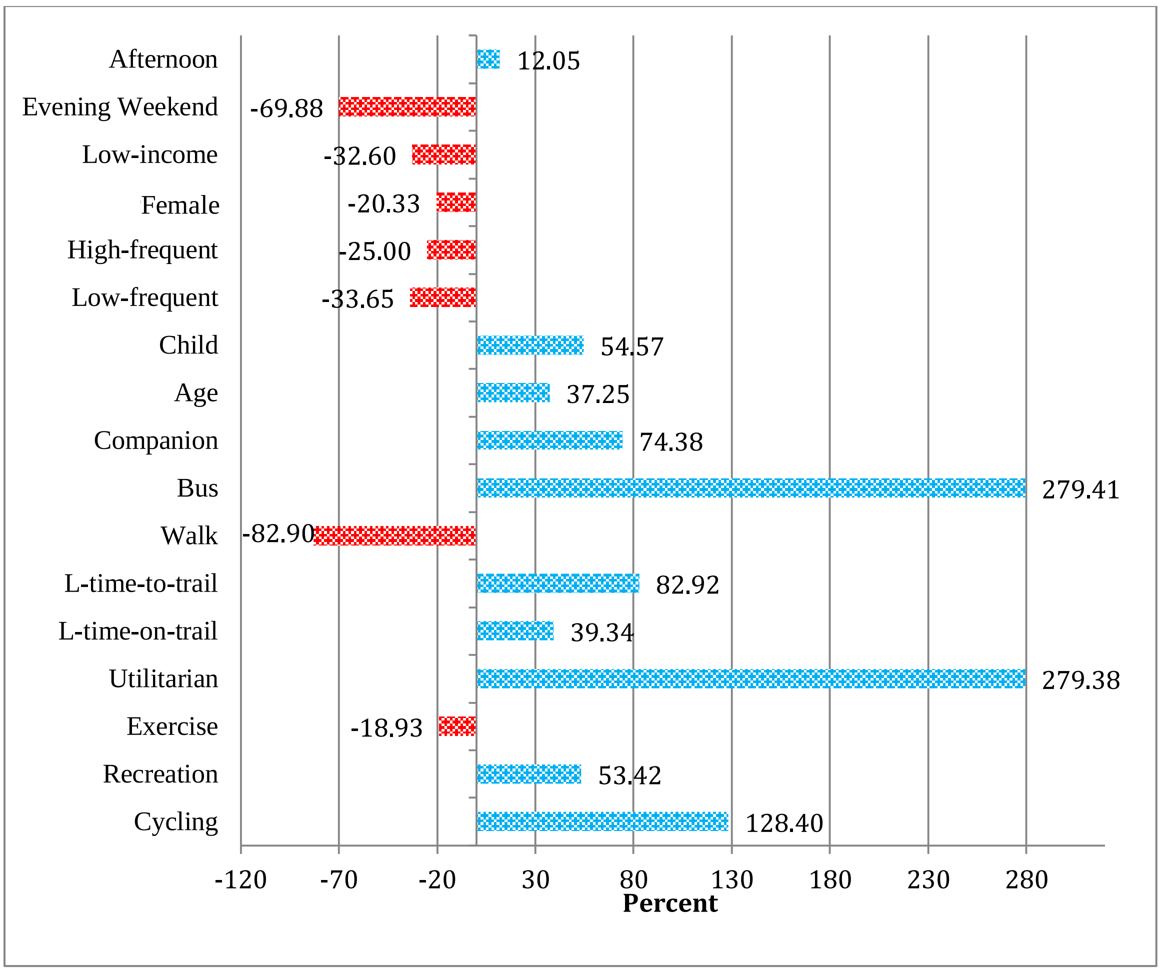


FIGURE 4.2 Pseudo-elasticity for the probability of expenditure with trail visit

4.6 Interaction Effects: Some Parsimonious Models

To explore the effects of additional theoretically-relevant variables, which were not significant in the two-step model for the sake of interdependencies with other variables, the influence of other variables is investigated using the same framework. The results of four parsimonious models encompassing more policy-relevant variables among other possibilities are summarized in Table 4.5. Although the probability of male users overall making expenditures is higher than female users, females generally do not spend more than males, and female cyclists are more likely to spend than male cyclists. Further, if a female cyclist decides to spend, she spends significantly more than other users. These results also indicate that the probability of spending is low when the time on trail is less than two hours. This probability diminishes significantly when the time on trail is declined to less than one hour. Cyclists in both of these time intervals, however, demonstrate a higher propensity to spend money, particularly, the cyclists who spend between one and two hours on a trail.

TABLE 4.5 The results of the two-step analysis for parsimonious models

Model	**Variable**	**First Step** (Dependent: Y1)			**Pseudo R^2**	**Second Step** (Dependent: Y2)			**Adjusted R^2**
		Coefficient	*t-test*	*p-value*		*Coefficient*	*t-test*	*p-value*	
1	*Constant*	-0.69	-6.07	0.000	0.039	0.96	21.92	0.000	0.03
	S-time-on-trail	-1.16	-6.50	0.000		-0.08	-1.11	0.269	
	M-time-on-trail	-0.92	-5.50	0.000		0.15	2.30	0.022	
2	*Constant*	-0.71	-3.13	0.002	0.008	1.01	11.66	0.000	-0.006
	S-time-to-trail	-0.81	-3.33	0.001		-0.04	-0.72	0.469	
	M-time-to-trail	-0.60	-2.32	0.019		0.01	0.12	0.901	
3	*Constant*	-1.29	-14.43	0.000	0.025	0.98	26.23	0.000	0.02
	Female	-1.06	-4.42	0.000		-0.15	-1.88	0.051	
	Female Cyclist	1.30	4.85	0.000		0.28	2.43	0016	
4	*Constant*	-0.697	-6.03	0.000	0.079	0.96	21.76	0.000	0.04
	S-time-on-trail	-2.14	-7.19	0.000		-0.24	-1.86	0.064	
	M-time-on-trail	-1.78	-5.93	0.000		-0.05	-0.40	0.693	
	S-cyclist Duration	1.71	5.32	0.000		0.20	1.47	0.143	
	M-cyclist Duration	1.23	3.96	0.000		0.24	1.70	0.090	

4.7 Summary

A common rationale for trail development is that users spend money and support retail businesses in trail corridors. Expenditures by local trail users do not constitute new regional economic impacts, but they are important locally and of interest to planners and business owners who view trails as mechanisms to spur local economic activity. Using the results of intercept surveys completed by 1,282 trail users on the Central Ohio Greenway trail network in 2014, this chapter estimated the probabilities and patterns that different types of trail users will make expenditures. Approximately one-fifth of trail users reported spending between US$15.00 and US$20.00 for food, drink, and other incidental items. Across all trail users the average expenditure by individuals was about US$3.00 per visit. All else equal, cyclists were more than twice as likely than other users to report expenditures. Users visiting trails principally for recreation were 53% more likely to spend, while users visiting trails mainly for exercise were about 19% less likely. Both longer trips to and on the trails were associated with higher spending. These results can be used to inform local planning, marketing, and economic development activities related to local trail networks.

Chapter 5

Urban Trails and Demand Response to Weather Variations

5.1 Introduction

The research studying factors associated with trail use has grown over the past 25 years, gaining momentum during the growth in demand for trail use. Trail managers and funding agencies need this information to plan systems and facilities, optimize investments, and increase efficiency of trail operations and maintenance. Among the factors that influence trail use, weather and climate have aroused the interest of planners, engineers, and managers for a number of practical reasons. For example, engineers routinely use monthly and seasonal adjustment factors to estimate annual average daily traffic (AADT) from short duration (e.g., 48 hour traffic counts). These adjustment factors sometimes are transferred and used over fairly large geographic regions. However, bicycle and pedestrian traffic varies much more in response to variations in weather, and these variations result in different monthly and seasonal patterns across the nation. Engineers currently lack information about the relative magnitude of these variations across the range of climatic zones that exist in the continental United States. Information about variation in bicycle and pedestrian traffic volumes in response to daily weather and climate is needed to develop the tools for estimating basic statistics such as AADT that are used for planning facilities, assessing exposure to risk, and other routine tasks. Information about the demand response to variations in weather also can help managers make more efficient operational decisions about whether to maintain trails in winter or when to re-surface facilities in summer. Information about demand response to weather also may inform the design of facilities, including the need for traffic controls.

Much of the previous research on the effects of weather on non-motorized traffic demand has been limited to a single mode, population group, facility, network, or city. Little is known about weather factors associated with trail demand for both pedestrian and bicyclists over different climate regions. This deficiency stems from the lack of comprehensive data. This chapter adds to the literature by systematically comparing behaviors of cyclists and pedestrians to weather on one or more trails in each of seven general climatic regions in the continental United States. In addition, it proposes a framework that for characterizing the effects of temperature as constant, increasing, or decreasing returns, and presents elasticities for weather, seasonal, and other temporal variables known to be associated with bicycling and walking.

The remainder of the chapter is structured as follows. First, a set of regional models is estimated that quantify the effects of variation on bicycle, pedestrian, and mixed mode (i.e., undifferentiated) trail traffic. To illustrate the complexity of these effects, the concept of "Demand Returns" is introduced along with measuring the vertex point of parabola functions. Third, the elasticities for different weather variables are calculated for each mode. The chapter is concluded by reviewing the key findings.

5.2 Bicycle and Pedestrian Volumes on Urban Trails

As summarized in Chapter 3, trail traffic volumes recorded at 15-minute intervals from January 1, 2014 through February 16, 2016 form the basis of this analysis. These data were aggregated to the daily level for purposes of modeling and estimation of average daily bicyclists (ADB) and average daily pedestrians (ADP). Only days with a complete record for the entire 24 hours were included in the final data. I focused on daily rather than hourly traffic because it is standard engineering practice to compare average daily traffic volumes across sites or on segments of a road.

ADB and ADP are used instead of the common annual average daily bicyclists (AADB) and annual average daily pedestrians (AADP) measurements because different numbers of days of valid counts were available for each, I wanted to retain all data, and I did not want to impute missing values that would be required to estimate AADP or AADB. Specifically, the number of days with valid counts over trail sites varies from 205 to 769 as outlined in Table 5.1, which does not cover the span of one or two years consistently but does capture weather variation at individual sites.

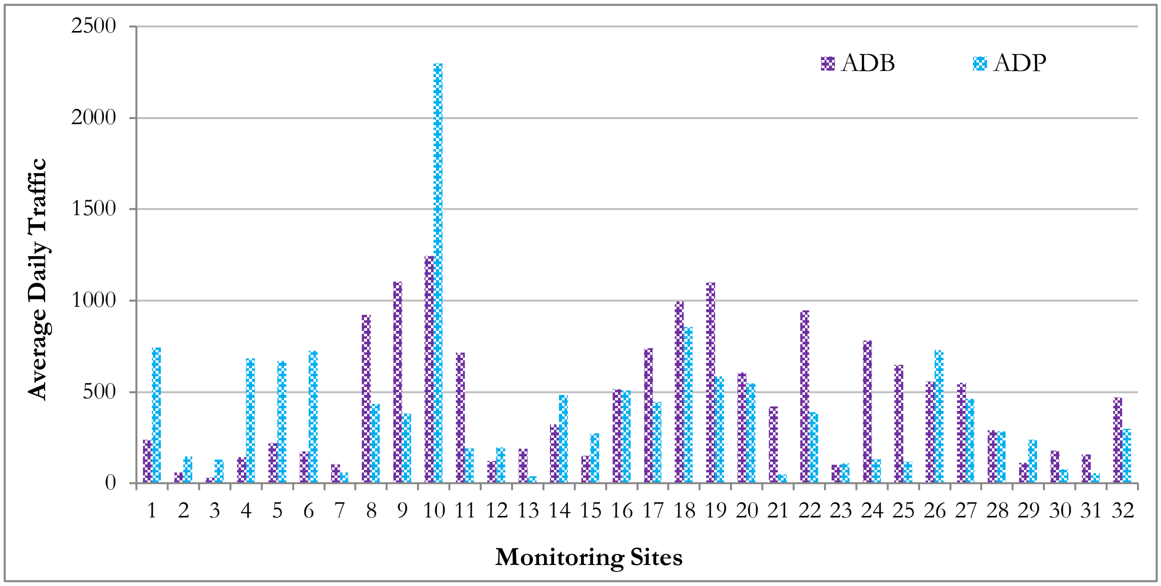
Across the 32 sites, ADB and ADP each spanned three orders of magnitude. ADB ranged from a low of 30 cyclists to a high of 1,242 cyclists. ADP ranged from 38 to 2,299. Table 5.1 summarizes descriptive statistics for ADB and ADP for all trail sites by climate regions. As noted, these numbers represent traffic volumes not individual visits to of each trail.

The relative magnitudes of ADB and ADP varied substantially across the monitoring sties and climate regions. At the monitoring site level, as shown in Figure 5.1.a, ADB and ADP were approximately equivalent at some locations, but there were large differences at many locations, indicating that different trails attract different types of users. Specifically, ADB exceeded ADP at 19 sites. At the climate regional level, ADP is significantly higher than ADB in very cold and cold regions, while ADB exceeded ADP in other regions. Many of these variations likely are associated with geo-spatial characteristics of the built environment and neighborhood socio-demographic factors that are beyond the scope of this inquiry and not analyzed here. At each site, variation in both bicycle and pedestrian traffic volumes is affected by temporal factors such as month-of-year and season that reflect variation in weather.

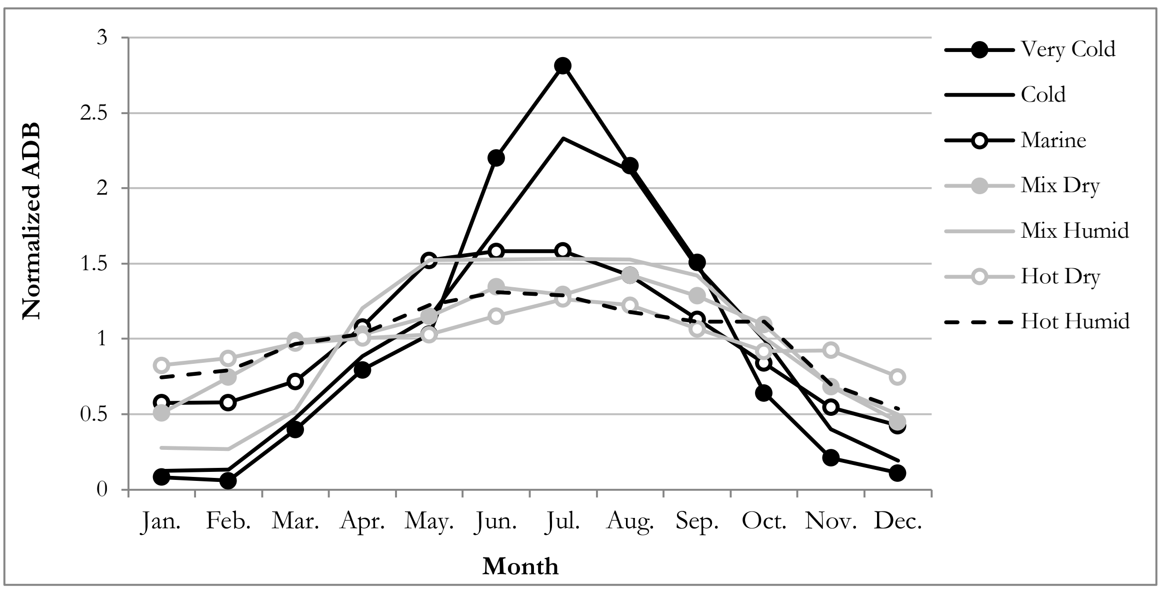
To illustrate these effects, the monthly normalized ADB and ADP are plotted for each climate regions in Figure 5.2.b and Figure 5.2.c, respectively. To calculate monthly normalized ADB and ADP, the monthly averages in the region for each month are divided by the averages for the period of record. As shown, seasonality is greatest in very cold and cold regions for both ADP and ADB. One caveat is that because very cold is a single location, it may reflect site-specific conditions more than the others. The curves are flatter in all regions for both ADP and ADB. However, a difference in the hot humid, hot dry regions is that summertime (July, Aug) ADB is greater than average daily traffic for the year. In conjunction, summertime ADP is lower, indicating that pedestrians may respond more negatively to heat than cyclists in the hottest regions in the U.S.

TABLE 5.1 Descriptive statistics for ADB and ADP for all trail sites by climate regions

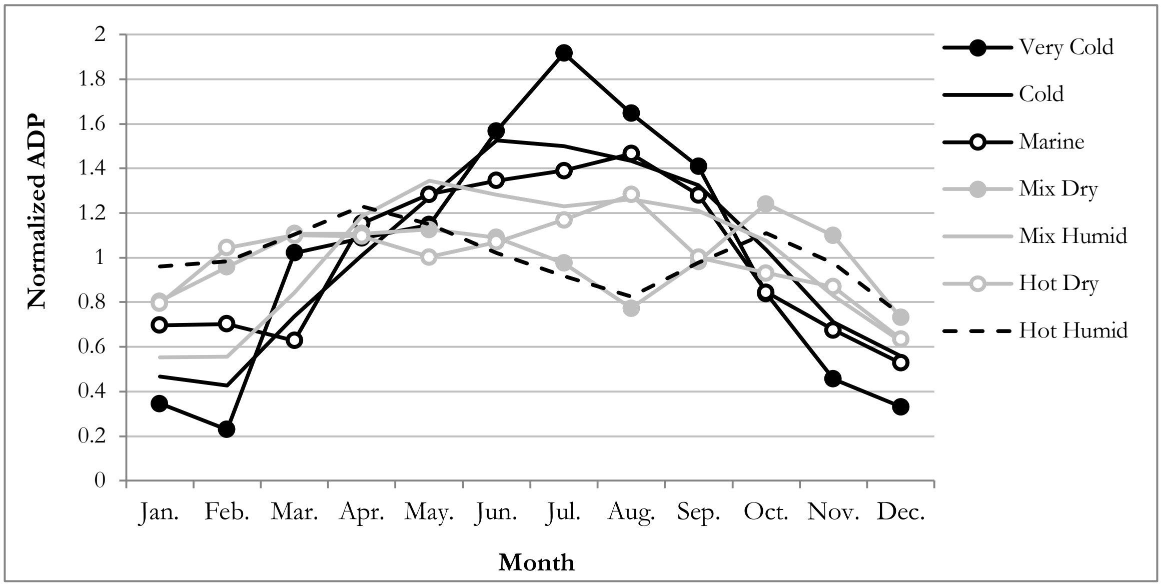
Region	Trail Site	Location	No. Days	Daily Bicyclists			Daily Pedestrians		
				Avg.	*Min*	*Max*	*Avg.*	*Min*	*Max*
Very Cold	1. Duluth Lake Walk	Duluth, MN	545	237.2	0	1242	743.6	4	2856
Cold	2. Descro	Billings, MT	629	57.2	0	212	145.9	19	357
	3. Kiwanis	Billings, MT	630	30.2	0	114	128.8	9	361
	4. Pikes Peak Greenway	Colorado Springs, CO	405	141.0	1	574	684.1	64	2118
	5. Portland Trails A	Portland, ME	619	221.5	0	984	666.8	0	3795
	6. Portland Trails B	Portland, ME	628	174.7	0	687	725.8	1	2241
	7. Rock Island	Colorado Springs, CO	205	105.6	0	258	58.3	0	133
	8 W. River Greenway	Minneapolis, MN	553	919.7	12	3799	433.0	2	1145
Marine	9. BGT	Seattle, WA	643	1104.3	0	3840	380.2	0	949
	10. Elliott Bay	Seattle, WA	608	1242.7	44	2577	2299	276	5065
	11. MTS Washington	Seattle, WA	638	715.1	0	1885	191.4	0	958
Mixed Dry	12. Paseo del Nordeste	Albuquerque, NM	598	120.0	7	274	193.6	2	469
	13. Paseo del Norte	Albuquerque, NM	629	189.2	2	572	38.6	2	186
Mixed Humid	14. Ballston Connector	Arlington, VA	743	322.4	0	938	483.4	0	1250
	15. Bluemont Connector	Arlington, VA	764	150.3	0	338	271.8	0	536
	16. CC Connector	Arlington, VA	754	512.4	2	1496	506.2	43	1809
	17. Custis Bon Air	Arlington, VA	749	737.7	6	1874	442.5	3	1073
	18. TR Island	Arlington, VA	711	994.6	5	2898	855.7	4	2651
	19. WOD Bon Air West	Arlington, VA	769	1100.5	4	3227	585.6	6	1741
	20. WOD Columbia Pike	Arlington, VA	761	606.3	0	2074	544.6	28	1902
Hot Dry	21. Chula Vista	San Diego, CA	691	419.0	21	952	48.2	4	144
	22. Coronado Bayshore	San Diego, CA	489	946.0	27	3189	388.7	2	944
	23. Escondido Inland	San Diego, CA	744	99.0	8	172	108.7	7	522
	24. Imperial Beach	San Diego, CA	627	781.0	33	1746	131.3	23	507
	25. Oceanside SLR River	San Diego, CA	638	647.3	28	1652	117.9	12	491
	26. SD Harbor	San Diego, CA	711	556.3	0	1752	728.7	0	1718
Hot Humid	27. FW Clear Fork A	Fort Worth, TX	566	550.2	2	2062	462.2	19	1998
	28. FW Clear Fork B	Fort Worth, TX	520	289.5	0	988	282.3	9	2874
	29. Miami Dade A	Miami, FL	485	111.7	37	183	238.5	1	766
	30. Miami Dade B	Miami, FL	576	177.5	49	352	75.3	23	377
	31. Tammany Trace	New Orleans, LA	628	157.0	1	828	55.3	1	281
	32. White Oak	Houston, TX	757	468.5	21	1564	295.8	62	779



a. Distribution of ADB and ADP over trail monitoring sites



b. Monthly normalized ADB for each climate regions



c. Monthly normalized ADP for each climate regions

FIGURE 5.1 A graphical distribution of ADB and ADP

5.3 Regional Weather Models

To examine the effects of weather variables on trail demand, a set of negative binomial regression models is developed, one for bicyclists and one for pedestrians for each of the seven climate regions, plus one general model for all regions that includes for both bicyclists and pedestrians. Across regions, the number of monitoring stations included in each regional model varies, ranging from one location in the very cold region to seven in both the cold and the mixed-humid regions.

The count outcome modeling is used because the dependent variable (daily traffic) is count data. The negative binomial regression is selected among all approaches for modeling counts in light of two basic criteria. First, the distribution of the count variable was checked and confirmed it is overdispersed and follows the negative binomial distribution. Second, the Akaike Information Criterion (AIC) was applied that confirmed the negative binomial modeling approach has a better fit on the data sample.

The negative binomial regression model allows heterogeneity within the classes, unlike the Poisson regression model that assumes the mean, λ_i, is constant or homogenous within the classes. The probability distribution of the negative binomial distribution is given as Equation 1:

$$P(y_i|X_i) = \frac{\Gamma(y_i+\vartheta_i)}{y_i!\Gamma(\vartheta_i)}\left(\frac{\vartheta_i}{\vartheta_i+\lambda_i}\right)^{\vartheta_i}\left(\frac{\lambda_i}{\vartheta_i+\lambda_i}\right)^{y_i} \quad (1)$$

In this equation, Y is a count of events, X_i is a vector of covariates, $\vartheta_i = \alpha^{-1}$, and α is known as the dispersion parameter. The form of the model equation for the negative binomial regression is written as Equation 2:

$$y_i = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots) \quad (2)$$

The models summarize the effects of variations in weather and temporal factors on bicyclists' and pedestrians' demand, while controlling for holiday, weekend, and seasonality. The explanatory variables used in the modeling are defined in Table 5.2. Table 5.3 and Table 5.4 outline the results of negative binomial regression models for bicyclists and pedestrians, respectively.

The purpose of estimating the climate zone models is to explore the feasibility of developing general models that can be used to characterize the effects of weather in areas with mostly homogeneous climates.

The stepwise modeling approach is employed to specify the model, choosing variables that were significant at the 90% confidence interval. Student's t-statistic is used to check the level of significance in hypothesis testing. The overall fit of the models is judged by measuring the Nagelkerke Pseudo R^2. This measurement fluctuates between 0 and 1: values closer to 1 indicates a better fit but cannot be interpreted as percentages as in standard OLS regression. As shown in Table 5.3 and Table 5.4, the Nagelkerke Pseudo R^2 ranges from 0.05 to 0.91 for different models. The bicyclists demand models have better fit than the pedestrian models, indicating bicyclists are more responsive to changes in weather, season, and day-of-week. Across the seven climate regions, five of the bicyclist models have the overall fit greater than 0.50. Only one pedestrian model has a fit greater than 0.50. As expected given the variation in the regional models, the All Regions models for both bicyclists and pedestrians perform better than some of the models and worse than others, with Nagelkerke Pseudo R^2 values of 0.38 and 0.20, respectively. These differences in the explanatory models demonstrate that bicyclists and pedestrians respond differently to weather and seasonality, and weather variables apparently are not major factors contributing to variations in daily use of either bicyclists or pedestrians.

TABLE 5.2 Descriptive of data and parameters used in the analysis

Variable	Definition	Average	St. Dev.
Weekend	1: If the counting day is weekend/ 0: Otherwise	0.28	0.45
Holiday	1: If the counting day is Federal Holiday/ 0: Otherwise	0.03	0.16
Winter	1: If the counting month is winter/ 0: Otherwise	0.26	0.44
Fall	1: If the counting month is fall/ 0: Otherwise	0.25	0.43
Spring	1: If the counting month is spring/ 0: Otherwise	0.22	0.41
Precip	Daily Precipitation in tenths of mm	24.31	79.83
D_Precip	1: If Precipitation is zero in a day/ 0: Otherwise	0.71	0.45
Precip^2	$= \text{Precip} \times \text{Precip}$	6965.25	64,754.42
Snow Depth	Daily snow depth	8.57	46.90
D_ Snow	1: If Snow depth is zero in a day/ 0: Otherwise	0.93	0.23
T_{avg}	Average daily temperature (Fahrenheit)	60.49	17.49
${T_{avg}}^2$	$= T_{avg} \times T_{avg}$	3964.96	1925.62
Dew point	Average daily dew point (Fahrenheit)	45.60	18.26
Dew point^2	$= \text{Dew point} \times \text{Dew point}$	2413.65	1524.34
Day light	The natural light of the day (Hour)	12.21	1.92
Avg. Wind Speed	Average daily wind speed (miles/hour)	7.69	3.53
Pedestrian	The counted number of pedestrians per day	421.70	499.96
Bike	The counted number of bicyclists per day	481.47	513.64

TABLE 5.3 Results of negative binomial regression models for bicyclists on trails

Variables	Coefficient of variables separated by climate regions							
	Very Cold	Cold	Marine	Mix Dry	Mix Humid	Hot dry	Hot Humid	All Regions
Day Light	0.12 (9.06)	Insignificant	0.07 (12.58)	0.03 (2.99)	0.08 (5.31)	0.05 (3.01)	0.21 (17.27)	0.14 (28.59)
Winter	Insignificant	-0.32 (-3.55)	Insignificant	0.06 (1.96)	0.18 (3.45)	-0.17 (-2.69)	Insignificant	-0.07 (-3.45)
Fall	Insignificant	0.12 (1.97)	Insignificant	Insignificant	0.1 (2.62)	-0.12 (-2.34)	0.11 (4.04)	Insignificant
Spring	-0.33 (-6.21)	0.43 (5.98)	Insignificant	Insignificant	Insignificant	-0.10 (-2.63)	Insignificant	-0.04 (-2.59)
Holiday	-0.25 (-2.42)	Insignificant	Insignificant	Insignificant	Insignificant	0.44 (6.4)	0.41 (6.44)	0.15 (4.06)
Weekend	Insignificant	0.32 (8.10)	Insignificant	0.14 (7.15)	Insignificant	0.56 (22.13)	0.66 (27.85)	0.24 (17.11)
T_{avg}	0.08 (15.71)	0.02 (4.53)	0.12 (11.80)	0.11 (19.71)	0.14 (26.52)	0.11 (3.66)	0.12 (9.72)	0.02 (7.56)
${T_{avg}}^2$	Insignificant	-0.0001 (-2.13)	-0.0008 (-9.93)	-0.0007 (-15.63)	-0.0007 (-18.04)	-0.0008 (-3.55)	-0.0006 (-7.84)	-0.0002 (-7.10)
D_Precip	0.14 (2.82)	0.41 (8.84)	0.25 (9.13)	0.15 (4.72)	0.18 (6.34)	0.12 (2.32)	0.25 (8.23)	0.27 (14.97)
Precip	-0.003 (-3.80)	-0.003 (-7.77)	-0.003 (-7.66)	-0.003 (-4.12)	-0.002 (-7.29)	-0.008 (-8.32)	-0.001 (-8.17)	-0.001 (-10.13)
$Precip^2$	6×10^{-6} (2.51)	1×10^{-6} (2.89)	3×10^{-6} (2.97)	7×10^{-6} (3.17)	2×10^{-6} (3.53)	1×10^{-5} (6.79)	1×10^{-6} (5.24)	7×10^{-7} (3.03)
Dew Point	-0.04 (-8.11)	Insignificant	-0.01 (-7.35)	-0.01 (-4.72)	-0.02 (-11.60)	-0.02 (-1.89)	0.05 (5.78)	0.03 (14.61)
Dew point^2	Insignificant	0.0006 (17.79)	Insignificant	0.0002 (4.41)	Insignificant	0.0002 (1.92)	-0.0007 (-9.41)	-0.0003 (-11.16)
Avg. Wind Speed	-0.02 (-4.80)	-0.027 (-5.07)	-0.03 (-7.93)	-0.02 (-10.64)	-0.02 (-6.81)	-0.04 (-6.23)	-0.02 (-8.03)	-0.03 (-16.59)
D_ Snow	0.32 (4.71)	0.39 (5.26)	2.61 (10.46)	0.7 (7.29)	1.16 (21.71)	Insignificant	1.30 (4.50)	1.35 (31.72)
Constant	1.2 (8.38)	2.66 (18.50)	-0.09 (-0.30)	0.31 (1.48)	-0.35 (-1.44)	2.01 (1.89)	-3.92 (-10.15)	1.08 (12.58)
Pseudo R^2	0.91	0.52	0.66	0.68	0.56	0.21	0.45	0.38

Note: The student's t-statistic test is reported in parenthesis.

TABLE 5.4 Results of negative binomial regression models for pedestrians on trails

Variables	**Coefficient of variables separated by climate regions**							
	Very Cold	Cold	Marine	Mix Dry	Mix Humid	Hot dry	Hot Humid	All Regions
Day Light	Insignificant	0.03 (2.92)	0.04 (2.81)	0.05 (1.86)	0.08 (8.37)	Insignificant	0.12 (8.86)	0.19 (37.91)
Winter	Insignificant	Insignificant	Insignificant	Insignificant	0.11 (3.35)	-0.17 (-3.36)	Insignificant	-0.25 (-11.78)
Fall	-0.10 (-2.99)	Insignificant	Insignificant	0.16 (2.38)	0.07 (2.74)	-0.19 (-4.79)	0.13 (4.04)	Insignificant
Spring	Insignificant	0.14 (3.50)	Insignificant	Insignificant	Insignificant	Insignificant	Insignificant	-0.24 (-13.62)
Holiday	Insignificant	0.16 (2.23)	Insignificant	Insignificant	0.22 (5.70)	Insignificant	0.31 (4.01)	0.2 (5.21)
Weekend	0.26 (7.27)	0.22 (8.39)	0.11 (2.20)	-0.14 (-2.66)	0.32 (22.51)	0.22 (6.41)	0.34 (12.04)	0.25 (17.63)
T_{avg}	0.06 (18.03)	0.09 (16.85)	0.07 (2.90)	0.06 (4.89)	0.09 (26.57)	0.15 (3.98)	0.08 (5.79)	0.01 (5.02)
${T_{avg}}^2$	Insignificant	-0.0008 (-15.76)	-0.0004 (-2.24)	-0.0004 (-4.47)	-0.0005 (-20.96)	-0.001 (-3.68)	-0.0004 (-4.97)	-0.0003 (-12.02)
D_Precip	0.11 (2.65)	0.25 (7.75)	0.27 (4.16)	0.17 (2.48)	0.1 (6.05)	0.15 (2.12)	0.12 (3.69)	0.16 (9.03)
Precip	-0.003 (-4.83)	-0.001 (-6.08)	-0.002 (-4.92)	Insignificant	-0.001 (-11.30)	-0.005 (-3.62)	-0.0003 (-2.88)	-0.001 (-7.14)
Precip^2	7×10^{-6} (3.28)	8×10^{-7} (2.98)	Insignificant	Insignificant	Insignificant	1×10^{-5} (2.89)	Insignificant	4×10^{-7} (2.14)
Dew Point	-0.02 (-5.32)	-0.04 (-8.88)	-0.01 (-1.97)	-0.01 (-3.76)	-0.01 (-10.90)	Insignificant	0.03 (3.21)	0.03 (12.06)
Dew point^2	-0.0001 (-3.72)	0.0007 (13.83)	Insignificant	Insignificant	Insignificant	Insignificant	-0.0006 (-6.59)	-0.0002 (-8.10)
Avg. Wind Speed	-0.03 (-6.02)	-0.06 (-19.33)	Insignificant	-0.02 (-3.79)	-0.01 (-8.67)	-0.02 (-2.14)	0.009 (2.46)	-0.008 (-4.13)
D_ Snow	Insignificant	Insignificant	Insignificant	Insignificant	0.21 (6.48)	Insignificant	1.01 (3.14)	0.2 (5.26)
Constant	4.86 (63.51)	3.97 (29.67)	3.77 (5.91)	2.5 (6.24)	2.22 (13.50)	-0.31 (-0.23)	-0.5 (-1.16)	2.89 (33.15)
Pseudo R^2	0.82	0.43	0.14	0.08	0.48	0.05	0.19	0.20

Note: The student's t-statistic test is reported in parenthesis.

From the response to weather factors, the following observations are drawn:

- Bicyclists and pedestrians in the same climate region respond differently to variations in specific weather variables such as temperature and precipitation (e.g., the effects of a variable such as temperature on the use of a trail in the cold region or the hot-humid region are different for bicyclists and pedestrians).
- Bicyclists and pedestrians in different climate regions both respond differently to variations in weather (e.g., cyclists respond differently to precipitation in different regions such as marine or cold; pedestrians different to temperature in mixed-dry and very cold regions).
- Although the direction of the effects of specific weather elements generally is the same, the magnitude of correlations of weather variables with bicyclists' and pedestrians' demand differs across climate regions.

With respect to specific variables, the daily average temperature, precipitation, dew point, average daily wind speed, and snow depth are tested in both modes across all climate regions. For the bicycling models, the daily average temperature, precipitation, and average wind speed are significant in all the models. Dew point and snow depth are significant in seven out of eight models. For the pedestrian models, the results differ in a few cases. The daily average temperature is significant in all climate regions, while precipitation, average wind speed, and dew point are significant in seven out of eight models. Noteworthy is that the snow depth dummy variable is insignificant in five out of eight models. This reveals bicyclists' demand is more sensitive to snow than pedestrians' demand.

The models are controlled by seasonal, weekend, and holiday variables. For the bicycling models, it is found that winter is significant in five out of eight models. However, fall and spring are significant in only 50% of models. Weekend is significant in more models than Holiday. For the pedestrian models, winter, fall, and spring are found significant in three, five, and two models, respectively. While weekend is significant in all models, the Holiday is found significant in 50% of models.

5.4 Demand Returns

This section introduces the concept of the "demand returns," as it is fundamental to understand how trail demand responds to variations in weather variables. This concept is tested using the results of the negative binomial regression models discussed in the preceding section. In its basic usage, the "demand returns" represents three distinct forms:

(1) **Constant returns:** Trail demand changes by the same proportion as the change in weather variables (i.e., the changes are linear).

(2) **Increasing returns:** Trail demand changes by a larger proportion than the change in weather variables.

(3) **Decreasing returns:** Trail demand changes by a lesser proportion than the change in weather variables.

To measure the demand returns, the quadratic form of weather variables is tested in the models reported in Table 5.3 and Table 5.4. The U- and ∩-shape of quadratic function enable measuring the response of demand to weather changes. Using a mathematical notation, the returning forms are formulated as per Equation 3, where $\mathrm{D_T}$ is the trail demand, $\mathrm{W_T}$ is the specific weather variable, and a, b, and c parameters stand for the coefficients of the function.

$$D_T = a{W_T}^2 + bW_T + c \tag{3}$$

$$\text{Increasing returns: } \begin{cases} W_T > \frac{-b}{2a} \ \forall a \neq 0, a > 0 \\ W_T < \frac{-b}{2a} \ \forall a \neq 0, a < 0 \end{cases} \tag{3.a}$$

$$\text{Decreasing returns: } \begin{cases} W_T > \frac{-b}{2a} \; \forall a \neq 0, a < 0 \\ W_T < \frac{-b}{2a} \; \forall a \neq 0, a > 0 \end{cases} \tag{3.b}$$

$$\text{Constant returns: } W_T = \frac{-b}{2a} \text{ or } a = 0 \tag{3.c}$$

The interpretation is as follows: if there is a statistically significant quadratic correlation between the demand and a weather variable of interest, the demand is either increasing or decreasing returns in response to the interest weather variable. It is increasing if the correlation forms the right side of the upward turned parabola or the right side of the downward turned parabola. It is decreasing if the correlation forms the left side of the upward turned parabola or the left side of the downward turned parabola. There is a constant return, if the quadratic correlation between the demand and the interest weather variable is statistically insignificant. With constant returns, the relationship between the weather variable and trail demand is assumed to be linear. This linear relationship is either increasing or decreasing depending on the sign of coefficients. It is useful to illustrate the method of examining demand returns for the negative binomial regression model in an example.

5.4.1 An example: demand response to daily average temperature

The response of trail users to daily average temperature is demonstrated using the results of the negative binomial regression model reported in Table 5.3 and Table 5.4. In very cold climate regions, T_{avg} is statistically significant in both bicyclist and pedestrian models with a positive value. However, T_{avg}^2 is not significant in either of the models. This indicates T_{avg} has constant return in very cold regions. That is, increasing the daily average temperature increases the trail demand with approximately the same proportion as the coefficient of T_{avg} is positive.

Looking at both the T_{avg} and T_{avg}^2 variables in marine climate regions, it is found that the coefficients of both variables are significant. In the bicycle model, the coefficient of T_{avg}^2 is negative indicating the parabola opens downward. The parameters of Equation 2 are substituted with the coefficients estimated by the bicyclist model as follows:

$$D_T = \exp(-0.0008 \times T_{avg}^2 + 0.12 \times T_{avg} - 0.09) \tag{4}$$

The first derivative of Equation 4 is then derived to find the vertex point or absolute maximum in this specific case. The result is presented in Equation 5.

$$(D_T)' = (0.12 - 0.0016 \times T_{avg})\exp(-0.0008 \times T_{avg}^2 + 0.12 \times T_{avg} - 0.09) \tag{5}$$

The first term is equaled to zero as per Equation 6 and the vertex point is calculated.

$$-0.0016 \times T_{avg} + 0.12 = 0 \ \rightarrow T_{avg} = 75\ °\mathrm{F} \tag{6}$$

This illustrates that the bicyclists' demand in the marine climate zone is characterized by decreasing returns up to a daily average temperature of 75°F. It is inferred when the daily average temperature approaches 75°F, the bicyclists' demand increases with a deceleration rate. Likewise, the pedestrians' demand increases with a deceleration rate followed by an increase in daily average temperature to the estimated vertex point of 87.5°F. The trail demand of bicyclists and pedestrians begins decreasing above a daily average temperature of 75°F and 87.5°F, respectively. This indicates pedestrians are more tolerant than bicyclists in responding to temperature in marine regions.

The quadratic function is tested for all available weather variables: daily average temperature, precipitation, dew point, average wind speed, and snow depth. The squared form of average wind speed and snow depth was not significant in any regions for both the bicyclists and pedestrians models. Hence, it is opted to do not embed the square of average wind speed and snow depth in the analysis. These results demonstrate that average wind speed and snow depth have constant returns in all regions and their changes are linear.

Table 5.5 summarizes the demand returns of daily average temperature, precipitation, and dew point along with their vertex point value for all climate regions. For practical interpretation of the demand returns, the range of the variable of interest should be considered. For example, the dew point variable exhibits increasing returns among bicyclists, but meteorological conditions limit the range of dew point, and demand for cycling should be interpreted over that range. The “constant” term in this table means the weather variable has constant returns (e.g., increases linearly over the range of the weather variable).

The effects of temperature, precipitation, and dew point vary by region and mode and warrant elaboration (Table 5.5). The coefficients on T_{avg} are significant and positive for both modes in all regions, while the coefficients on ${T_{avg}}^2$ are significant but negative for all regions except very cold (Tables 5.3 and 5.4). These results mean that bicycling and walking increase linearly in response to temperature in very cold regions but that in all other regions, bicycling and walking is characterized by decreasing returns. That is, in every other region, bicycling and walking increase to a particular point and then decrease. These inflection points, or vertices, are the points at which some bicyclists and pedestrians find the temperatures too high and become less likely to use a trail. From an analytic perspective, this result can be interpreted by considering the parabolic shape of the squared temperature term. Specifically, given the negative sign on the squared term, the underlying shape is a downward parabola. This shape means that demand increases with an increase in a daily average temperature up to the vertex point, but with a decelerating rate (i.e., with decreasing returns). An increase in a daily average temperature above the vertex point, however, decreases the trail demand with an accelerating rate (i.e., with increasing returns).

The vertex points for ${T_{avg}}^2$ vary by mode both across and within climate regions (Table 5.5). For example, in mixed-dry regions, the bicyclists demand increases with a decelerating rate up to a daily average temperature of 78.5 °F. Above this temperature, the bicyclists demand begins decreasing with an accelerating rate. This change occurs above 75 °F for pedestrians’ demand in the same region. The comparable values (i.e., vertices) for bicyclists and walkers in the hot dry region are 68.7 °F and 75 °F, respectively.

As for precipitation, the squared term is positive and significant in all climate regions for bicyclists and positive and significant in three regions for pedestrians (Tables 5.3 and 5.4). In marine, mixed-humid, and hot-humid regions, the squared term is not significant, and pedestrian demand has a constant return (i.e., decreases linearly in response to precipitation). In mixed dry region, precipitation is not significant after controlling for other weather effects (Table 5.4). For the regions in which the squared term is significant, all the coefficients are positive, and the underlying form is that of upward parabola, which means demand decreases with increases in precipitation up to the vertex point, but with a decelerating rate (i.e., with decreasing returns). The vertex point fluctuates between 21.4 and 150.0 mm among climate regions, depending on the mode. The lowest vertex point for precipitation occurs for bicycling in mixed-dry regions, while the highest vertex point for precipitation occurs in cold regions, also for bicycling. An implication of these results (i.e., the positive sign on the squared term implies an upward shaped parabola) is that use at some point would increase again after particular rainfall volumes. This result, which makes no intuitive sense, is an artifact of this common modeling approach and not believed to be important in most practical applications. Overall, these results indicate that bicyclists on trails are less affected by precipitation than pedestrians on trails.

TABLE 5.5 Vertex point of weather variables in different climate regions classified by mode

Variable	Mode	Climate Regions						
		Very Cold	*Cold*	*Marine*	*Mix Dry*	*Mix Humid*	*Hot Dry*	*Hot Humid*
T_{avg} (°F)	Bicycle	Constant	100	75	78.5	100	68.7	100
	Walk	Constant	56.2	87.5	75	90	75	100
Precipitation (mm)	Bicycle	25.0	150.0	50.0	21.4	50.0	40.0	50.0
	Walk	21.4	625	Constant	-	Constant	25.0	Constant
Dew Point (°F)	Bicycle	Constant	0	Constant	25	Constant	50	35.7
	Walk	100	28.5	Constant	Constant	Constant	-	25

The effects of dew point may be interpreted similarly. Demand in response to dew point is more variable across regions and mode than in response to temperature or precipitation (Table 5.5). It also is more likely to be characterized as constant returns.

5.5 Elasticity Analysis

To quantify the effects of independent variables used in the models of trail demand, the elasticity of continuous variables and marginal effects of dummy variables are calculated. Table 5.6 outlines the results. The elasticity represents the percent change in the dependent variable when one of the independent variables changes by one percent, while other independent variables are fixed. For dummy variables, the marginal effects measurement shows the demand effects between the two conditions in percentage. Two main methods of elasticity calculation are the arc elasticity method and the point elasticity method. In this study, the arc elasticity method is used, which measures the elasticity at the average. In elasticity interpretation it should be kept in mind that elasticities are estimated for marginal changes, so they are meaningful for small changes around the average.

The marginal effects of the dummy variables for seasonality vary across the regions (Table 5.6). In cold regions, bicyclists' demand is 80.2% lower in winter than in summer. Likewise, in hot dry regions, the bicyclists demand in winter is 98.4% lower than in summer. However, in mix humid and mix dry regions the result is reversed. The bicyclists demand in winter is 121.9% and 10.5% higher than summer in mix humid and mix dry regions, respectively. In marine regions, it is not found any seasonal effects on demand for bicycling after controlling for weather variables such as average daily temperature and precipitation. This result is also true for very cold regions, where there is not any winter and fall effects on bicyclist demand and only bicyclists' demand is 95.4% lower in spring than in summer. The seasonal effect on pedestrians' demand is fairly low, and, like demand for cycling, varies across regions. Although there are no seasonal effects in marine regions, the demand of pedestrians is high in mixed humid regions and low in hot dry regions for both winter and fall.

TABLE 5.6 Results of elasticity and marginal effects for bicyclist and pedestrian models

Variables	Climate regions							
	Very Cold	Cold	Marine	Mix Dry	Mix Humid	Hot dry	Hot Humid	All Regions
				Bicyclist Models				
Day Light	1.43	Insignificant	0.92	0.39	0.98	0.70	2.67	1.80
Winter	Insignificant	-80.25	Insignificant	10.53	121.92	-98.42	Insignificant	-35.76
Fall	Insignificant	30.56	Insignificant	Insignificant	70.15	-70.48	34.33	Insignificant
Spring	-95.44	109.08	Insignificant	Insignificant	Insignificant	-58.75	Insignificant	-22.87
Holiday	-63.56	Insignificant	Insignificant	Insignificant	Insignificant	246.32	127.98	76.17
Weekend	Insignificant	80.25	Insignificant	23.38	Insignificant	309.96	203.40	118.45
T_{avg}	3.42	1.21	6.98	6.69	8.34	7.96	8.85	1.82
T_{avg}^2	Insignificant	-0.36	-2.71	-2.80	-2.70	-3.85	-3.76	-0.95
D_Precip	34.64	104.57	268.07	24.65	123.18	66.00	77.81	133.95
Precip	-0.06	-0.07	-0.09	-0.02	-0.08	-0.06	-0.07	-0.04
$Precip^2$	0.02	0.008	0.01	0.008	0.01	0.03	0.02	0.005
Dew Point	-1.28	Insignificant	-0.78	-0.62	-1.13	-1.13	3.14	1.80
Dew $point^2$	Insignificant	0.95	Insignificant	0.33	Insignificant	0.63	-2.87	-0.84
Avg. Wind Speed	-0.27	-0.24	-0.20	-0.21	-0.17	-0.24	-0.21	-0.26
D_Snow	79.02	98.96	2729.93	110.03	758.14	Insignificant	405.21	651.16
				Pedestrian Models				
Day Light	Insignificant	0.38	0.54	0.72	1.03	Insignificant	1.58	2.40
Winter	Insignificant	Insignificant	Insignificant	Insignificant	62.38	-44.54	Insignificant	-109.13
Fall	-83.11	Insignificant	Insignificant	18.57	39.19	-49.78	31.09	Insignificant
Spring	Insignificant	62.02	Insignificant	Insignificant	Insignificant	Insignificant	Insignificant	-105.48
Holiday	Insignificant	70.31	Insignificant	Insignificant	123.22	Insignificant	72.57	87.10
Weekend	203.86	98.36	111.59	-16.37	177.01	56.51	80.60	108.27
T_{avg}	2.63	4.57	4.41	3.71	5.49	10.76	6.05	1.16
T_{avg}^2	Insignificant	-2.45	-1.58	-1.81	-2.11	-4.92	-2.75	-1.56
D_Precip	91.06	109.51	260.02	20.11	58.22	38.04	29.10	71.50
Precip	-0.08	-0.03	-0.06	Insignificant	-0.03	-0.03	-0.01	-0.02
$Precip^2$	0.03	0.005	Insignificant	Insignificant	Insignificant	0.01	Insignificant	0.003
Dew Point	-0.74	-1.42	-0.52	-0.37	-0.69	Insignificant	2.048	1.47
Dew $point^2$	-0.19	1.20	Insignificant	Insignificant	Insignificant	Insignificant	-2.35	-0.60
Avg. Wind Speed	-0.31	-0.62	Insignificant	-0.19	-0.14	-0.10	0.07	-0.06
D_ Snow	Insignificant	Insignificant	Insignificant	Insignificant	117.81	Insignificant	238.04	87.89

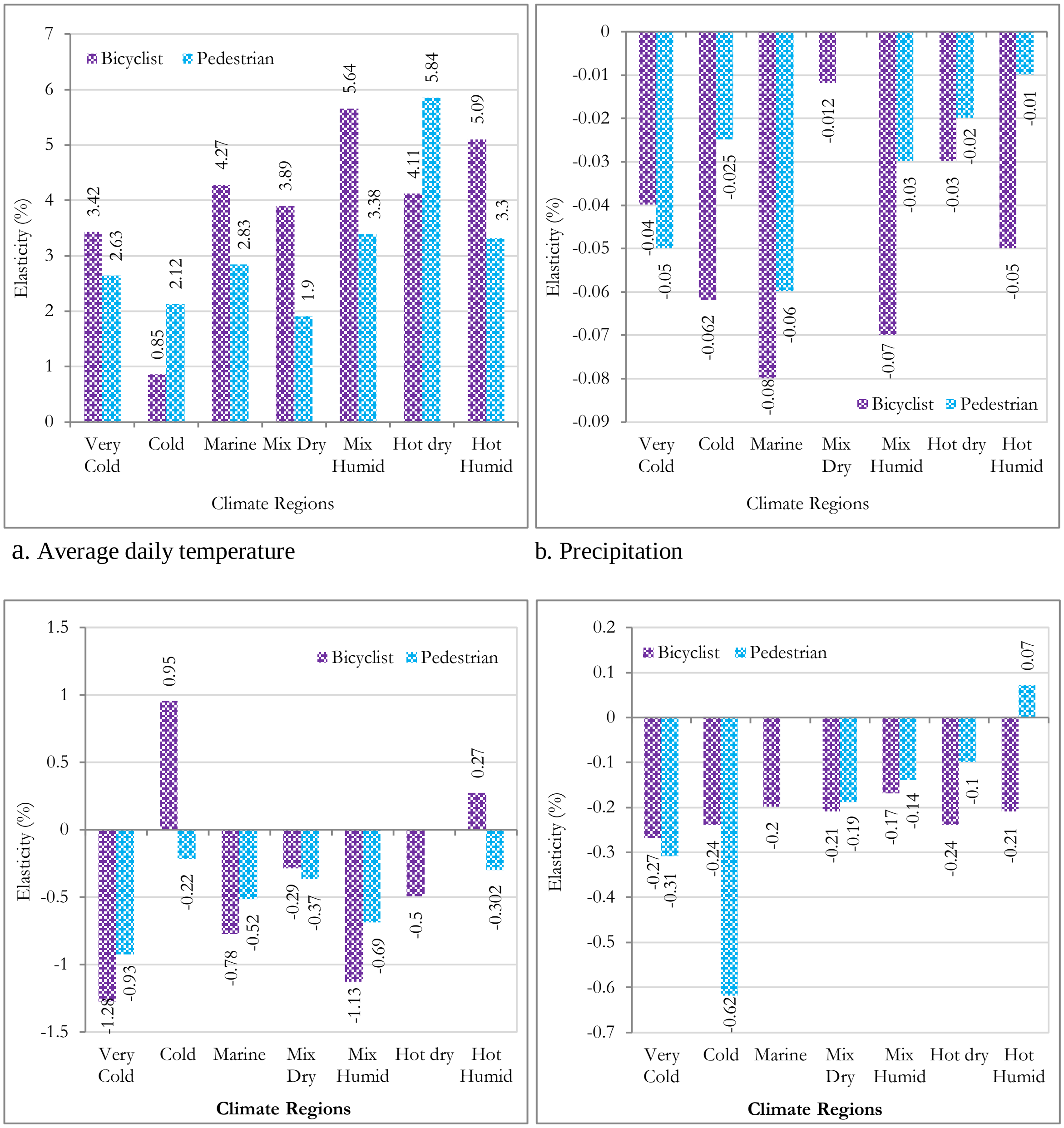
As far as the day of week and holidays are concerned, the bicyclists demand is two to three times higher in hot dry and hot humid regions. However, the effect of the day of week and holidays on pedestrians' demand is fairly low in these two climate regions. This means the demand of bicyclists is more sensitive to weekend and holidays than the demand of pedestrians in hot dry and hot humid regions. The bicyclists demand in very cold regions is 63.5% lower on holidays than other days of the year when controlling for seasonality and other factors. However, the pedestrians demand in very cold regions in weekends is two times of other days of the week. The marginal effects of weekend are fairly significant on pedestrians' demand over all climate regions, although the direction and magnitude of effect are mixed. The pedestrians demand in weekends is more than other days of the week in all regions but mix dry, varying from 56.5% in hot dry regions to 203.8% in very cold regions. In mix dry regions, the pedestrians demand in weekends is 16.3% than other days of the week.

As far as the weather effects are concerned, daily average temperature is the most important variable in trail demand. The results indicate that the bicyclists are more sensitive to daily average temperature than pedestrians in five of the climate regions. For instance, a 1% increase in the average daily temperature in very cold regions increases the bicyclists' and pedestrians' demand by 3.4% and 2.6%, respectively. As alluded to previously, the bicyclists and pedestrians respond to the daily average temperature differently below and above the absolute maximum temperature or vertex point. Although an increase in a daily average temperature increases the trail demand with a deceleration rate below the vertex point, the trail demand starts decreasing with an acceleration rate above the vertex point. According to Table 5.5, the vertex point in mix humid regions for bicyclists and pedestrians equals 100°F and 90°F, respectively. Having the elasticity results, it is then inferred that a 1% increase in the average daily temperature below the 100°F and 90°F is followed by 5.6% and 3.3% increase in bicyclists' and pedestrians' demand, respectively. Above the 100°F and 90°F, a 1% increase in the average daily temperature results in 5.6% and 3.3% decrease in bicyclists' and pedestrians' demand, respectively.

To illustrate how pedestrians and bicyclists respond to various weather variables quantitatively and make the comparison of elasticities easier, Figure 5.2 plots the column chart of elasticities for continuous variables. As shown in Figure 5.2.a, the average daily temperature has a more impact on bicyclists' demand than pedestrians' demand in all regions, but cold and hot dry regions. It is also inferred that the average daily temperature play a more effective role in mix humid, hot dry, and hot humid regions than other climate regions on trail demand.

Figure 5.2.b shows the variation in trail demand in response to precipitation. Bicyclists' demand is more affected by precipitation than pedestrians' demand in all regions, but very cold regions. It is also found that precipitation significantly affects trail demand in marine and mixed humid regions, while there is not a significant effect in mix dry regions, particularly on pedestrians' demand. Figure 5.2.c indicates the response of pedestrians and bicyclists to dew point is mixed over regions. In cold and hot humid regions, an increase in dew point decreases the pedestrians' demand, while it increases the bicyclists' demand. The dew point does not have any impacts on the pedestrians' demand in hot dry regions. However, the trail demand is significantly affected by dew point in very cold and mix humid regions.

Figure 3.d represents the variation in trail demand in response to the average wind speed. Interestingly, a 1% increase in the average wind speed decreases the bicyclists' demand by 0.21%, while it increases the pedestrians' demand by 0.07% in hot humid regions. In all other regions, however, pedestrian and bicyclists respond to the average wind speed similarly. Bicyclists are more sensitive to the average wind speed than pedestrians in very cold and particularly cold regions. In cold regions, for example, the bicyclists' demand is decreased 2.5 times more than the pedestrians' demand following a 1% increase in the average wind speed.



a. Average daily temperature

b. Precipitation

c. Dew point

d. Average wind speed

FIGURE 5.2 Elasticity of continuous weather variables in different climate regions

5.6 Summary

Engineers and planners need information about factors that affect demand for bicycling and walking to plan and manage transportation infrastructure. This chapter presented a set of econometric models that summarize the effects of variation in temperature, precipitation, wind speed, dew point, and hours of daylight on daily bicycle and pedestrian trail traffic volumes. This chapter made three contributions to the literature on non-motorized traffic monitoring and management. First, it summarized trail traffic monitoring results for 32 monitoring stations on multiuse trails in 13 cities in the United States, including locations across climate regions and zones classified by the U.S. Department of Energy. The monitoring results include estimates of average daily bicyclists (ADB) and average daily pedestrians (ADP) for the period, January 1, 2014 through February 16, 2016. Second, it introduced the concept of demand returns by testing the parabola form of the weather factors in the models, and measuring the vertex points of demand functions where use shifts from increasing to decreasing or vice versa in response to linear changes in the weather variable. Third, it compared regional elasticities for each weather variable for both bicyclists and pedestrians. The results showed (1) daily trail traffic varies substantially – over three orders of magnitude – across the monitoring stations included in the study; (2) the parabola form works well for variables such as temperature, where trail use is associated with warmer temperatures, but only up to a point at which higher temperatures then decrease use; and (3) bicyclists and pedestrians respond differently to variations in weather, and their responses vary both within and across regions. Transportation planners and trail managers can use these results to estimate the effects of weather and climate on trail traffic and to plan and manage facilities more effectively.

Chapter 6

A Performance Assessment of Demand Models

6.1 Introduction

Unlike motorized traffic demand, which is fairly consistent throughout a year, non-motorized travel demand varies significantly in response to external factors such as weather and season (Habib et al., 2014). In addition, land use and the built environment exert different influences on decisions to drive, bike, and walk. To understand differences in demand for walking and cycling, analysts need continuous pedestrian and bicyclist traffic data collected over long periods of time in different urban contexts and geographic regions. While trail traffic data are increasingly becoming available, much of previous research has been confined to particular facilities, cities, or metropolitan regions (e.g., Wang et al., 2013; Lindsey et al., 2007). Consequently, efforts to transfer trail demand models and apply them in different locations have met with limited success (Wang et al. 2016).

Historically, traffic counts of pedestrians and bicyclists on trails were collected manually on a case by case basis, which has limited the duration of counts, been monotonous for field personnel, expensive, and sometimes unreliable (Ryus et al., 2014). Over the past 15 to 20 years, however, emerging automated technologies for counting pedestrians and bicyclists have overcome these limitations and facilitated continuous traffic counts analogous to those collected for motorized traffic (Pettebone et al., 2010). Automated monitors may count bicyclists and pedestrians separately or as mixed mode traffic (i.e., undifferentiated bicyclists and pedestrians) depending on their design and the location in which they are used. For example, passive infrared devices, which count people passing by sensing temperature differentials with background ambient conditions, do not differentiate between cyclists and pedestrians and hence yield only mixed mode counts if installed on trails or sidewalks. Inductive loops and pneumatic tubes on trails or in bike lanes count bicyclists but not pedestrians. These technologies can, however, be combined with infrared monitors to produce separate bicycle and pedestrian counts. Much of the previous research on trail traffic demand has been limited to analysis and modeling of mixed mode counts obtain through deployment of passive or active infrared sensors. The main reasons for reliance on infrared monitors have been cost, simplicity in deployment and data collection, and availability. Infrared technology is old, and portable units for measuring trail traffic that can be deployed by non-specialists are available for a few hundred dollars. Integration of infrared devices with pneumatic tubes on trails is cumbersome and requires experienced personnel and more time. Installation of inductive loops requires specialists to cut through concrete and therefore is more expensive. However, because the needs for demand data have increased, integrated technologies that combine infrared and inductive loops for producing mode-specific measures of demand now are available at reasonable costs.

Because of their availability and the integration of new capabilities such as wireless data transmission, public agencies throughout the world increasingly are deploying integrated infrared and inductive loop systems. Examples of agencies and nonprofit organizations in the U.S. now using these technologies to monitor trail traffic include the North Carolina and Minnesota Departments of Transportation, the Delaware Valley Regional Plan Commission, and the cities of Portland and Seattle. In 2014, to support its efforts to increase accessibility to urban trails across the United States, the nonprofit Rails to Trails Conservancy (RTC) launched a new initiative, the Trail Modeling and Assessment Platform (T-MAP) that included deployment of integrated infrared and inductive loop monitors in 13 urban areas across the U.S. An objective of T-MAP is to produce trail demand models to support development of new trails (Rails to Trails Conservancy, 2016).

This chapter presents new trail demand models based on data from the T-MAP traffic monitors. The remainder of this chapter is structured as follows. First, a descriptive analysis of the data used in this study is represented, especially, the variation in ADP, ADB, and ADM over the study locations. Second, a set of econometrics models is developed to regress the trail demand against the 5 D's of the built-environment and socioeconomic characteristics. Specifically, bicycle-only, pedestrian-only, and mixed-mode demand models are developed and compared with one another. Third, the results are discussed a post-validation technique is introduced to advance the prediction accuracy. The chapter is concluded by summarizing the key findings.

6.2 Trail Traffic Data

Much of the previous research has been devoted to estimating annual average daily traffic (AADT) rather than average daily traffic because AADT is the standard metric reported for motorized traffic. Trail traffic data, however, is often incomplete, and analysts often have to manage problems associated with missing data. For the modeling and estimation purposes, it is decided to model average daily traffic rather than AADT because (1) different numbers of days of valid counts were available for each trail and (2) only 17 monitoring stations included more than 350 consecutive days after cleaning. To calculate average daily traffic, first the 15-minute volumes were aggregated to the daily level for both bicycle and pedestrian travel modes, and included only days with a complete record for the entire 24 hours. The daily volumes are then averaged over January 1, 2014 through February 16, 2016 to determine average daily bicyclists (ADB), average daily pedestrians (ADP), and average daily mixed-modes (ADM). Table 6.1 summarizes ADB, ADP, and ADM over monitoring stations.

Annual average daily bicyclists (AADB), annual average daily pedestrians (AADP), and annual average daily mixed-modes (AADM) are also added to Table 6.1 for comparing annual average daily and average daily measures. To calculate annual average daily traffic, the daily volumes is averaged over the number of valid days in a year, which is reported in Table 6.1, for each monitoring station.

TABLE 6.1 Annual average daily and average daily measures over monitoring stations

Trail Site	Total Days	Days in a Year	Average Daily			Annual Average Daily		
			ADB	*ADP*	*ADM*	*AADB*	*AADP*	*AADM*
Ballston Connector	743	352	322.4	483.4	805.9	449.3	649.1	1098.4
BGT	643	238	1104.3	380.2	1484.6	1149.3	392.1	1541.5
Bluemont Connector	764	358	150.3	271.8	422.1	157.3	283.6	441.0
CC Connector	754	354	512.4	506.2	1018.6	527.7	498.7	1026.5
Chula Vista	691	326	419.0	48.2	467.2	433.8	49.9	483.7
Coronado Bayshore	489	359	946.0	388.7	1334.7	1004.9	425.9	1430.8
Custis Bon Air	749	342	737.7	442.5	1180.2	779.7	457.3	1237.0
Descro	629	360	57.2	145.9	203.2	54.5	138.9	193.5
Duluth Lake Walk	545	355	237.2	743.6	980.9	273.7	820.7	1094.5
Elliott Bay	608	246	1242.7	2299.0	3541.7	1178.5	2226.4	3404.9
Escondido Inland	744	340	99.0	108.7	207.7	101.2	113.9	215.1
FW Clear Fork A	566	327	550.2	462.2	1012.4	496.4	458.1	954.6
FW Clear Fork B	520	246	289.5	282.3	571.9	265.0	286.4	551.4
Imperial Beach	627	359	781.0	131.3	912.4	765.7	129.5	895.2
Kiwanis	630	360	30.0	128.8	158.9	29.7	127.3	157.0
Miami Dade A	485	299	111.7	238.5	350.2	117.5	247.1	364.6
Miami Dade B	576	359	177.5	75.3	252.9	181.0	72.8	253.9
MTS Washington	638	268	715.1	191.4	906.6	711.6	193.5	905.1
Oceanside SLR River	638	312	647.3	117.9	765.3	686.6	138.6	825.3
Paseo del Nordeste	598	361	120.0	193.6	313.6	118.6	180.1	298.7
Paseo del Norte	629	359	189.2	38.6	227.9	187.6	36.1	223.8
Pikes Peak Greenway	405	166	141.0	684.1	825.2	137.5	682.3	819.9
Portland Trails A	619	356	221.5	666.8	888.3	209.1	642.5	851.6
Portland Trails B	628	355	174.7	725.8	900.5	165.7	700.5	866.3
Rock Island	205	0	105.6	58.3	163.9	0	0	0
SD Harbor	711	339	556.3	728.7	1285.0	636.2	711.5	1347.7
Tammany Trace	628	358	157.0	55.3	212.4	153.1	56.2	209.4
TR Island	711	332	994.6	855.7	1850.4	1027.0	893.6	1920.7
W. River Greenway	553	343	919.7	433.0	1352.8	950.8	445.0	1395.8
White Oak	757	354	468.5	295.8	764.4	493.6	308.4	802.0
WOD Bon Air West	769	362	1100.5	585.6	1686.2	1151.9	647.8	1799.7
WOD Columbia Pike	761	355	606.3	544.6	1151.0	640.3	507.6	1148.0

To compare the average daily and annual average daily traffic in the sample, two-sample mean-comparison and two-sample variance-comparison tests are conducted and reported in Table 6.2. The results reveal no significant differences between average daily and annual average daily traffic in the sample. The demand modeling analysis thus has implications for modeling the annual average daily traffic as well. Table 6.3 depicts the statistics of variables used in the demand modeling process.

TABLE 6.2 Results of two-sample mean- and variance-comparison tests

Comparison	Sample	Mean	Variance	Mean Comparison		Variance Comparison	
				t-test	P-value	f-test	P-value
ADB vs. AADB	ADB	465.22	359.77	-0.11	0.90	0.93	0.42
	AADB	476.13	372.03				
ADP vs. AADP	ADP	416.03	420.98	-0.06	0.95	1.02	0.47
	AADP	422.58	416.41				
ADM vs. AADM	ADM	881.26	676.02	-0.10	0.91	0.98	0.48
	AADM	898.71	681.48				

TABLE 6.3 Descriptive of data and parameters used in the analysis

Variable	Definition	Average	St. Dev.
WATER	Total water area in acres	75.22	187.40
LAND	Total land area in acres	1246.48	4674.12
NETDENS	Network density: Facility miles of multi-modal links/(Mile)^2	3.42	3.07
HIGH_EDU	Percentage of people holding bachelor and higher degree	0.43	0.28
ACCESS	Jobs within 45 minutes auto travel time	184,269.3	184,269.3
WATERDENS	$=$ WATER $\div$ LAND	0.31	0.71
WRKAGE	Percentage of people older than 16 years	0.83	0.08
LOW_EDU	Percentage of people holding diploma and below degree	0.08	0.10
BIKE	Average daily bicyclists	465.22	359.77
PEDESTRIAN	Average daily pedestrians	416.03	420.97
MIXED-MODE	$=$ BIKE $+$ PEDESTRIAN	881.26	676.01
ROADDENS	Total road network density	19.79	9.97
PRECIP	Daily Precipitation in tenths of mm	23.93	12.86
RESDEN	Residential density: Household units/Acre	4.68	5.01

6.3 Trail Demand Models

To estimate pedestrian and bicyclist traffic demand, previous research modeling daily counts has tested the negative binomial regression model as a special form of generalized linear model. This is a valid methodological approach as pedestrian and bicycle traffic volumes are count data with non-negative values. Testing the negative binomial regression model, however, is inappropriate when it comes to describe and predict annual average daily or average daily traffic because the variable under the study is not count data. Although the simple linear regression model is deemed convenient to predict annual average daily or average daily traffics, it is limited because when used in practice, it can predict negative values. A way of coping with this limitation is testing the generalized linear model (GLM) using the logarithmic link function.

Nelder and Wedderburn (1972) were first to introduce the generalized linear model, which later expanded by McCullagh and Nelder (1989). The GLM is an extension of the simple linear regression model, which takes both non-normal response distributions and transformations to linearity into consideration. This model allows testing Gaussian, Poisson, Binomial, Gamma, Inverse Gaussian, and Negative Binomial family distributions along with a relevant link function. The general form of GLM is given by Equation 1. In this equation, $E(Y)$ is the expected value of the dependent variable, which is assumed to be generated from a particular distribution in the exponential family, μ is the mean of the distribution, g is the link function, X is a set of explanatory variables, and β is a vector of unknown parameters.

$$E(Y) = \mu = g^{-1}(\beta X) \tag{1}$$

The GLM fitting procedure comprises: (1) selecting the fitting error distribution and (2) determining the link function. The logarithmic link function is chosen to control the positivity of traffic demand predictions. For selecting the fitting error distribution, the Akaike Information Criteria (AIC) is calculated along with the normality test, which enables measuring the quality of each distribution relative to other distributions. The lower the AIC of a model is, the more relevant distribution becomes. Table 6.4

summarizes the results of the AIC measurement for each distribution, while the link function is fixed to logarithmic. The results of the AIC analysis suggest the Gamma distribution over Gaussian and Inverse Gaussian for all three models. This is confirmed by the normality test.

TABLE 6.4 Results of the AIC measurement for different error distributions

Models	**Akaike Information Criteria (AIC)**		
	Gaussian	Inverse Gaussian	Gamma
Bicyclist	14.63	19.21	**14.34**
Pedestrian	14.95	18.74	**14.12**
Mixed-mode	15.90	21.40	**15.62**

Following the distribution and link function selection, the subsequent steps are adopted to achieve a parsimonious model that is easy to present and interpret in practice:

- The bivariate regression models are tested to select variables that are highly correlated with the trail demand followed by a correlation analysis among retained variables.
- Only the significant variables at the 90% confidence interval are embedded in the model, while controlling for the multicollinearity issue. A Student's t-test is performed to test the null-hypothesis that the estimated coefficient is statistically different from 0. The severity of multicollinearity is also quantified by the variance inflation factor (VIF).
- Among two highly correlated variables, the variable selection is judged measuring the goodness-of-fit of the models. The higher AIC represents a better model.
- The sign of coefficients is inspected to control for whether they are confirming the conceptually expected signs.

Table 6.5 depicts the final trail demand models. To give the reader an understanding of how much the selected variables improve describing the trail demand, the McFadden's

Pseudo R-squared is calculated. This indexes the improvement of the fitted model over the null model and falls between 0 and 1, while the greater the value stands for the better fit. Looking at Table 6.5, it is found that the mixed-mode model has a better fit than individual mode models. The McFadden's Pseudo R-squared for the mixed-mode model equals 0.71. This means a 71% improvement over the null model is offered by the full model. There is not a significant difference between the goodness-of-fit of the bicyclist and pedestrian demand models. The McFadden's Pseudo R-squared for the bicyclist and pedestrian models equal 0.63 and 0.61, respectively.

TABLE 6.5 Bicycle, pedestrian, and mixed-mode trail demand models

Variables	**Bicyclist**		**Pedestrian**		**Mixed-mode**	
	Coefficients	z-test	Coefficients	z-test	Coefficients	z-test
Constant	5.29	21.74 (0.000)	2.89	2.35 (0.019)	3.78	4.53 (0.000)
NETDENS	-0.18	-4.83 (0.000)	-0.06	-1.65 (0.100)	-0.13	-4.47 (0.000)
HIGH_EDU	0.79	1.70 (0.089)	-	-	1.01	2.68 (0.007)
ACCESS	4.42×10^{-6}	3.40 (0.001)	2.43×10^{-6}	2.48 (0.013)	2.49×10^{-6}	2.59 (0.010)
WATERDENS	0.28	1.74 (0.083)	0.46	2.70 (0.007)	0.35	2.69 (0.007)
LOW_EDU	-	-	-2.51	-2.37 (0.018)	-	-
WRKAGE	-	-	3.28	2.29 (0.022)	2.71	2.65 (0.008)
AIC	14.12		13.92		15.53	
Null Deviance	23.88		26.68		17.91	
Residual Deviance	8.84		10.43		5.03	
McFadden's Pseudo R^2	0.63		0.61		0.72	
No. of Observations	32		32		32	

6.4 Built-Environment, Socioeconomic, and Trail Demand

The elasticity of variables is calculated to give the reader a sense of the quantitative impact of built-environment and socioeconomic characteristics on trail demand. The elasticity of demand used in this study represents the average percentage change in the mean of dependent variable associated with a one percent change in an independent variable. The elasticity of demand is calculated for each trail and the weighted average is taken over all trails. The results are depicted in Figure 6.1.

As far as built-environment variables are concerned, it is found the network density, job accessibility, and water proportion significant in the demand models. The network density in terms of facility miles of multi-modal links per square mile is negatively correlated with trail demands. It is speculated that providing alternative facilities reduces the trail demand. However, the magnitude of impact varies significantly between bicyclist, pedestrian, and mixed-modes. The elasticity analysis indicates a 1% increase in network density in terms of facility miles of multi-modal links per square mile decreases the demand of bicyclists by 0.63%, pedestrians by 0.23%, and mixed-mode by 0.47%. This reveals the bicyclists demand is about three times more sensitive to network density than pedestrians demand. A positive correlation is also found between the accessibility to jobs and trail traffic demand. The elasticity analysis signifies that 0.81% increase in bicyclists demand follows a 1% increase in the cumulative accessibility to jobs by automobile within 45 minutes. A 1% increase in the cumulative accessibility to jobs by automobile within 45 minutes also increases the mixed-mode demand by 0.45%. This increase equals 0.44% in pedestrians demand.

The water proportion, which is the ratio of total water area to total land area in acres, is another effective built-environment variable on all three models. This variable has a positive correlation with all bicyclists, pedestrians, and mixed-modes traffic demands. The results pinpoint that a 1% increase in the water proportion increases the demand of bicyclists, pedestrians, and mixed-mode by 0.08%, 0.14%, and 0.11%, respectively.

As far as socioeconomic variables are concerned, it is found the education and work age variables significant in the demand models. As expected, an increase in the percentage of more-highly educated people dwelling near the pedestrian and bicyclists trails increases the trail traffic demand. Specifically, a 1% increase in the percentage of people with college education or above increases the bicyclists and mixed-mode traffic demand by 0.34% and 0.44%, respectively. A 1% increase in the percentage of people with high-school education or above also increases the pedestrians demand by 0.21%. Comparing the magnitude of educational impacts between bicyclists and pedestrians, it is inferred that bicyclists demand is more sensitive to educational level than pedestrians demand. A positive correlation further is found between the percentage of work age in each category and both pedestrian and mixed-mode traffic demand. This variable, however, was found insignificant in the bicyclist demand model. The elasticity of this variable indicates that a 1% increase in the percentage of work age population is followed by 2.74% and 2.26% increases in pedestrian and mixed-mode demand, respectively. It is speculated that working individuals are more willing to use trails for walking to work rather than biking.

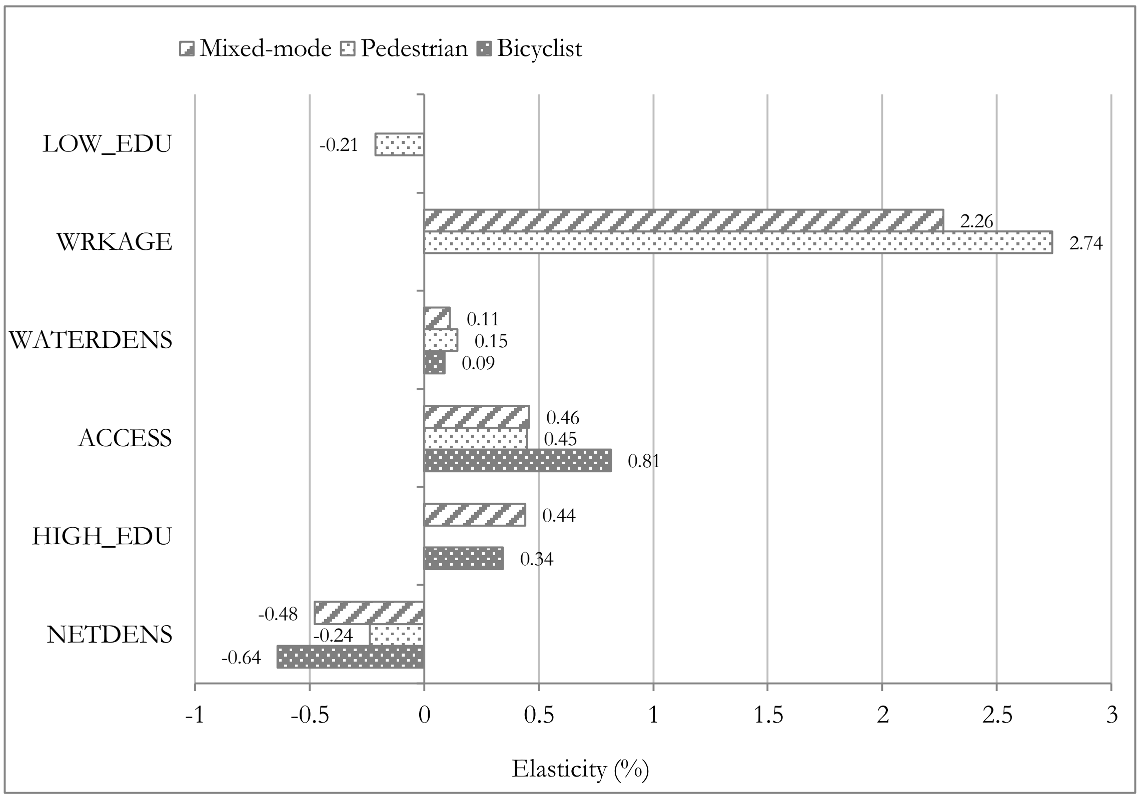


FIGURE 6.1 Elasticity analysis of trail traffic demand models

6.5 Cross-validation

Predictive models are practical tools to provide estimates of trail traffic demand. The performance of the models, however, is overestimated when it is simply measured using the sample for model development. From the practical side, conducting cross-validation is essential to help ensure that a model can serve its intended purpose (Kohavi, 1995). This section therefore employs cross-validation to evaluate the predictive validity of demand models used to forecast average daily trail traffic volumes. This avoids an optimistic impression of the predictive effectiveness of the trail demand models when applied to future observations. Cross-validation is a computational technique to use all available observations as training and test examples (Fushiki, 2011). This technique partitions the data with n number of observations into k ($k = 2, 3, \dots, n$) chunks. This is then followed by training k models on a different combination of $k - 1$ chunks and testing on the left out chunk. The most extreme form of cross-validation is known as leave-one-out cross-validation, where k equals n. Although this form is computationally expensive, it provides an almost unbiased estimate. The low number of observations in the present study, however, allows us to select the leave-one-out method for the cross-validation of the trail traffic models.

To measure the accuracy of prediction for each cross-validation, the Relative Percentage Error (RPE) measurement is used as per Equation 2. In this equation, $\hat{d}_i$ and d_i are predicted and observed demands, respectively.

$$RPE = \frac{\widehat{|d_i - d_i|}}{d_i} \times 100 \tag{2}$$

Figure 6.2 displays the cross-validation results for each trail traffic model separately. As for the bicycle demand model, the relative percentage error varies between 1.4% and 549.3% with an average of 65.4% over trail sites. The relative percentage error for the pedestrian demand model, however, fluctuates between 2.1% and 434.1% with an average of 85.3% over trail sites. Comparing the Mean Relative Percentage Error (MRPE) of the models, it is inferred that the bicycle demand model performs 23.3% better than the pedestrian demand model. As shown in Figure 2, the mixed-mode demand model outperforms both the bicycle and pedestrian demand models. The relative percentage error of this model varies between 0.1% and 138.5% with an average of 45.9% over trail sites. This result is evidence that the mixed-mode demand model performs 29.8% and 46.2% more accurate than the bicycle and pedestrian demand models, respectively.

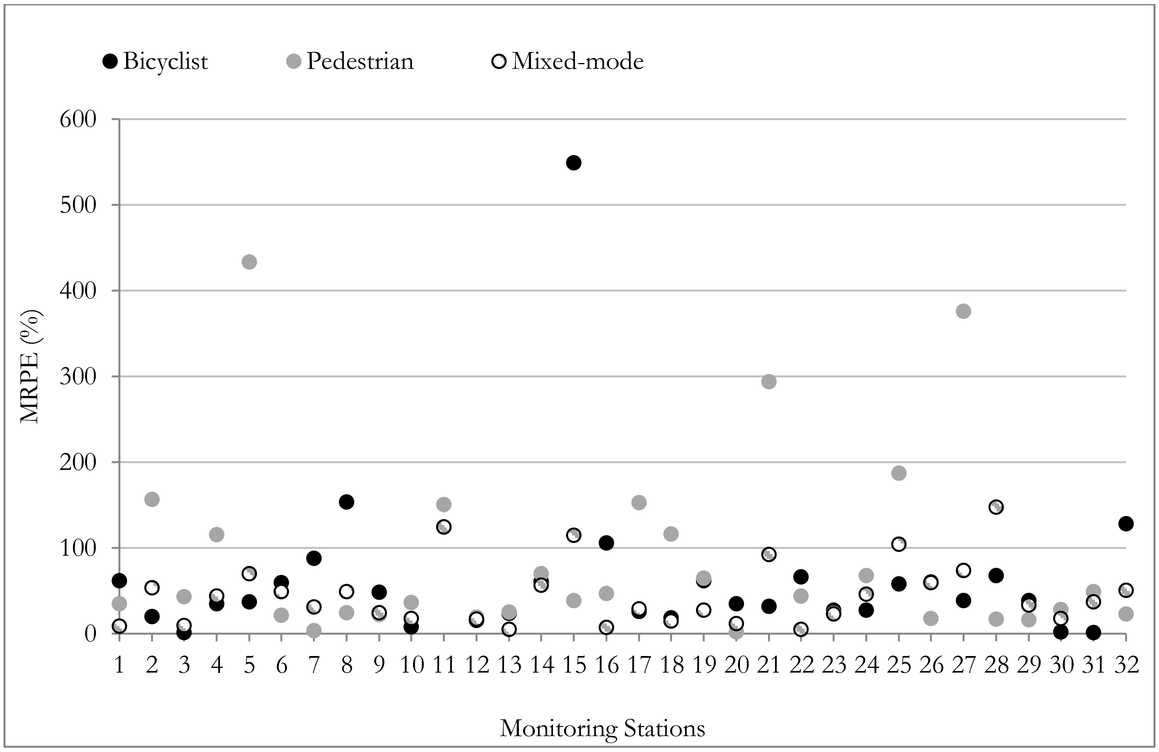


FIGURE 6.2 MRPE analysis over all stations

6.6 Do Mode-specific Models Produce Better Estimates of Total Demand?

The preceding section investigated the prediction accuracy of the models using the cross-validation technique. This section attempts to test whether the accuracy of the total (mixed-mode) travel demand improves when we use multimodal devices. The hypothesis is that, because different factors are known to affect bicycle and pedestrian demand, estimating total demand by summing mode-specific totals may be preferable to estimating mixed-mode models to predict total demand. To test this hypothesis, the accuracy of mixed-mode demand model is compared employing two approaches: (1) estimating the mixed-mode demand using the mixed-mode model and (2) estimating the mixed mode demand using the individual bicyclists and pedestrian models. The latter approach simply estimates the pedestrian and bicyclists demands and sums up the estimated values to estimate mixed-mode demand. Using the results of the cross-validation, Figure 6.3 depicts the relative percentage error derived from both approaches.

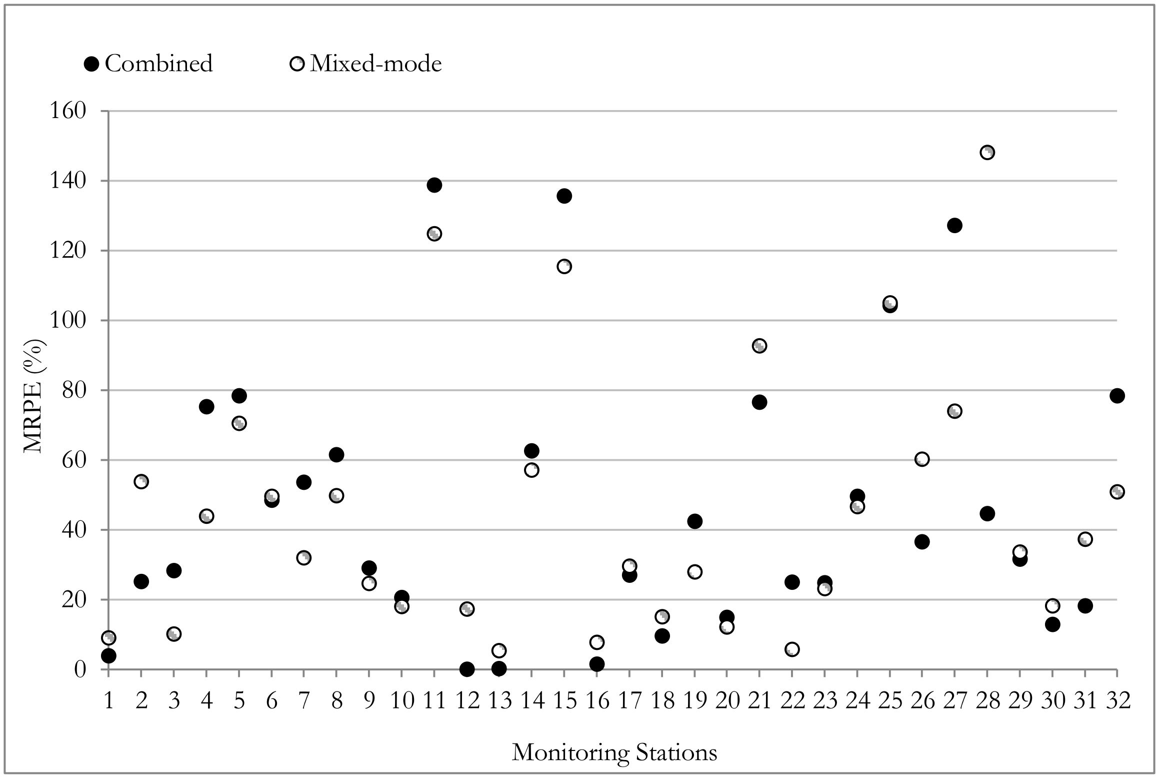


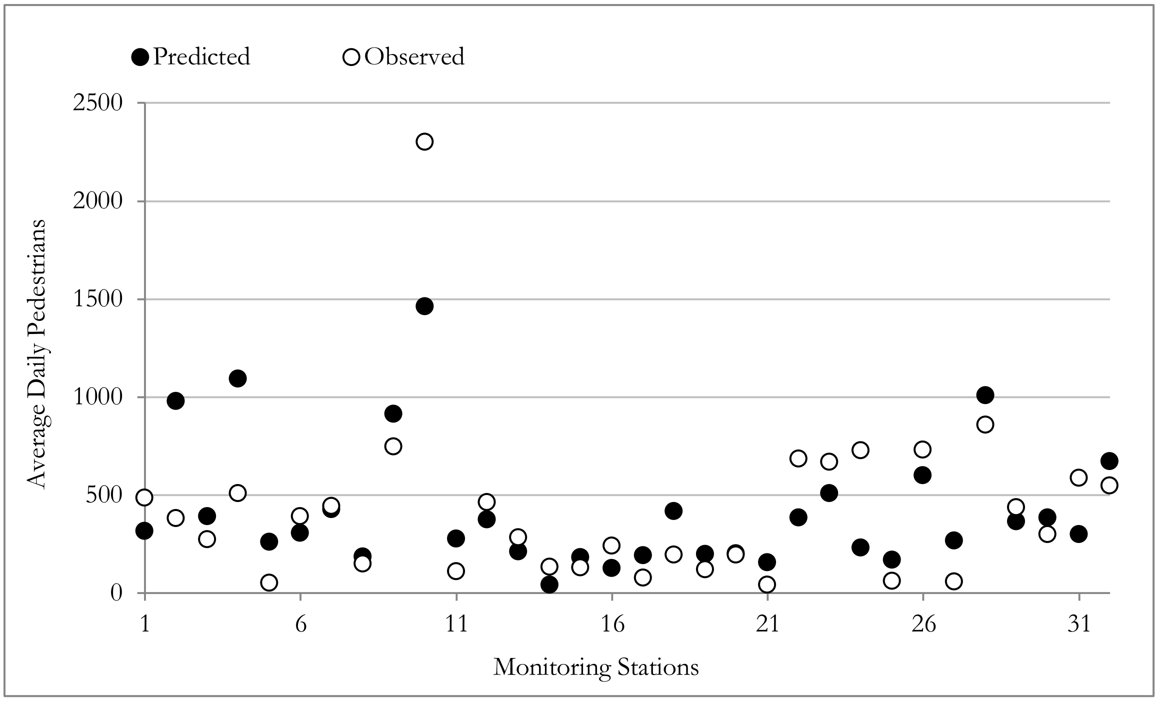
FIGURE 6.3 Comparing MRPE of mixed-mode and combined models

Comparing the two approaches, it is found that a significant positive correlation between the accuracy of both approaches over trail sites. This means that the accuracy of both approaches is relatively close. Calculating MRPE over trails further indicates there is not a significant difference between the accuracy of both approaches on average. The MRPE measurement equals 45.9% and 46.4% using the first and second approach, respectively. The result leads us to the conclusion that using multimodal devices does not improve the prediction accuracy of mixed-mode demand. Using multimodal devices, however, has certain benefits in theory and practice that should not be ignored by planners and advocated. First, different built-environment and socio-economic characteristics affect the bicyclists and pedestrian demand, which should separately be captured for relevant management. Second, the impact of built-environment and socio-economic characteristics varies between bicyclists and pedestrians demand.

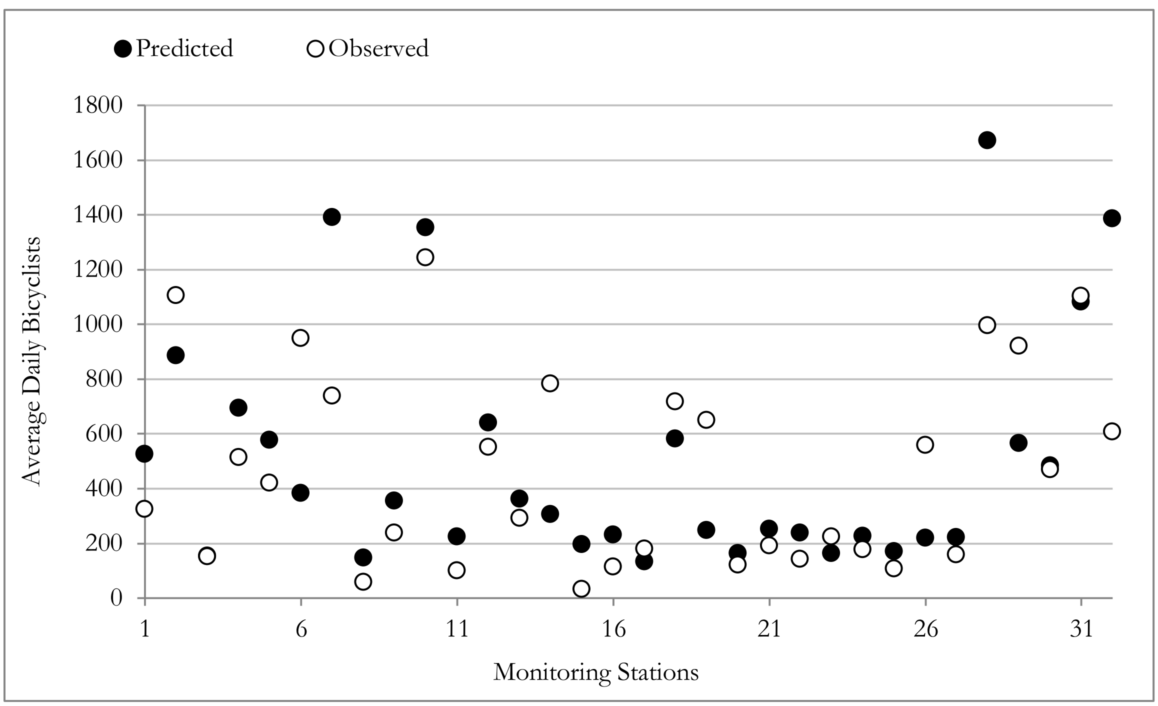
6.7 Post Validation Analyses: A Step toward Boosting the Accuracy

Although there is a well-established literature discussing cross-validation, post-analysis of modeling results has received little attention. Understanding the performance behavior of predictive models along with the factors that affect this behavior enables us to minimize the prediction error and maximize the performance of predictive models. Despite its practical function, previous research has confined analysis to developing and validating models, and, other than through ad hoc re-specification of models, has rarely attempted to boost the accuracy of the models using more systematic statistical procedures. I believe, however, that post-validation has the potential to improve the prediction accuracy of the models. This section aims to present an objective evaluation of the errors to understand how and to what extent the post-validation is able to boost the accuracy of the models.

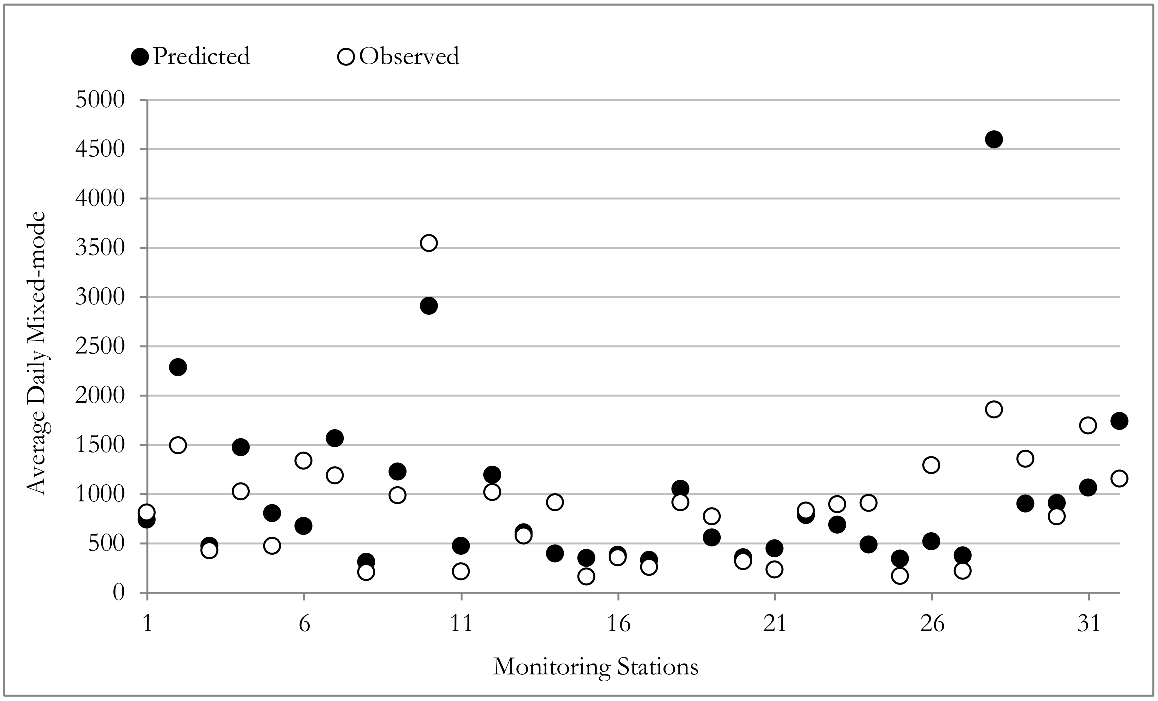
A desirable outcome in trail demand analysis is to develop a model that provides a good approximation of observed demand. When the initial model fails in this objective, a modeling process follows a specification search to identify and eliminate errors from the original specification of the hypothesized model. Figure 6.4 compares the result of cross-validation with observed trail demand over trail monitoring stations. Looking at Figure 6.4, it is understood that the bicyclist demand model overestimates the ADB in 22 stations and underestimates the ADB in the other 10 stations. The ADP, however, is overestimated in 18 stations and is underestimated in the other 14 stations. Similar behavior is observed in the estimation result of the mixed-mode model. The model overestimates and underestimates ADM in 21 and 11 trail monitoring stations, respectively. A closer look reveals the underestimations and overestimations almost occur in similar stations.



a. Bicyclists demand model



b. Pedestrian demand model



c. Mixed-mode demand model

FIGURE 6.4 Comparing observed and predicted trail traffic demand

To identify and eliminate errors to the extent possible, I employ the following error correction steps:

Step 1: The errors are regressed against variables tested in the modeling process using bivariate regression model, and the coefficients of the significant variables at the 90% confidence interval are selected as the potential correction factors.

Step 2: The correction factors derived from Step 1 are multiplied by their corresponding variables for each observation to calculate correction values as per Equation 3. In this equation, α is correction factor and X stands for the explanatory variables.

$$C = \left| \sum_{i=1}^{n} \alpha_i X_i \right| \quad (3)$$

Step 3: The estimated demand is corrected using correction value for each mode as per Equation 4. In this step, I add correction values starting with the most significant values. I keep adding until the overfitting the corrected demand, in which the error gets worse, and then stop adding correction factors and go back to the best point.

$$\widehat{d_{ic}} = \begin{cases} \widehat{d_i} + C & \widehat{d_i} < d_i \\ \widehat{d_i} - C & \widehat{d_i} > d_i \\ \widehat{d_i} & \widehat{d_i} = d_i \end{cases} \tag{4}$$

The correction factor for each demand model is summarized as follows:

ADB: $C = -0.08 \times BIKE - 90.87 \times HIGH\_EDU - 0.00025 \times ACCESS$

ADP: $C = -0.10 \times PEDESTRIAN - 144.25 \times HIGH\_EDU - 3.56 \times NETDENS$

ADM: $C = -1.03 \times PRECIP - 3.10 \times RESDEN - 4.60 \times NETDENS$

The $\widehat{d_{ic}}$ parameter is calculated for each demand model over all stations. Figure 6.5 plots the results. On average, all three demand models show a clear trend of decreasing prediction errors following the correction implementation. The MRPE for bicycle demand model decreases from 65.4% to 47.6% and for pedestrian demand model decreases from 85.3% to 57.9%. This improvement, however, is lower for the mixed-mode model. The MRPE for mixed-mode model reduces from 45.9% to 39.4%. This trajectory indicates that the proposed post-validation method has the potential to reduce the prediction error by 32.1%, and emphasizes the important role of post-validation in predicting trail traffic demand.

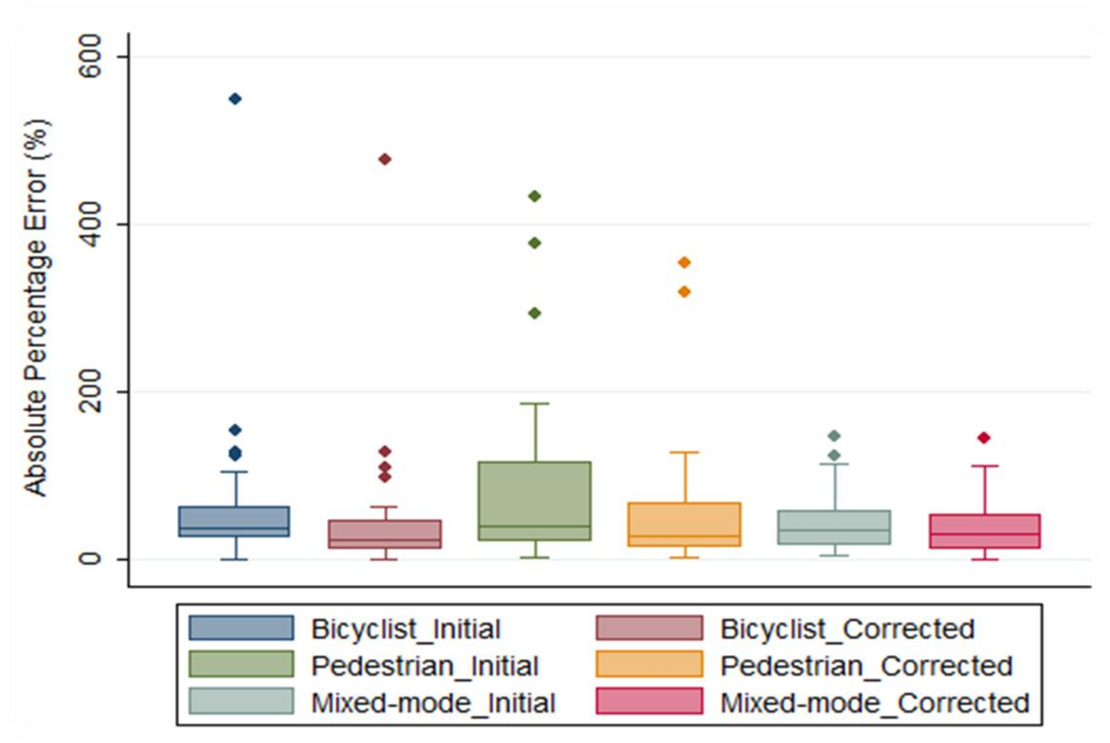


FIGURE 6.5 Box-plot for absolute percentage error

6.8 Summary

This chapter presented new trail demand models based on data from 32 locations throughout all major climatic regions in the continental U.S., which were collected between January 1, 2014 and February 16, 2016. This chapter contributed fourfold to the literature on trail traffic demand analysis. First, it developed a set of econometrics models to predict average daily pedestrians (ADP), average daily bicyclists (ADB), and average daily mixed-mode traffic (ADM) using 5 D's of the built environment, namely density, diversity, design, distance to transit, and destination accessibility, and socio-economic characteristics. Second, it tested the performance of trail demand models in predicting ADB, ADP, and ADM using the leave-one-out cross-validation technique and compared the relative accuracy of the models. Third, it assessed the performance of separate bicycle and pedestrian demand models in predicting mixed-mode travel demand. Fourth, it introduced a post-validation technique to advance the prediction accuracy of trail traffic demand models. The results indicated: (1) with only a few exceptions, ADP and ADB are correlated with different variables, and the magnitude of effects of variables that are the same varies significantly between the two modes; (2) the mean relative percentage error (MRPE) for bicyclist, pedestrian, and mixed-mode models equals 65.4%, 85.3%, and 45.9%; (3) although using multimodal monitoring networks enables us to juxtapose the bicyclist demand with pedestrian demand, there is not a significant improvement in predicting total demand using multimodal sensors; (4) a new post-validation procedure improved the demand models, reducing the MRPE of bicyclist, pedestrian, and mixed-mode models by 27.2%, 32.1%, and 14.1%. Overall, the models can be used in practical applications such as selection of route corridors and prioritization of investments where order-of-magnitude estimates suffice.

Chapter 7

Closing Remarks

The federal government, states, local governments, private philanthropic foundations, and nonprofit organizations have invested billions of dollars in multi-use trail projects. Trails attract citizens for utilitarian, recreational, and other daily travel needs, and they improve access to destinations, increase physical activity and improve health, provide enjoyment and increase well-being, and contribute to economic development. Planners and engineers need tools to ensure existing and proposed trail networks maximize these benefits. This thesis attempted to response to this need by developing tools using new, comprehensive data sets that are mode-specific and represent variation in climatic regions across the U.S. in new modeling frameworks that enable prediction of both user expenditures and demand for trail use. This chapter summarizes and highlights the main contributions of this thesis along with providing an in-depth discussion over their implementations and limitations.

7.1 A Review of Findings

Apart from the introduction, the literature review, and the description of data used for the purpose of analyses, the main body of the thesis is comprised of three distinct chapters. Despite the differences in approach, methods, and data, each chapter has similar objectives. The principal objectives and findings of each chapter are reviewed in the following items:

Chapter 4 used the results of intercept surveys to profile trail users in the Columbus, Ohio metropolitan region and to model their trail-related expenditures. Key findings include:

(1) Different people visit trails for different activities and reasons. Cycling is the predominant mode of use on these trails. Recreation and exercise or both are the primary reasons for visiting; relatively small proportions of trail use are for utilitarian purposes such as commuting or shopping. Trail users are disproportionately male.

(2) Many of the trail users use trails three or more times per week. The typical visit is between one and two hours long, and the users visit multiple trails in the network. Most of the users are middle-aged; nearly three-fourths have college or graduate degrees, and more than half report household incomes above $75,000 per year. Nearly half visit with friends, and a significant proportion visit with children, indicating trails serve social purposes and meet family needs.

(3) About one-fifth of users say they spend modest amounts of money, typically between US$15 and US$20 for refreshments and dining, on a trail visit. Across all trail users this result indicates an average expenditure by individual trail users of about US$3 per visit.

(4) Different groups of users constitute different markets that are more likely to spend, and decisions to spend are associated with different factors than decisions about amounts to spend. Pseudo-elasticities are helpful in assessing how probabilities of spending change across sub-categories of users. When the purpose of a trail visit is recreation (opposed to other purposes), the probability of making expenditure increases by 66 percent, but when the main purpose is exercise, the probability diminishes by nearly 18%. Trail users who walk to trails are 80% less likely to spend than those who reach trails by other modes. Similarly, trail users who travel less than one hour to visit a trail are 42% less likely to spend. Cyclists who visit trails for recreation and spend longer periods traveling both to and on the trails are more likely to spend than other types of users who visit for different purposes. People in groups are more likely to spend, but the amount spent does

not increase significantly with group size. Trail users who visited the trail in afternoon are more likely to spend on the trail while morning users spend significantly less money. Trail users who visited the trail in evening on weekends are less likely to spend on trail.

Chapter 5 obtained separate daily bicycle and pedestrian counts from 32 automated monitors on urban multiuse trails in 13 cities, including at least one monitoring station in each of seven US DOE regional climate zones. Average daily bicycle and pedestrian traffic both vary over three orders of magnitude across monitoring locations.

Negative binomial regression models were used to estimate the effects of weather on daily bicycle and pedestrian trail traffic. I explicitly modeled the complex relationship between the weather factors and both bicyclists' and pedestrians' demand by testing the parabola form of weather factors. I introduced the concept of demand returns and calculated the vertex point of parabola functions. The results showed that the weather effects can exhibit constant, increasing, or decreasing returns. To quantify the magnitude of these effects, elasticities and marginal effects were calculated for continuous and dummy variables. The weather variables in the models included average temperature, precipitation, snow, dew point, and average wind speed. I controlled for seasons, weekends, and holidays. The results both confirmed and extended findings reported previously in the literature.

It was shown that the effects of temperature, precipitation, snow, dew point, and wind speed generally are consistent and significant in the expected direction for both bicycle and pedestrian demand, but that the magnitude of the effect varies. In addition, on some trails in some zones, the variables have no significant effects. It was further shown that that vertex points exist for temperature and precipitation at which point demand moves from increasing to decreasing returns, or vice-versa. These effects, and the specific values at which vertex points occur, also vary by region. Relatively few variables have constant returns. The estimates of the elasticity of demand in response to specific variables vary by mode and region. To summarize:

(1) Bicyclists and pedestrians in the same climate region respond differently to variations in weather.
(2) Bicyclists in different climate regions respond differently to variations in weather.
(3) Pedestrians in different climate regions respond differently to variations in weather.

Several factors may explain these variations, each of which warrants additional research. First, it is likely that trail users in particular regions have acclimatized to regional climates. This factor, which could be explored with survey research, would help to account for differences in response to specific weather variables across regions. Second, it also is likely that these differences are associated with variations in the proportions of trips made for different purposes across the trails. Urban trails like those included in this study are used for utilitarian purposes such as commuting as well as recreation and fitness or health. Some research has shown that bicycle commuters are less affected by weather than are recreational cyclists and that pedestrians generally are less affected by weather than are cyclists. Trip purposes cannot be determined directly from counts, so this factor cannot be assessed directly, but it also would be explored with survey research. Third, some of the observed differences may be associated with the available of alternative or substitute opportunities. This factor would require field investigation and survey research to explore.

Chapter 6 sought to answer four questions relevant to modeling trail traffic demand as follows:

(1) How much do built-environment and socio-economic characteristics describe bicyclist and pedestrian trail traffic demand? Most of the variation observed in average daily trail traffic can be explained by differences in contiguous geo-spatial characteristics. The national T-MAP dataset, UESPA's Smart-Growth dataset, and regression modeling were used to measure the effects of the built-environment and neighborhood socioeconomic characteristics on trail ADP, ADB, and ADM separately. McFadden's Pseudo R^2 values for the models were 0.63,

0.61, and 0.72, respectively, indicating very good fit for the models. The magnitude of effects was compared within and between the trail traffic demand models. Although some built environment variables influence both bicycle and pedestrian trail traffic, ADP and ADB generally are described by different sets of variables. For those variables that are significant in both ADP and ADB models, the magnitude of their effects differs. These results underscored the importance of developing separate models to realistically capture the behavior of bicyclists and pedestrians.

(2) How accurately can trail traffic models predict demand? The developed models predicted traffic accurately enough for general planning purposes but not for purposes of design and other site-specific engineering applications. The prediction accuracy of the models was tested using the leave-one-out cross-validation technique. The MRPE for bicyclist, pedestrian, and mixed-mode models were 65.4%, 85.4%, and 45.9%, respectively, for the system, overall. This level of accuracy is acceptable for applications such as comparisons of alternative corridors for trail development where order of magnitude estimates are sufficient. On the other hand, the accuracy is not sufficient for site-specific engineering and other applications that require precise measures. For example, a common concern of local engineers involves safety at uncontrolled mid-block trail crossings. The estimates of ADB or ADP produced by these models are not accurate enough for application of warrants for traffic signals or pedestrian hybrid beacons.

(3) Can using multimodal devices predict total (i.e., mixed-mode) travel demand more accurately? The analyses showed that the accuracy of estimates of total demand obtained by summing estimates of bicycle and pedestrian traffic from mode-specific models is not significantly different than estimates of total demand from the model based on mixed-mode counts. The practical implication of this finding is that if total demand is the primary statistic of interest, and there is no immediate need for mode-specific estimates of demand, then use of less costly

infrared monitors to build data sets may be warranted. For example, state departments of transportation and recreation often collaborate in funding, development, and management of state-wide multiuse trail networks. Estimates of total demand derived from models built from undifferentiated mixed-mode trail counts may be sufficient for prioritizing investments in new trail segments or various maintenance activities such as repaving. Conversely, engineers responsible for developing new facilities in densely populated metropolitan regions may need separate estimates of bicycle and pedestrian traffic to better integrate trails into existing transportation and park networks.

(4) How and to what extent are trail traffic models improved by using post-validation techniques? The results indicated that we can reduce error in prediction by up to 27% through use of new post-validation procedures. These procedures derive from the observation that error is not uniformly distributed across sites and is strongly correlated with particular explanatory variables in the demand models. By capturing these relationships, it was demonstrated that the potential to improving the prediction accuracy of demand models. The proposed post-validation procedure improved the accuracy of the models and reduced MRPE of bicyclist, pedestrian, and mixed-mode models by 27.2%, 32.1%, and 14.1%.

7.2 Implementations and limitations

These results of Chapter 4 have more implications for planning and managing trails than for decisions to invest in trails because they do not answer fundamental questions about whether the benefits of trails outweigh their costs. The results are useful, however, in helping policy-makers and planners understand which local users are likely to spend and, if they do spend, the factors that affect spending. Decision-makers can use this information for purposes of market segmentation and to target efforts to meet their needs and to enhance their trail experiences. For example, these results indicate that owners of firms adjacent to or near trails might profit more by marketing to cyclists who live further from the trails than to walkers who live in the immediate neighborhoods near trails.

Marketing trails as a family-oriented, fun activity also may be warranted. In the long term, maximizing the efficiency of allocation of resources for trail development and management depends on understanding and addressing the needs and preferences of different users.

The results of Chapter 5 and Chapter 6 have practical implications for trail management and monitoring. Most importantly, they underscore the fact that demand and user patterns vary across the U.S. and that these factors need to be considered when analyzing use. Understanding of traffic magnitudes and seasonal and weekend-weekday differences in traffic can inform decisions about investment, marketing, maintenance, and traffic patrols. For example, these results indicate generally trail use is higher on weekends than weekdays. If a management objective is to minimize disruptions of use, trail maintenance and other activities that potentially affect use should be scheduled on weekdays. More generally, data about trail use collected with technologies analogous to those used for motorized traffic on road and street networks can inform transportation planning and ensure that the evidence base for all transportation modes is similar. For example, traffic control warrants pedestrian crossings typically require three inputs: vehicular volumes, non-motorized traffic volumes, and crossing width. These warrants historically have been evaluated using weekday peak hour traffic when vehicular volumes are highest. These data suggest that, to account for the highest non-motorized trail traffic volumes, evaluation should also include weekend traffic. A very practical use of these models is to use them (or models like them) for estimating traffic volumes for individual trails on days when counts are not available.

The results also have implications for trail monitoring and reflect both its potential and the challenges inherent in establishing comprehensive monitoring networks. With the increased availability of comparatively low-cost automated monitoring devices, many new initiatives to monitor bicycle and pedestrian traffic have been launched. As illustrated here, these initiatives can generate information about both traffic volumes and, with additional analyses, the effects of weather and other variables on patterns of use. Yet these newer devices are not without limitations. The original data collection network included 50 locations. Eighteen stations are excluded, or 36% of the locations, after conducting manual counts to validate the automated observations. Data quality problems at a particular monitoring station can have a variety of explanations, including improper or inconsistent installation (especially of the inductive loop); natural interference, such as insects or weather damage (with the infrared sensor and wiring); false readings, in which the counter is triggered by something other than a trail user, such as animals or cars/trains on an adjacent right of way; or equipment malfunction. The experience demonstrates the paramount importance of manual validation of any automated data collected in varied field settings.

Overall, the results provide substantial support for recommendations in the Federal Highway Administration's *Traffic Monitoring Guide* that call for year-round continuous, automated counters to be used in conjunction with portable counters that can monitor traffic for at least seven days. The variations in seasonality and weekend-weekday use across regions underscores the need for local, automated continuous counters that can serve as reference sites for short-duration samples. For example, the data show that seasonal use patterns in Duluth and Minneapolis, Minnesota, which are only about 135 miles apart, are very different. This result confirms that seasonal factors should not be transferred across regions. Because day-of-week patterns vary markedly across sites, and, in contrast to vehicular traffic, trail use often is higher on weekends, short duration traffic samples should be a minimum of seven days, which implies installation of equipment for nine days. As noted, research to determine the geographic range over which the effects of weather are relatively consistent is a high priority. To state this conclusion in other way, it is advisable for practitioners to develop comparable models based on data in their immediate geographic location. In the absence of local data, using models from comparable climates is a second-best alternative that at least recognizes patterns of use vary.

A limitation of the study is that the information of only one or two monitoring stations in some regions was available and within-region variation of the effects of weather have not evaluated on trail use. The findings make it clear, for example, that seasonal use of trails varies across regions and that trail users in different regions respond differently to variations in weather. This is evidence that practitioners should not transfer elasticities across regions. Many researchers and practitioners will want do know, however, the extent to which elasticities measured in a specific location can be transferred elsewhere within a region. Additional research is needed to answer this question and to characterize within-region variation.

Another area of research concerns the question of how to best capture the non-linear effects of weather variables on trail use by bicyclists and pedestrians. The quadratic form was used, found it worked well for temperature, but also noted the interpretation with respect to precipitation seemed counterintuitive over sections of the parabolic form. Other approaches warrant investigation. Additional investigation of the interaction effects among season and the squared weather teams also could be fruitful.

An elusive objective of researchers, federal, state and local agencies, and nonprofit organizations has been the development of demand models that produce valid, reliable measures of bicycle and pedestrian traffic and can be applied generally in multiple locations. In its Non-motorized Travel Analysis Toolkit, the FHWA has illustrated how models can be calibrated for application in different jurisdictions, but attempts to apply models that have been published (e.g., like those in Prince George's County) remain relatively rare. Agencies and foundations that fund trail construction increasingly are seeking measures of demand to assess competing applications. RTC is using demand models like these to assist its partners across the U.S. in planning and development of new trails. Continued efforts to refine these models through integration of other datasets will strengthen future efforts. Similarly, studies of efforts to apply and validate direct demand models are warranted.

References

Bachand-Marleau, J., Lee, B., & El-Geneidy, A. (2012). Better understanding of factors influencing likelihood of using shared bicycle systems and frequency of use. Transportation Research Record: Journal of the Transportation Research Board, (2314), 66-71.

Baechler, M. C., Williamson, J., Gilbride, T., Cole, P., Hefty, M., & Love, P. M. (2010). Guide to Determining Climate Regions by County (No. PNNL-17211). Richland, WA: Pacific Northwest National Laboratory.

Bergström, A., & Magnusson, R. (2003). Potential of transferring car trips to bicycle during winter. Transportation Research Part A: Policy and Practice, 37(8), 649-666.

Brandenburg, C., Matzarakis, A., & Arnberger, A. (2007). Weather and cycling—a first approach to the effects of weather conditions on cycling. Meteorological applications, 14(1), 61-67.

Brownson, R. C., Housemann, R. A., Brown, D. R., Jackson-Thompson, J., King, A. C., Malone, B. R., & Sallis, J. F. (2000). Promoting physical activity in rural communities: walking trail access, use, and effects. American journal of preventive medicine, 18(3), 235-241.

Buck, D., & Buehler, R. (2012). Bike lanes and other determinants of capital bikeshare trips. In 91st Transportation research board annual meeting.

Burchfield, R. A., Fitzhugh, E. C., & Bassett, D. R. (2012). The association of trail use with weather-related factors on an urban greenway. Journal of Physical Activity and Health, 9(2), 188-197.

Corcoran, J., Li, T., Rohde, D., Charles-Edwards, E., & Mateo-Babiano, D. (2014). Spatio-temporal patterns of a Public Bicycle Sharing Program: the effect of weather and calendar events. Journal of Transport Geography, 41, 292-305.

Coutts, C. (2008). Greenway accessibility and physical-activity behavior. Environment and Planning B: Planning and Design, 35(3), 552-563.

Coutts, C. & Miles, R. (2011). Greenways as green magnets: The relationship between the race of greenway users and race in proximal neighborhoods. Journal of Leisure Research, 43(3), 317-333.

Dow, W. H., & Norton, E. C. (2003). Choosing between and interpreting the Heckit and two-part models for corner solutions. Health Services and Outcomes Research Methodology, 4(1), 5-18.

Downward, P., Lumsdon, L., & Weston, R. (2009). Visitor expenditure: the case of cycle recreation and tourism. Journal of Sport & Tourism, 14(1), 25-42.

Fabos, J. G. (1995). Introduction and overview: the greenway movement, uses and potentials of greenways.

Fabos, J. G. (2004). Greenway planning in the United States: its origins and recent case studies. Landscape and urban planning, 68(2), 321-342.

Farber, S., Argueta, J., & Hughes, S. (2003). 2002 User survey for the Pennsylvania Allegheny trail alliance. University of Pittsburgh, University Center for Social and Urban Rese.

Federal Highway Administration (2017). Nonmotorized Travel Analysis Toolkit. Hosted by the Pedestrian and Bicycle Information Center; http://nmtk.pedbikeinfo.org/ui/#/; accessed 8/11/2017).

Fernández-Heredia, Á., Monzón, A., & Jara-Díaz, S. (2014). Understanding cyclists' perceptions, keys for a successful bicycle promotion. Transportation research part A: policy and practice, 63, 1-11.

Flynn, B. S., Dana, G. S., Sears, J., & Aultman-Hall, L. (2012). Weather factor impacts on commuting to work by bicycle. Preventive medicine, 54(2), 122-124.

Frechtling, D. C. (2006). An assessment of visitor expenditure methods and models. Journal of Travel Research, 45(1), 26-35.

Fushiki, T. (2011). Estimation of prediction error by using K-fold cross-validation. Statistics and Computing, 21(2), 137-146.

Global Historical Climatology Network (2015), NOAA. https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/global-historical-climatology-network-ghcn; accessed 8/29/2017.

Gobster, P. H. (1995). Perception and use of a metropolitan greenway system for recreation. Landscape and Urban Planning, 33(1-3), 401-413.

Gobster, P. H. (2005). Recreation and leisure research from an active living perspective: taking a second look at urban trail use data. Leisure Sciences, 27(5), 367-383.

Gobster, P. H., Sachdeva, S., & Lindsey, G. (2017). Up on The 606: Understanding the Use of a New Elevated Pedestrian and Bicycle Trail in Chicago, Illinois. Transportation Research Record: Journal of the Transportation Research Board, (2644), 83-91.

Gujarati, D. N. (2012). Basic econometrics. Tata McGraw-Hill Education.

Habib, K. N., Mann, J., Mahmoud, M., & Weiss, A. (2014). Synopsis of bicycle demand in the City of Toronto: Investigating the effects of perception, consciousness and comfortability on the purpose of biking and bike ownership. Transportation research part A: policy and practice, 70, 67-80.

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

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

Haynes, M., & Andrzejewski, S. (2010). GIS based bicycle & pedestrian demand forecasting techniques. TMIP Webinar.

Helbich, M., Böcker, L., & Dijst, M. (2014). Geographic heterogeneity in cycling under various weather conditions: Evidence from Greater Rotterdam. Journal of Transport Geography, 38, 38-47.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). Applied choice analysis: a primer. Cambridge University Press.

Jones, M. G., Ryan, S., Donlon, J., Ledbetter, L., Ragland, D. R., & Arnold, L. (2010). Measuring Bicycle and Pedestrian Activity in San Diego County and its Relationship to Land Use, Transportation, Safety, and Facility Type. Berkeley: Institute of Transportation Studies-UC Berkeley Traffic Safety Center.

Kraemer, J. D., Zaccaro, H. N., Roffenbender, J. S., Baig, S. A., Graves, M. E., Hauler, K. J., ... & Mulroy, F. E. (2015). Assessing the potential for bias in direct observation of adult commuter cycling and helmet use. Injury prevention, 21(1), 42-46.

Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. In Ijcai (Vol. 14, No. 2, pp. 1137-1145).

Kuzmyak, J. R., Walters, J., Bradley, M., & Kockelman, K. M. (2014). Estimating bicycling and walking for planning and project development: A guidebook (No. Project 08-78).

Lachenbruch, P. A. (1976). Analysis of data with clumping at zero. Biometrische Zeitschrift, 18(5), 351-356.

Lindsey, G. (1999). Use of urban greenways: insights from Indianapolis. Landscape and urban planning, 45(2), 145-157.

Lindsey, G., Han, Y., Wilson, J., & Yang, J. (2006). Neighborhood correlates of urban trail traffic. Journal of Physical Activity and Health, 3(S1), S134-S152.

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

Lindsey, G., Wilson, J., Anne Yang, J., & Alexa, C. (2008). Urban greenways, trail characteristics and trail use: implications for design. Journal of Urban Design, 13(1), 53-79.

Liu, C., Susilo, Y. O., & Karlström, A. (2015). The influence of weather characteristics variability on individual’s travel mode choice in different seasons and regions in Sweden. Transport Policy, 41, 147-158.

Liu, C., Susilo, Y. O., & Karlström, A. (2014). Examining the impact of weather variability on non-commuters’ daily activity–travel patterns in different regions of Sweden. Journal of Transport Geography, 39, 36-48.

Liu, X., & Griswold, J. (2009). Pedestrian volume modeling: a case study of San Francisco. Yearbook of the Association of Pacific Coast Geographers, 71(1), 164-181.

Lumsdon, L., Downward, P., & Cope, A. (2004). Monitoring of cycle tourism on long distance trails: the North Sea Cycle Route. Journal of Transport Geography, 12(1), 13-22.

Maine DOT. (2001). Bicycle tourism in Maine economic impacts and marketing recommendations.

MNCPPC (2016). Maryland-National Capital Park and Planning Commission. Trails Master Plan for Prince George’s County - DRAFT. Department of Parks and Recreation, Prince George’s County, Maryland. http://history.pgparks.com/Page63338.aspx; accessed 8/11/2017.

Maslow, A. L., Reed, J. A., Price, A. E., & Hooker, S. P. (2012). Associations between sociodemographic characteristics and perceptions of the built environment with the frequency, type, and duration of physical activity among trail users. Preventing chronic disease, 9(1), 1-10.

McCullagh, P., & Nelder, J. A. (1989). Generalized Linear Models, no. 37 in Monograph on Statistics and Applied Probability.

Miranda-Moreno, L., & Nosal, T. (2011). Weather or not to cycle: Temporal trends and impact of weather on cycling in an urban environment. Transportation Research Record: Journal of the Transportation Research Board, (2247), 42-52.

Miranda-Moreno, L., Nosal, T., Schneider, R., & Proulx, F. (2013). Classification of bicycle traffic patterns in five North American Cities. Transportation Research Record: Journal of the Transportation Research Board, (2339), 68-79.

Miranda-Moreno, L., & Fernandes, D. (2011). Modeling of pedestrian activity at signalized intersections: land use, urban form, weather, and spatiotemporal patterns. Transportation Research Record: Journal of the Transportation Research Board, (2264), 74-82.

Moore, R. L. (1992). The impacts of rail-trails: A study of the users and property owners from three trails. United States Govt Printing Office.

Motoaki, Y., & Daziano, R. A. (2015). A hybrid-choice latent-class model for the analysis of the effects of weather on cycling demand. Transportation Research Part A: Policy and Practice, 75, 217-230.

Mundet, L., & Coenders, G. (2010). Greenways: a sustainable leisure experience concept for both communities and tourists. Journal of Sustainable Tourism, 18(5), 657-674.

National Oceanic and Atmospheric Administration (NOAA), National Centers for Environmental Information (2015). “U.S. Climate Regions.” http://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php; accessed 7/29/2015.

Nankervis, M. (1999). The effect of weather and climate on bicycle commuting. Transportation Research Part A: Policy and Practice, 33(6), 417-431.

Nelder, J. A., & Baker, R. J. (1972). Generalized linear models. Encyclopedia of Statistical Sciences.

Nosal, T., & Miranda-Moreno, L. F. (2014). The effect of weather on the use of North American bicycle facilities: a multi-city analysis using automatic counts. Transportation research part A: policy and practice, 66, 213-225.

Pan, Y, & Jackson, R. T. (2008). Ethnic difference in the relationship between acute inflammation and serum ferritin in US adult males. Epidemiology and Infection, 136(3), 421-431.

Pettebone, D., Newman, P., & Lawson, S. R. (2010). Estimating visitor use at attraction sites and trailheads in Yosemite National Park using automated visitor counters. Landscape and Urban Planning, 97(4), 229-238.

Quality Controlled Local Climatological Data, NOAA (2015): http://www.ncdc.noaa.gov/qclcd/qclcddocumentation.pdf and https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/quality-controlled-local-climatological-data-qclcd; accessed 7/30/2015.

Rails to Trails Conservancy (2016), www.traillink.com, Accessed on 4 October 2016.

Ramsey, K., & Bell, A. (2014). The Smart Location Database: A Nationwide Data Resource Characterizing the Built Environment and Destination Accessibility at the Neighborhood Scale. Cityscape, 16(2), 145.

Rogerson, P. A. (2010). Statistical methods for geography: a student's guide. Sage Publications.
Ryan, R. L., Fábos, J. G., & Allan, J. J. (2006). Understanding opportunities and challenges for collaborative greenway planning in New England. Landscape and Urban Planning, 76(1), 172-191.
Ryus, P., Ferguson, E., Laustsen, K. M., Schneider, R. J., Proulx, F. R., Hull, T., & Miranda-Moreno, L. (2014). Guidebook on pedestrian and bicycle volume data collection (No. qt11q5p33w). Institute of Transportation Studies, UC Berkeley.
Saneinejad, S., Roorda, M. J., & Kennedy, C. (2012). Modelling the impact of weather conditions on active transportation travel behaviour. Transportation research part D: transport and environment, 17(2), 129-137.
Schneider, R., Arnold, L., & Ragland, D. (2009). Pilot model for estimating pedestrian intersection crossing volumes. Transportation Research Record: Journal of the Transportation Research Board, (2140), 13-26.
Schneider, R. J., Henry, T., Mitman, M. F., Stonehill, L., & Koehler, J. (2013). Development and application of the San Francisco pedestrian intersection volume model.
Searns, R. M. (1995). The evolution of greenways as an adaptive urban landscape form. Landscape and urban planning, 33(1-3), 65-80.
Shafer, C. S., Lee, B. K., & Turner, S. (2000). A tale of three greenway trails: user perceptions related to quality of life. Landscape and Urban Planning, 49(3), 163-178.
Spencer, P., Watts, R., Vivanco, L., & Flynn, B. (2013). The effect of environmental factors on bicycle commuters in Vermont: influences of a northern climate. Journal of Transport Geography, 31, 11-17.
Thomas, T., Jaarsma, R., & Tutert, B. (2013). Exploring temporal fluctuations of daily cycling demand on Dutch cycle paths: the influence of weather on cycling. Transportation, 40(1), 1-22.
Tin, S. T., Woodward, A., Robinson, E., & Ameratunga, S. (2012). Temporal, seasonal and weather effects on cycle volume: an ecological study. Environmental Health, 11(1), 12.
Toma, M. J., Hoag, J., & Griffin, R. (2003). Coastal Georgia Greenway Market Study and Projected Economic Impact.
Troped, P. J., Saunders, R. P., & Pate, R. R. (2005). Comparisons Between Rail-Trail Users and Nonusers and Men and Women's Patterns of Use in a Suburban Community. Journal of Physical Activity and Health, 2(2), 169-180.
Wang, G., Macera, C. A., Scudder-Soucie, B., Schmid, T., Pratt, M., & Buchner, D. (2005). A cost-benefit analysis of physical activity using bike/pedestrian trails. Health promotion practice, 6(2), 174-179.
Wang, X., Lindsey, G., Hankey, S., & Hoff, K. (2013). Estimating mixed-mode urban trail traffic using negative binomial regression models. Journal of Urban Planning and Development, 140(1), 04013006.
Wolff, D., & Fitzhugh, E. C. (2011). The relationships between weather-related factors and daily outdoor physical activity counts on an urban greenway. International journal of environmental research and public health, 8(2), 579-589.

Wang, J., Hankey, S., Wu, X., & Lindsey, G. (2016). Monitoring and Modeling of Urban Trail Traffic: Validation of Direct Demand Models in Minneapolis, Minnesota, and Columbus, Ohio. Transportation Research Record: Journal of the Transportation Research Board, (2593), 47-59.

Wang, X., Lindsey, G., Schoner, J. E., & Harrison, A. (2015). Modeling bike share station activity: Effects of nearby businesses and jobs on trips to and from stations. Journal of Urban Planning and Development, 142(1), 04015001.

Weiler, H. (1964). A Significance Test for Simultaneous Quanta and Quantitative Responses. Technometrics, 6(3), 273-285.