Bicycle and Pedestrian Traffic Monitoring and AADT Estimation in a Small Rural College Town

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ABSTRACT

Non-motorized (i.e., bicycle and pedestrian) traffic patterns are an understudied but important part of transportation systems. A key need for transportation planners is traffic monitoring programs similar to motorized traffic. Count campaigns can help estimate mode choice, measure infrastructure performance, track changes in volume, prioritize projects, analyze travel patterns (e.g., annual average daily traffic [AADT] and miles traveled [MT]), and conduct safety analysis (e.g., crash, injury and collision). However, unlike for motorized traffic, non-motorized traffic has not been comprehensively monitored in communities throughout the U.S. and is generally performed in an ad hoc fashion. My thesis explores how to (1) best count bicycles and pedestrians on the entire transportation network, rather than only focus on off-street trail systems or specific transportation corridors and (2) estimate AADT of bicycles and pedestrians in a small college town (i.e., Blacksburg, VA).

I used a previously developed count campaign in Blacksburg, VA to collect bicycle and pedestrian counts using existing monitoring technologies (e.g., pneumatic tubes, passive infrared, and RadioBeam). I then summarized those counts to (1) identify seasonal, daily, and hourly patterns of non-motorized traffic and (2) develop scaling factors (analogous to those used in motor vehicle count programs) derived from the continuous reference sites to estimate long-term averages (i.e., AADT) for short-duration count sites.

I collected ~40,000 hours of bicycle and pedestrian counts from early September 2014 to January 2016. The count campaign included 4 continuous reference sites (~ full year-2015 counts) and 97 short-duration sites (≥ 1-week counts) that covered different road and trail types (i.e., major road, local road, and off-street trails). I used 25 commercially available counters (i.e., 12 MetroCount MC 5600 Vehicle Classifier System [pneumatic tube counters], 10 Eco-counter "Pyro" [passive infrared counters], and 3 Chambers RadioBeam Bicycle-People Counter [radiobeam counters]) to conduct the traffic count campaign. Three MetroCount, 4 Eco-counter, and 1 RadioBeam counter were installed at the 4 continuous reference sites; the remaining counters were rotated on a weekly basis at the short-duration count sites.

I validated automated counts with field-based manual counts for all counters (210 total hours of validation counts). The validation counts were used to adjust automated counts due to systematic counter errors (e.g., occlusion) by developing correction equations for each type of counter. All automated counters were well correlated with the manual counts (MetroCount R^2 [absolute error]: 0.90 [38%]; Eco-counter: 0.97 [24%]; RadioBeam bicycle: 0.92 [19%], RadioBeam pedestrian: 0.92 [22%]). I compared three bicycle-based classification schemes provided by MetroCount (i.e., ARX Cycle, BOCO and Bicycle 15). Based on the validation counts the BOCO (Boulder County, CO) classification scheme (hourly counts) had similar R^2 using a polynomial correction equation (0.898) as compared to ARX Cycle (0.895) and Bicycle 15 (0.897). Using a linear fit, the slope was smallest for BOCO (1.26) as compared to ARX Cycle (1.29) and Bicycle 15 (1.31). Therefore, I used the BOCO classification scheme to adjust the automated hourly bicycle counts from MetroCount.

To ensure a valid count dataset was used for further analysis, I conducted quality assurance and quality control (QA/QC) protocols to the raw dataset. Overall, the continuous reference sites demonstrated good temporal coverage during the period the counters were deployed (bicycles: 96%; pedestrians: 87%) and for the calendar year-2015 (bicycles: 75%; pedestrians: 87%). For short-duration sites, 98% and 94% of sites had at least 7 days of monitoring for bicycles and pedestrians, respectively; no sites experienced 5 days or less of counts.

I analyzed the traffic patterns and estimated AADT for all monitoring sites. I calculated average daily traffic, mode share, weekend to weekday ratio and hourly traffic curves to assess monthly, daily, and hourly patterns of bicycle and pedestrian traffic at the continuous reference sites. I then classified short-duration count sites into factor groups (i.e., commute [28%], recreation [11%], and mixed [61%]). These factor groups are normally used for corresponding continuous reference sites with the same patterns to apply scaling factors. However, due to limitations of the number (n=4) of continuous reference sites, the factor groups were only used as supplemental information in this analysis.

To impute missing days at the 4 continuous reference sites to build a full year-2015 (i.e., 365 days) dataset, I built 8 site-specific negative binomial regression models (4 for bicycles and 4 for pedestrians) using temporal and weather variables (i.e., daily max temperature, daily temperature variation compared to the normal 30-year averages [1980-2010], precipitation, wind speed, weekend, and university in session). In general, the goodness-of-fit for the models was better for the bicycle traffic models (validation R^2 = ~0.70) as compared to the pedestrian traffic models (validation R^2 = ~0.30). The selected variables were correlated with bicycle and pedestrian traffic and cyclists are more sensitive to weather conditions than pedestrians. Adding model-generated estimates of missing days into the existing observed reference site counts allowed for calculating AADT for each continuous reference site (bicycles volumes ranged from 21 to 179; pedestrian volumes ranged from 98 to 4,232).

Since a full year-2015 dataset was not available at the short-duration sites, I developed day-of-year scaling factors from the 4 continuous reference sites to apply to the short-duration counts. The scaling factors were used to estimate site-specific AADT for each day of the short-duration count sites (~7 days of counts per location). I explored the spatial relationships among bicycle and pedestrian AADT, road and trail types, and bike facility (i.e., bike lane). The results indicated that bicycle AADT is significantly higher ($p < 0.01$) on roads with a bike lane (mean: 72) as compared to roads without (mean: 30); bicycle AADT is significantly higher ($p < 0.01$) on off-street trails (mean: 72) as compared to major roads (mean: 33). Pedestrian AADT is significantly higher ($p < 0.01$) on local roads (mean: 693) as compared to off-street trails (mean: 111); this finding is likely owing to the fact that most roads on the Virginia Tech campus are classified as local roads.

In Chapter 5, I conclude with (1) recommendations for implementation (e.g., counter installation and data analysis), (2) key findings of bicycle and pedestrian traffic analysis in Blacksburg and (3) strengths, limitations, and directions for future research. This research has the potential to influence urban planning; for example, offering guidance on developing routine non-motorized traffic monitoring, estimating bicycle and pedestrian AADT, prioritizing projects and measuring performance. However, this work could be expanded in several ways; for example, deploying more continuous reference sites, exploring ways to monitor or estimate pedestrians where no sidewalks exist and incorporating other spatial variables (e.g., land use variables) to study pedestrian volumes in future research.

The overarching goal of my research is to yield guidance for jurisdictions that seek to implement systematic bicycle and pedestrian monitoring campaigns and to help decision making to encourage healthy, safe, and harmonious communities.

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1 INTRODUCTION

1.1 Motivation for counting non-motorized traffic

Non-motorized traffic generally includes cyclists, pedestrians and other non-motorized road and trail users (e.g., skateboard, inline skateboard, and wheelchair). To understand the entire transportation network within a given area, it is necessary to perform both motorized and non-motorized traffic monitoring. However, unlike for motorized traffic, non-motorized traffic has not been comprehensively monitored in communities throughout the U.S. and is generally performed in an ad hoc fashion (FHWA, 2013).

Distinctions between patterns of non-motorized traffic and motorized traffic are obvious. According to the *Traffic Monitoring Guide* (FHWA, 2013) and *NCHRP REPORT 797 Guidebook on Pedestrian and Bicycle Volume Data Collection* (Ryus et al., 2014), there are some major differences: (1) non-motorized traffic varies more than motorized traffic by time of day and season of year, and is more sensitive to changes in weather (Ryus et al., 2014), (2) non-motorized trips are comparatively shorter and more associated with adjacent land uses (Ryus et al., 2014), (3) non-motorized traffic is more difficult to detect and monitor with existing technologies (i.e., error rates are often unknown; FHWA, 2013).

To induce more non-motorized monitoring, federal, state and local governments have stressed the need to conduct bicycle and pedestrian data collection campaigns and have promoted non-motorized travel by targeted funding and pilot demonstration projects. The FHWA recommended in a policy statement in 2010 that "Collecting data on walking and biking trips: the best way to improve transportation networks for any mode is to collect and analyze trip data to optimize investments."

A total of $7.2 billion for 22,000 dedicated bicycle and pedestrian projects has been funded by the federal government since 1992 (Advocacy Advance, 2012). To promote the integration of multimodal facilities, policy initiatives like Complete Streets (National Complete Streets Coalition, 2015) need data and models covering all modes of transportation.

1.2 Research goals and objectives

To address the research gap of systematic non-motorized traffic (i.e., bicycle and pedestrian) data collection and analysis, this research uses a bicycle and pedestrian count campaign for a small college town (Blacksburg, VA) to estimate spatial and temporal patterns of non-motorized traffic. A key goal is to identify best practices for counting bicycles and pedestrians on an entire transportation network, rather than only focus on off-street trail systems or specific transportation corridors (Hankey, Lindsey, & Marshall, 2014; Nordback et al., 2013; Nosal & Miranda-Moreno, 2014). This research summarizes the count dataset to identify seasonal, daily, and hourly patterns of non-motorized traffic. The aim is to develop scaling factors (analogous to those used in motor vehicle count programs) derived from continuous reference sites to estimate long-term averages (i.e., Annual Average Daily Traffic [AADT]) for short-duration count sites; Figure 1).

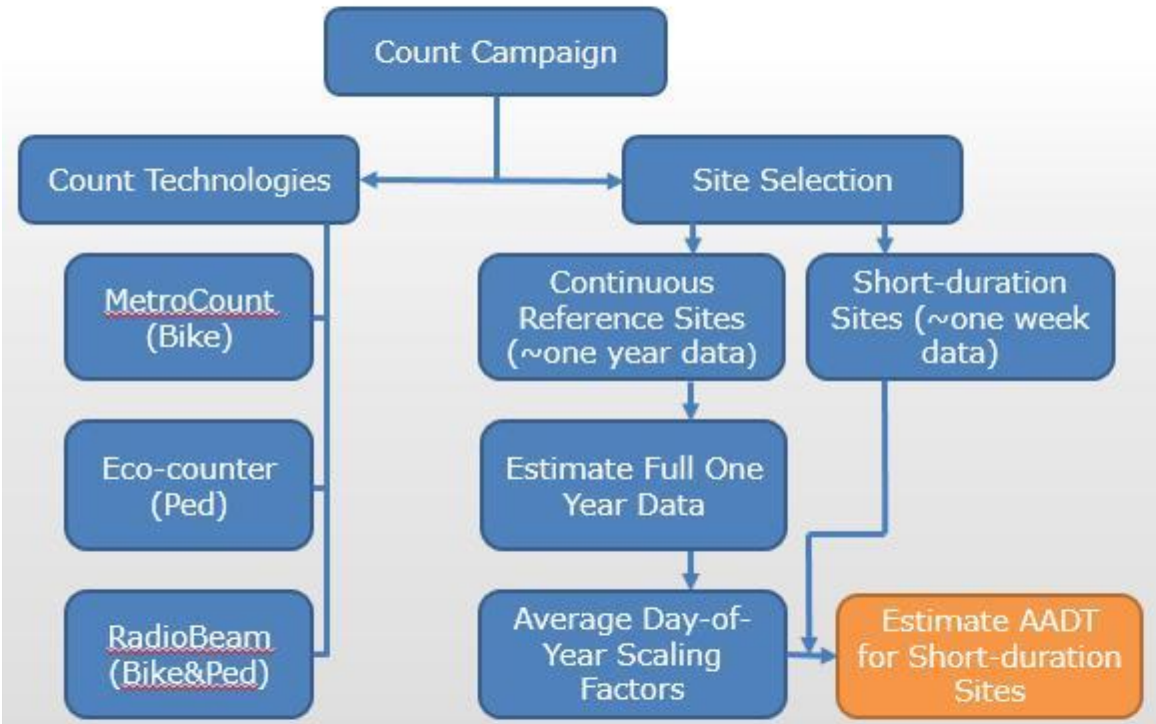


Figure 1. Research flow chart.

1.3 Benefits of non-motorized traffic

Non-motorized traffic patterns are an understudied but important part of transportation systems. Systematically collecting non-motorized traffic counts and promoting these modes would be beneficial for: (1) transportation analysis (e.g., infrastructure performance measure, project prioritization and evaluation), (2) environment, health and safety (e.g., pollution, health, safety and energy), (3) socio-economic impact (e.g., employment and economic growth; Ryus et al., 2014). These benefits highlight the significance of planning for non-motorized traffic.

1.3.1 Transportation analysis

Non-motorized modes have enriched multi-modal development (Guo, Bhat, & Copperman, 2007a), and more investment in non-motorized transportation facilities would strengthen their competitiveness (Poudenx, 2008; Heinen, Maat, & van Wee, 2013; Schneider, 2013). Planners and public officials monitor non-motorized facility demand to conduct better performance measures (e.g., facility use, management, and prioritization of limited bicycle and pedestrian resources; Lindsey et al., 2007; Porter, Suhrbier, & Schwartz, 1999). Many jurisdictions have tested the use of counts for project prioritization and evaluation; for example, the San Francisco Municipal Transportation Agency (SFMTA) has collected bicycle counts since 2006 to evaluate the bicycle network and prioritize bicycle facilities (San Francisco Municipal Transportation Agency, 2011). The District Department of Transportation (DDOT) used before-and-after bicycle counts to assess volume changes to demonstrate project success and develop best practices (Ryus et al., 2014).

1.3.2 Environment, health and safety

Motorized traffic produces air, noise, and water pollution (i.e., ozone, CO, black carbon, and toxic damages) that harm and threat human health, animal habitat and the environment (Chester & Hovath, 2008; Haines & Dora, 2012). By contrast, although there is also some pollution embedded in non-motorized production (i.e., manufacturing bicycles or shoes), the emissions are much lower compared to motorized traffic (Brand et al., 2014; Maibach, Steg, & Anable, 2009). Calculating the complete life cycle of transportation modes, passenger cars account for 436 grams of CO_2 per passenger per mile traveled, while bicycles only emit 34 grams of CO_2 per passenger per mile traveled (European Cyclists Federation, 2011). Another consideration is exposure to vehicle pollution for cyclists and pedestrians, for example, cyclists breathe more heavily (Frank et al., 2010). Extensive studies highlight that the physical activity benefits outweigh risks from air pollution (Andersen et al., 2015; de Hartog et al., 2010; Rojas-Rueda et al., 2011).

Cycling and walking yield valuable health benefits for individuals and society (Pucher & Buehler, 2010; Rabl & de Nazelle, 2012). Higher levels of cycling and walking generally contribute to lower obesity rates (Bassett et al., 2008). Normalized Difference Vegetation Index (NDVI) highlights vegetative density and health, which reveals positive correlations with trail traffic (Lindsey et al., 2006). Evidence shows that the health benefits of cycling outweigh the health risks from traffic injuries (Andersen et al., 2000; Bassett et al., 2008; Huy et al., 2008; Gordon-Larsen et al., 2009). Furthermore, increased cycling and walking activities lead to increased longevity in life (Andersen et al., 2000; Cavill et al., 2008). Wang (2005) also found that every $1 direct investment in trails led to $2.94 indirect medical benefit.

Although non-motorized traffic has higher per-mile casualty rates than motorized traffic, shifting to cycling and walking tends to decrease the total crash costs (Kahlmeier et al., 2014; Litman, 2013). Moreover, areas with higher cycling and walking rates have lower per capita traffic death rates (Ministry of Transport/ Public Works and Water Management, 2009; Kenworthy & Laube, 2000). In this case, non-motorized traffic counts could be used to quantify exposure and identify before-and-after safety effects (Strauss, Miranda-Moreno, & Morency, 2014). For example, the City of Oakland used model-generated volumes and crash data in the pedestrian master plan to identify dangerous intersections (Ryus et al., 2014).

More vehicle production and use leads to more consumption of natural resources, such as petroleum and coal (Fulton, 2001; Chester & Hovath, 2008). As a result, non-motorized trips contribute to relatively large energy savings when they substitute short urban trips that result in high emission rates per mile due to cold starts (engine efficiency) and congestion (US DOT & FHWA, 1993).

1.3.3 Socio-economic benefits

Studies show that the reduction of vehicle ownership and use would provide various types of savings (e.g., vehicle operating costs, repair costs and residential parking, quality of life, traffic fatalities, and pollution)(Steg & Gifford, 2005; Litman, 2013). It also creates jobs. For example, Garrett-Peltier (2011) estimated the employment impact of improving transportation infrastructure for bicycles and pedestrians, and found that every $1 million invested in bicycle projects could add a total of 11.4 jobs within the state where these projects are located; similarly, a $1 million investment in pedestrian-only projects creates 10 jobs. A $1 million investment in road infrastructure (no bicycle or pedestrian components) only creates 7.75 jobs. Non-motorized facilities may stimulate home values, drive business spending, and spur economic development (Pedestrian and Bicycle Information Center, 2014). Cycling and walking conserve much more space (i.e., bike lanes/paths, sidewalks) than vehicles (i.e., wide roads). Providing facilities such as sidewalks, bike lanes, and crosswalks also avoid an inconvenient and socially unjust barrier to mobility (Pedestrian and Bicycle Information Center, 2014).

2 LITERATURE REVIEW

2.1 Data collection efforts

In the US renewed interest in non-motorized transportation has appeared since the adoption of the Intermodal Surface Transportation Efficiency Act (ISTEA) in the early 1990s, which aims to “Develop a National Intermodal Transportation System that is economically efficient, environmentally sound, provides the foundation for the nation to compete in the global economy and will move people and goods in an energy-efficient manner."

The lack of bicycle and pedestrian data has been a common problem. In 2000, the report *Bicycle and Pedestrian Data: Sources, Needs & Gaps* summarized the existing data sources and their quality; however, consistent state, regional and local data was not available. The primary data sources are classified by the following types: (1) usage, trip, and user characteristics, (2) preferences, needs, and attitudes of cyclists and pedestrians, (3) facility characteristics, (4) crash and safety data, and (5) relevant expenditures. Moreover, research studies and manuals for practice have provided additional sources (U.S. Department of Transportation Bureau of Transportation Statistics, 2000).

The National Household Travel Survey (NHTS) and U.S. Census have been the only national level data available for limited bicycle and pedestrian survey-based information. For example, the U.S. Census data only counts commute trips, excluding people who are for business, recreation and shopping (Jones et al., 2010).

Following NHTS, since 2002, the National Survey of Bicyclist and Pedestrian Attitudes and Behavior (NHTSA) have become the first benchmark of bicycle and pedestrian transportation. The telephone interviews only include activities for people age 16 or over (National Survey of Pedestrian and Bicyclist Attitudes and Behaviors, 2002). Also the surveys rely on samples of the population and may under-represent subgroups, which is especially important for bicycle data considering it is less than 1% mode share (Jones et al., 2010).

The state, regional, and local agencies have developed various methodologies to collect bicycle and pedestrian data, however, as mentioned earlier, the data at these levels of government is not consistently available (Schneider et al., 2005). Therefore, they have to be tailored to suit the specific needs of the localities (Greene-Roesel et al., 2008). While a few local agencies collected bicycle and pedestrian data routinely, most jurisdictions conducted data collection efforts for specific purposes (U.S. Department of Transportation Bureau of Transportation Statistics, 2000).

The lack of consistency in non-motorized data has made it difficult to justify funding, inform exposure rates, and other issues (Jones et al., 2010). To fill this gap, some agencies and companies (e.g., Alta Planning + Design, ITE Pedestrian & Bicycle Council) have conducted the National Bicycle & Pedestrian Documentation Project (NBPD) to provide publicly available data collection guidance, such as consistent count and survey materials, standard count dates and times, and count location attributes. The City of Berkeley developed a pedestrian demand model based on urban form, land use, and pedestrian behaviors, thus providing valuable information to prioritize multimodal projects (Alta Planning + Design, 2000). The City of San Mateo integrated bicycle and pedestrian counts into the Bicycle Master Plan adopted in 2011. The Washington State Bicycle and Pedestrian Documentation Project in 2008 assessed the growth in multimodal trips, and later was in conjunction with the National Bicycle and Pedestrian Documentation (NBPD) project (Ryus et al., 2014). A national count archive under development is also promoting data collection (Nordback et al., 2014).

Considering the high cost of data collection, agencies are exploring two major innovative solutions: (1) automated count technology and (2) incorporating non-motorized travel data into existing motorized travel data protocols (Jones et al., 2010).

2.2 Monitoring technologies

Similar to motorized traffic (i.e., cars and trucks), there are various monitoring technologies for counting non-motorized traffic. However, due to their special characteristics, counter design and configuration are modified to suit bicycle and pedestrian monitoring.

Two major issues arise when monitoring bicycles and pedestrians: (1) whether to monitor cyclists only, pedestrians only, or combined traffic and (2) conduct continuous or short-duration counts (FHWA, 2013). According to the *Traffic Monitoring Guide* (FHWA, 2013) and *NCHRP REPORT 797 Guidebook on Pedestrian and Bicycle Volume Data Collection* (Ryus et al., 2014), there are 14 existing and emerging counting technologies for non-motorized monitoring (Table 1). Among them, I'll mainly discuss and apply four types of technologies (i.e., manual counting, pneumatic tubes, passive infrared, and radiobeam).

Table 1. Existing and emerging counting technologies for non-motorized travel[1]

Technology	Bicycle/Pedestrian	Count Duration	Detection Width	Overall Cost	Maximum User Volume	Strengths and Weaknesses	Installation Considerations
Manual field-based counting	Both (Separated)	≤4 hours	>75 feet	Very high	≤600/hour	S: flexible and mobile W: short-term; high costs	Trained to classify users; positioned to view easily; short-term only
Manual video counting	Both (Separated)	≤4 hours; longer counts available	>75 feet	Very high	≥600/hour	S: flexible; no field-base work required W: short-term; high costs	Installed high enough; clearly recorded; require site visits
Automated video counting	Both (Separated)	≤48 hours	>75 feet	High	≥600/hour	S: minimal labor W: short-term; outdoor processing	Installed high enough; avoid vibration; require vendor processing
Pneumatic tubes	Bicycle	Short-duration and long-term	<20 feet	Low	≤200/hour;	S: portable; capture speed/direction; easy W: vulnerable to snowplowing	Installed across the paved surface; avoid street sweeping; secure using tape/metal
Inductive loop detectors	Bicycle	Short-duration (<6 months) and long-term	<20 feet	Low	≤600/hour; higher volumes corrected	S: used for on-road bicycle facilities W: not possible to cover entire facility	Require pavement saw-cutting; data logger stored in an adjacent utility box; avoid electromagnetic interference
Active infrared	Pedestrian or combined	Short-duration and long-term	<20 feet	Low	≥600/hour	S: movable; may be combined with other technology; precise W: mounting device required	The receiver and transmitter should be installed facing each other on each side; avoid bus stops/street corners
Passive infrared	Pedestrian or combined	Short-duration and long-term	<20 feet	Low	≤600/hour; higher volumes corrected	S: small, portable and easy; may be combined with other technology	Placed on one side of the corridor/existing infrastructure; pointing toward a fixed object; avoid bus stops/street

[1] The table content is retrieved from *NCHRP REPORT 797 Guidebook on Pedestrian and Bicycle Volume Data Collection* (Ryus et al., 2014)

						W: may be affected by extreme temperatures	corners/reflection from foliage/windows
Piezoelectric strips	Bicycle	Long-term	<20 feet	High	N/A	S: capture speed W: not in mixed-flow traffic; specialized installation	Require pavement cuts; data logger stored in a nearby utility box; avoid intersections
Radiobeam	Both (Separated)	Short-duration and long-term	<20 feet (single-frequency); <13 feet (multiple-frequency)	Medium	≤200/hour; higher volumes corrected	S: movable, easy; hidden in post W: mounting device required; limited monitoring distance	Placed on both sides of the corridor/existing infrastructure; pointing toward a fixed object; avoid bus stops/street corners/metals/electronic signals
Thermal	Both (Separated)	N/A	N/A	N/A	N/A	N/A	Mounted above the detection area; require an external power source
Laser scanners	Bicycle, pedestrian or combined	Short-term	N/A	N/A	N/A	N/A	Primarily indoors; electrical power supply required; horizontal scanners require locations with no obstruction; vertical mounted overhead;
Pressure and acoustic pads	Bicycle (pressure pads); pedestrian (acoustic pads)	Long-term; short-term (pressure pads)	N/A	High	N/A	S: can be in-ground W: user direct pass required; only for pedestrians; unpaved trails used	Require users to pass directly above the sensor; commonly used on unpaved trails
Magnetometers	Bicycle	Short-duration and long-term	N/A	High	N/A	S: can be in-ground W: small detection area; limited application	Suited to rural locations; require users to pass directly above the sensor; installed in the ground
Fiberoptic pressure sensors	Bicycle	Long-term	N/A	High	N/A	S: mixed-flow traffic W: no rigorous test	Require excavating a slot to place a fiberoptic cable

2.2.1 Manual counting

The National Bicycle and Pedestrian Documentation Project (NBPD, Alta Planning + Design, 2012) recommends the 2-hour peak-period for manual counts. Manual counts are the most prevalent approach in the U.S., and of respondents who performed counts, 93% included manual counts for pedestrian counting and 87% for bicycle counting (Ryus et al., 2014). One study conducted at 10 different intersections with high volumes in San Francisco found that manual counts with either sheets or clickers systematically undercounted pedestrian volume compared with video recordings, and the error rates ranged from 8% to 25% for 15-minute intervals; there was no strong relation between the accuracy of the field-based counts and the pedestrian volume. Also, video counts are similar to field-based counts (Diogenes et al., 2007) in that manual counts can be performed on the video footage or automated counts from video images use computer algorithms to identify bicycles and pedestrians (Ryus et al., 2014).

2.2.2 Pneumatic tubes

Counters with pneumatic tubes include general purpose counters (GPCs) and bike-specific counters (BSCs). Relevant tests found that pneumatic tubes undercounted, except occasional over-count at higher volumes (Ryus et al., 2014). More tests conducted in New Zealand indicated that off-road undercounted 0% to 15% (ViaStrada Ltd, 2009). To compare the accuracy of BSCs to GPCs, a study found the BSC performance is very reliable and accurate when counting bicycles striking the tubes up to 27 feet away from the counter, with average accuracy between 94% and 95%. However, accuracy fell to 57% when cyclists ride 33 feet away (Hyde-Wright et al., 2014).

2.2.3 Passive infrared

Another commonly used technique is passive infrared, which detects bicycles and pedestrians by comparing the temperature of the background with the radiation (heat) from crossing bicycles and pedestrians (Ryus et al., 2014). Studies indicate that passive infrared counters undercount more when pedestrian volumes increase (Schneider et al., 2013). However, no conclusive evidence of this finding exists (Ryus et al., 2014). Researchers compared several existing technologies (i.e., infrared, laser scanner, computer vision), and found that a dual sensor passive infrared counter works with practical and cost effective accuracy to count outdoor pedestrians based on cost, feasibility and commercial availability (Greene-Roesel et al., 2008).

2.2.4 Radiobeam

RadioBeam counters position a transmitter and receiver oppositely sides of a facility and a user is counted when the radiobeam is interrupted. Tests have shown that the RadioBeam undercounts bicycles (pedestrians) by 31.2% (26.3%) with separate counting, and undercounts by 3.6% with combined counting; however, it's difficult to evaluate the accuracy with specific settings and installations (i.e., RadioBeam has advanced settings to allow counting on the hour, and installations should avoid electronic signals, Ryus et al., 2014). Limited tests done in New Zealand claimed that the RadioBeam counter was their best counting technology used for 20 years (ViaStrada Ltd, 2009).

2.2.5 Other technologies

Below is a brief introduction to other count devices that are available. Inductive loop detectors monitor the changes in the produced magnetic field by the metal parts of a bicycle (e.g., frame, spokes, and pedals) (Ryus et al., 2014). Overall, there is a 3% undercount on the separated path and a 4% undercount on the shared roadway (Nordback & Janson, 2010; Nordback et al., 2011). However, the bypass errors (impossible to cover the entire road width) caused by cycling around the detection zone and installment requirements of pavement saw cuts reveal its limitations. Active infrared counters use an infrared beam between an emitter and a receiver installed on opposite sides of a trail. Jones et al. (2010) found that an active infrared sensor was more accurate when oriented at a 45-degree angle to the facility, and it undercounted 12% to 18% for all travelers, and 25% to 48% for pedestrians. Piezoelectric strips emit an electric signal when bicycles cross the traveled path, and a test on a paved multi-use trail showed they undercounted 11.4% (Ryus et al., 2014). Other technologies are also available, however, limited information exists on accuracy: (1) thermal counters are mounted above the detection area to detect body heat, (2) laser scanners use laser pulses and reflections to count bicycles and pedestrians, (3) pressure and acoustic pads detect the passage of energy waves caused by bicycles and pedestrians, (4) magnetometers detect bicycles through changes in the produced magnetic field by the metal parts, and (5) fiberoptic pressure sensors use embedded fiberoptic cable to detect the changed pressure (Ryus et al., 2014). Emerging techniques such as mobile devices with GPS or Bluetooth capabilities also supplement the monitoring package. With these technologies, monitoring non-motorized traffic is possible and may help to better characterize the entire transportation system.

2.3 Modeling and analysis methods for count data

Collecting and monitoring non-motorized data is the first step; modeling and analyzing the data can provide useful information for policy makers. The existing methods mainly include summary statistics, traffic estimation, and spatial modeling.

2.3.1 Summary statistics

Summary statistics (e.g., mean, standard deviation, skewness) of obtained non-motorized traffic data can show the travel patterns and general profiles, such as volume variations throughout a certain period of time (e.g., day, week, month and season), volume variations under different conditions (e.g., weather and special events), and how traffic differs with street functional class and bicycle and pedestrian facilities (FHWA, 2013). For example, Lindsey et al. (2013) summarized valid count percentages and calculated the adjustment equations with the data collected from counters (e.g., active infrared, inductive loop). Time of day, day of week, weekend and weekday ratios are calculated to analyze the non-motorized traffic patterns (Borah et al., 2010). Hourly and daily bicycle traffic patterns are used to classify locations as utilitarian, recreational and mixed patterns. Typical utilitarian patterns reach two peaks during commuting hours (e.g., AM/PM) on weekdays, and volumes are higher on weekdays than weekends. Typical recreational patterns present the peak volume during mid-day or afternoon on weekdays, and weekends experience more traffic than weekdays (Miranda-Moreno et al., 2013).

2.3.2 Traffic estimation

Sometimes due to counter malfunction, unpredicted incidents, or monitoring difficulties, the counts for some existing locations are not available. Researchers have found ways to build models to estimate non-motorized traffic at specific sites. For example, to impute the volumes for missing days to cover daily traffic volumes for 365 days (one full year) at each site, researchers used the average weekday/weekend volumes for the respective month of the year (Lindsey, Hankey, & Wang, 2013). Another useful method especially for count data is the negative binomial regression model (Cao, Handy, & Mokhtarian, 2006). Studies estimate non-motorized traffic in response to variations in weather and day of week. The results also indicate that negative binomial models outperform the estimated outcome by ordinary least squares regression (Wang et al., 2014; Lindsey et al., 2013). Other studies also echo this finding (Cao et al., 2006; Kim & Susilo, 2013).

2.3.3 Spatial modeling

Ordinary least squares (OLS) regression is often used to model the spatial patterns of non-motorized traffic based on neighborhood-level variables (Haynes, Andrzejewski, & Peers, 2010; Jones et al., 2010; Lindsey et al., 2006). Geographic Information Systems (GIS) can be used to analyze non-motorized traffic, for example, urban trail traffic modeling (Lindsey et al., 2008), traffic at signalized intersections (Strauss & Miranda-Moreno, 2013; Schneider, Arnold, & Ragland, 2010) and assembling geographic covariates (e.g., built, natural, and socioeconomic environments; Zahran et al., 2008). GIS tools often work with aggregate-level models (e.g., measures of potential demand and sketch plan method) and network simulation tools can model the travel behaviors within the assigned networks (Aoun et al., 2015). For example, the City of San Francisco applied spatial models to estimate local walking activities (Schneider, Henry, & Koehler, 2012). MoPeD (Model of Pedestrian Demand) is a simulation tool for pedestrian spatial patterns based on regional travel models (traditional four-step travel demand models; National Center for Smart Growth Research and Education, 2008). Real-time GPS is applied to estimate the bicycle speeds on facilities of on-street, off-street, and mixed traffic to measure bicycle accessibility (El-Geneidy, Krizek, & Iacono, 2007).

2.4 Factors influencing non-motorized traffic

To build better models to estimate non-motorized traffic, it is essential to understand variables that influence travel patterns (i.e., built environment, temporal and weather, socio-economic factors).

2.4.1 Built environment

The built environment impacts bicycle and pedestrian activities (Buehler & Pucher, 2012; Dill, 2009; Pucher, Dill, & Handy, 2010; Troped et al., 2014; Wang et al., 2016; Miranda-Moreno, Morency, & El-Geneidy, 2011; Caulfield, 2014; Knuiman et al., 2014; Mitra & Buliung, 2012). For example, cyclists and pedestrians assess travel distance as a major criterion to choose a transport mode (Rietveld, 2000). Generally, a longer distance leads to a much lower share of cycling (Moritz, 1998; Pucher & Buehler, 2006; Cervero & Radisch, 1997; Dickinson et al., 2003; Parkin., Wardman, & Page, 2004). Higher densities of roadways and blocks have lower car ownership and use (Litman, 2006), and contribute to higher level of cycling activities (Guo, Bhat, & Copperman, 2007b; Parkin. et al., 2004; Pucher & Buehler, 2006; Southworth, 2005; Zahran et al., 2008). Mixed use of land containing convenience stores, offices, or restaurants can increase bicycle activities (Cervero, 1996; Cervero & Duncan, 2003; Jones et al., 2010; Pucher & Buehler, 2006; Moudon et al., 2005; Pikora et al., 2003; Cui, Mishra, & Welch, 2014; Faghih-Imani et al., 2014). Meanwhile, bicycle facilities (i.e., bike lanes and paths) are associated with increased levels of bicycle commuting (Krizek, Barnes, & Thompson, 2009; Nelson & Allen, 1997; Pucher & Buehler, 2006; Dill & Carr, 2003; Buehler & Pucher, 2012), and cyclists show a preference to bicycle facilities compared to roads without (Hunt & Abraham, 2007; Wardman, Hatfield, & Page, 1997; Brand et al., 2014; Buehler, 2012; Fishman et al., 2014; Sanders & Cooper, 2013; Kang & Fricker, 2013; Winters et al., 2011).

Moreover, car parking facilities pose more threats to cyclists, because cars sometimes need to cross bicycle facilities to park (Heinen, Wee, & Maat, 2010). Roads without parking are considered safer than roads with parking (Stinson & Bhat, 2005). In mixed traffic, roads with fewer travel lanes and less motorized traffic appeal to cyclists (Caulfield, Brick, & McCarthy, 2012; Chataway et al., 2014; Dill et al., 2014; Winters et al., 2011). More specifically, cyclists prefer two motorized lanes to four lanes (Petritsch et al., 2006; Shankwiler, 2006). Some traffic facilities (i.e., stop signs and traffic lights) cause delays (Heinen et al., 2010), so cyclists choose routes to avoid such facilities (Sener, Eluru, & Bhat, 2009; Dill et al., 2014).

Topography, either natural settings or built environment (i.e., slopes, hilly attractions), is associated with bicycle and walking activities. Studies indicate that slope has a negative effect on cyclists (e.g., physical effort, propensity to cycle; Rietveld & Daniel, 2004; Parkin. et al., 2004; Timperio et al., 2006; Rodríguez & Joo, 2004). However, Moudon et al. (2005) analyzed the recreational users, and contended that there is no significant effect on the bicycle share due to slope; hilly terrain could create an upward/downward exercising/entertaining experience for cyclists in certain areas (Stinson & Bhat, 2005).

2.4.2 Temporal and weather effect

Bicycle and pedestrian volumes are influenced by the time of day (i.e., morning and afternoon peaks). Jones et al. (2010) found that the 6 a.m. to 9 p.m. period accounts for a consistent 95% of the total volumes within one day. Niemeier (1996) added that there is greater variability in the p.m. peak period than in the a.m. peak period.

Weather conditions (i.e., temperature, wind, and precipitation) affect bicycle and pedestrian activities in various ways across many cities/countries (e.g., Canada, Australia, Boulder, Minneapolis; Ahmed et al., 2012; Flynn et al., 2012; Miranda-Moreno & Nosal, 2011;

Nosal & Miranda-moreno, 2012; Phung et al., 2006; Rose & Figliozzi, 2011; Thomas et al., 2009). Temperature may be a better predictor of non-motorized traffic volume than the amount of precipitation (Niemeier, 1996). The variation of seasonal weather affects bicycle commuting, and typically bicycle activity is highest in summer or autumn (Guo et al., 2007b), declining in winter, and resurgent in spring (Nankervis, 1999).

Weather conditions demonstrate more sensitivity toward recreational demand than utilitarian demand (Thomas, Jaarsma, & Tutert, 2013). Precipitation is referred to as the biggest barrier for cyclists (Brandenburg, Matzarakis, & Arnberger, 2004; Nankervis, 1999). However, Cervero & Duncan (2003) suggested that rainfall (number of inches on the day of the trip) is insignificant toward cyclists, which may be explained by the use of different measurements (i.e., number of rainy days and number of inches per day; Heinen et al., 2010). Rose et al. (2011) quantified and compared weather effects on bicycles in Melbourne, Australia, and Portland, Oregon, and found that weather in the morning has the greatest impact. Researchers used data in Auckland, New Zealand to analyze the influence of weather variables, and found: (1) with 1 °C increase in temperature, the bicycle volume increased by 3.2% (hourly) and 2.6% (daily), (2) with 1 mm increase in rainfall, the volume decreased by 10.6% (hourly) and 1.5% (daily), (3) with 1 km/h increase in wind speed, the volume decreased by 1.4% (hourly) and 0.9% (daily), and (4) sunny days added 26.2% bicycle volume compared to days without sun and that one extra hour of sunshine would increase bicycle volume by 2.5% (Tin et al., 2012). Hours of daylight are also related to the seasons (Heinen et al., 2010) and darkness has a negative effect on cyclists (Gatersleben & Appleton, 2007), especially for women (Bergström & Magnusson, 2003; Cervero & Duncan, 2003).

Some studies claim that pedestrians are more sensitive to adverse weather conditions, especially during weekends. More specifically, temperature, humidity, wind speed and direct and lagged effects of precipitation influence pedestrian activities (Miranda-Moreno & Lahti, 2013). However, others found that cyclists (rather than pedestrians) in Minneapolis are actually more sensitive to weather condition (i.e., precipitation) (Hankey et al., 2012). The impact of weather on pedestrians is large in a business and commercial downtown area (Aultman-Hall, Lane, & Lambert, 2010).

2.4.3 Socio-economic factors and attitude

Socio-economic factors (i.e., gender, age, income, education) are related to bicycle and pedestrian travel (Cervero, 2002), and the findings are mixed on the global scale (Heinen et al., 2010; Howard & Burns, 2001; Krizek, Johnson, & Tilahun, 2005; Jones, Mcclintock, & Maddox, 2001; Pucher, Komanoff, & Schimek, 1999; Räsänen & Summala, 1998; Rietveld & Daniel, 2004; Shaw & Gallent, 1999; Garrard, Rose, & Lo, 2008). However, generally in the U.S., women cycle less than men (Emond, Tang, & Handy, 2009; Garrard et al., 2012), and students cycle more (Buehler & Pucher, 2012).

Obviously, a positive attitude towards cycling would be beneficial to the use of non-motorized traffic (Dill & Voros, 2008) while a negative perception on cars would stimulate choosing alternative modes (Stinson & Bhat, 2005). Meanwhile, other people's perception and choice of mode are also reflected in individuals, for example, if more workers bike then more co-workers will follow (Dill & Voros, 2008). Supportive policies for bicycles and pedestrians would act to increase users (Pucher, Dill, & Handy, 2010); however, the policy effect on cycling demand is difficult to measure (Thomas et al., 2013).

2.5 Scaling factors

Motorized traffic count programs have been well-established and provide detailed instructive guidelines for collecting data. Agencies analyze short-term count data and develop AADT adjustment factors for further estimation (Figliozzi et al., 2014). Similarly, AADT is also an essential indicator for non-motorized traffic, from which cities/counties conduct safety studies, report facility use and secure transportation funding. Thus, reliable estimation of AADT is needed for non-motorized traffic (Nordback et al., 2013).

Most counts consist of short-duration and long-term reference sites. The common approach is to use reference sites to estimate scaling factors and create groups of similar counting locations (factor groups), thus annualizing these short-duration counts to a longer scale (e.g., one year). Traditionally, day-of-week and month-of-year factors have been used to scale from daily traffic into monthly and annual averages (Esawey et al., 2013; Nordback, Marshall, & Janson, 2014). Researchers use day-of-week (ratio of average day of week traffic to AADT) and month-of-year (ratio of average monthly traffic to AADT) methods to estimate AADT from short-duration counts. Hankey et al. (2014) introduced and proved that day-of-year scaling factors work with a smaller error than the previous methods, especially from 1-week short-duration counts. Nosal et al. (2014) also proved similar daily scaling factors (disaggregate method) outperformed the traditional methods.

Short-duration counting for at least 1 week between April and October has a satisfactory minimum of error (Nordback et al., 2013). Miranda-Moreno et al. (2013) derived four classifications: (1) utilitarian, (2) mixed-utilitarian, (3) mixed-recreational, and (4) recreational, to set up factor groups to scale non-motorized traffic. Since weather is considered a significant factor for non-motorized activities, integration of weather into the existing scaling factors would improve estimates, however, the reliability degrades over time (Esawey et al., 2013).

3 DATA COLLECTION, PROCESSING AND QUALITY CONTROL

To systematically monitor the bicycle and pedestrian traffic in Blacksburg, VA, this research makes use of a traffic count campaign that covers different road and trail types (i.e., major road, local road, and off-street trails) using commercially available counting technologies (i.e., pneumatic tubes, passive infrared, and RadioBeam). This chapter introduces data monitoring and collection, data processing, and data adjustment and correction. The goal of these tasks is to provide a clean database for further traffic analysis.

3.1 Monitoring technologies and equipment

Based on description of automated counters in Chapter 2, this research applies three existing automated counter technologies as well as manual field-based counts (validation counts) to monitor bicycle and pedestrian traffic patterns: MetroCount MC 5600 Vehicle Classifier System (pneumatic tube counters), Eco-counter "Pyro" (passive infrared counters), and Chambers RadioBeam Bicycle-People Counter (RadioBeam counters). The major considerations of choosing these counters are previous performance, location type, portability and cost. MetroCount counts bicycles on roads with mixed traffic and requires easy installation and low cost (~$1000 per unit). Eco-counter counts pedestrians only on sidewalks with a cost of ~$3000 per unit. RadioBeam separately counts bicycles and pedestrians on off-street trails with limited monitoring distance (~10 feet; ~$4500 per unit).

3.1.1 Manual field-based counts

Manual field-based counts are the most common and labor intensive method to collect traffic counts. For example, the person has to stay at corners or specific location to conduct the counting activity (normally for two to four hours a time). Sometimes the manual counting also documents information such as weather, location, direction and even gender (for group analysis) and helmet use (for safety analysis).

This research includes manual field counts for ~230 hours at 8 locations with the assistance of a graduate course (UAP 5864 Topics in Transport Policy) in spring, 2015. The 8 locations include: (1) locations with a variety of bicycle and pedestrian traffic volumes selected with input from the Town of Blacksburg and (2) a subset of count locations with high bicycle traffic volumes (i.e., Kent St, Smithfield Road). The purpose of manual field-based counting is to adjust counts retrieved from automated counters for further analysis (i.e., counter validation). I designed a standard screenline field-based manual count form, and attached a reference map to inform volunteers of traffic direction and screenline location (Table 21 and Table 22, Appendix A). The purpose is to document traffic counts on a 2-hour basis using 15-minute bins for both bicycles and pedestrians (if applicable) for both directions of travel. Additional information included on the forms was other travel modes (i.e., skateboards or rollerblades), date, start and end time, and general weather conditions.

3.1.2 Automated counting

As discussed in Chapter 2, there are several existing technologies that are being used to monitor non-motorized traffic. This research mainly uses three technologies (i.e., pneumatic tubes, passive infrared, and RadioBeam) to monitor the bicycle and pedestrian travel patterns in Blacksburg, VA.

3.1.2.1 MetroCount pneumatic tubes

This research uses the MetroCount MC 5600 Vehicle Classifier System (pneumatic tube counters) to monitor bicycles on the roads (Figure 2). The working mechanism is to detect air pulses triggered by passing bicycles/vehicles through the two parallel pneumatic tubes fastened to the road with cleats, washers, flaps, or tape. The air pulses transmit to the A/B poles of the receiver unit on the roadside, and the time gap of A/B is analyzed by the counter to recognize the passing objects (i.e., bicycles or vehicles) and log speeds and traffic numbers with specific time bins (i.e., 15 minutes, 30 minutes, and 60 minutes). Two pneumatic tubes with a precisely 1-meter interval were installed and parameters were set for the counter accordingly.[2]

[2] Detailed instructions go to: http://metrocount.com/products/portable-traffic-survey/.

Figure 2. MetroCount counter package.

I installed the counter at the near side of the bicycle lane (if there is one) and tied it to a tree or pole with a chain (for protection). When fastening the two pneumatic tubes (equal length), one needs to face the traffic (for safety) and keep the parallel tubes perpendicular with the road. Then, allow 10% length of each tube to be pulled through the fixed cleats with nails to ensure the straightness and proper contact with incoming traffic flow. Major roads were installed with two MetroCount counters on each half of the road (considering the width of the major roads); local roads were normally installed with only one counter. Pneumatic tubes were stretched onto the sidewalks for roads with sidewalks (considering some cyclists may ride on the sidewalks instead; Figure 3).

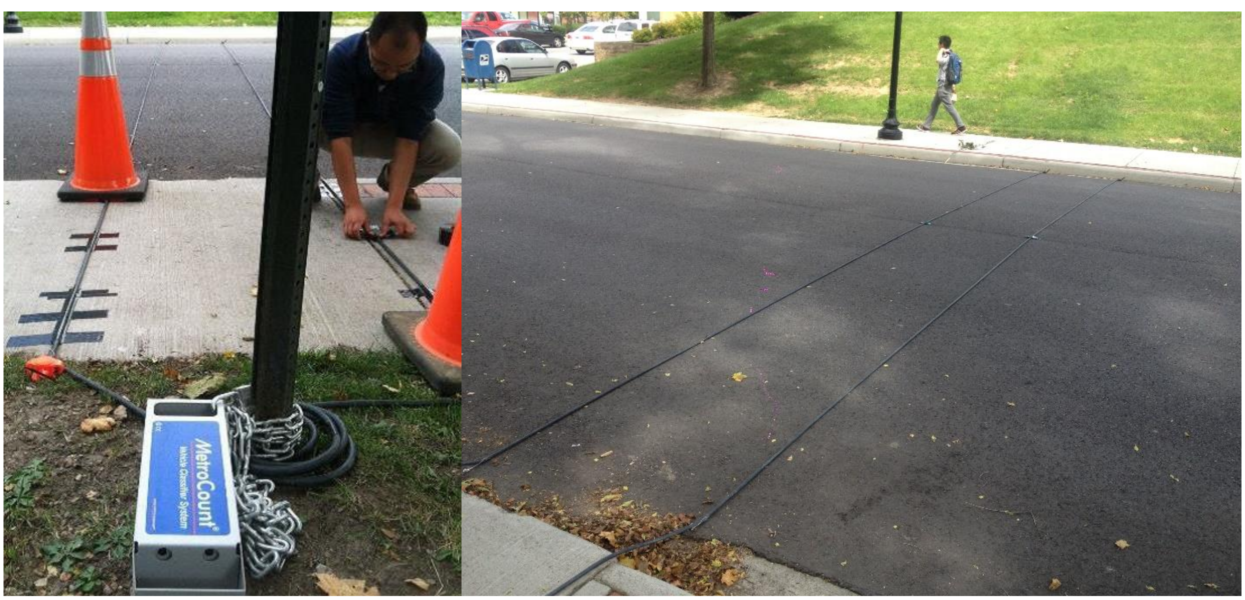


Figure 3. MetroCount counter installation.

3.1.2.2 Eco-counter Pyro passive infrared counter

I used the Eco-counter “Pyro” (passive infrared counters) to detect pedestrians by comparing the temperature of the background with the radiation (heat) from crossing pedestrians. These counters are suitable to be attached vertically onto a pole with tightening collars, however, due to the lack of suitable permanent poles on the sidewalks, home-made poles fixed in concrete stanchions were used to make the counters portable (Figure 4). The detection range is around 15’ (with a cone shaped beam) which requires counters to point at a fixed object (e.g., wall), rather than a moving object (bush) or reflective surface (metal). The counters were positioned so that the lenses of the sensor face the path (sidewalk) rather than the road. The appropriate height of the counter is approximately 700 to 800 mm (Figure 5). The counter can detect two people simultaneously when they pass in a staggered fashion and has a data logging capacity for up to 10 years. To wake up the counter, one needs to wave the Eco-counter magnetic key over the activation zone to activate the unit.[3]

Figure 4. Eco-counter "Pyro" package.

[3] Detailed instructions go to: http://www.eco-compteur.com/en/products/pyro-range/pyro-box.

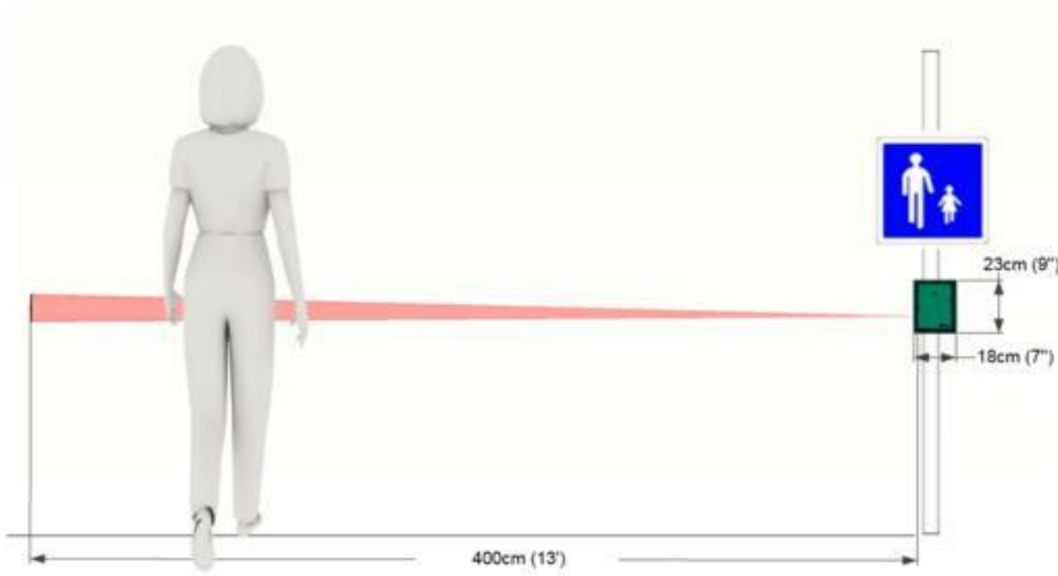


Figure 5. Eco-counter "Pyro" working mechanism (retrieved from Eco-counter website).

3.1.2.3 RadioBeam Bicycle-People Counter (Chambers Electronics RBBP8)

Another technology is RadioBeam, which is normally used on off-street trails. This research uses the RadioBeam Bicycle-People Counter (RBBP8) with a protective housing and data logger to monitor bicycle and pedestrian volumes separately (Figure 6). The RBBP8 has two protective housings that are installed on both sides of the trail at 65 cm above ground level (Figure 7). Once a bicycle or pedestrian passes, a count is registered. More specifically, the counter uses two beams (at two frequencies). One detects the passing pedestrian, the other detects metal (i.e., bicycles). The device can then collect separate counts of bicycles/pedestrians. Normally the two units are positioned up to 3 meters apart. It is important to note that underground cables or other electromagnetic interference may influence the data or even ruin the logger, so periodic checking and testing are needed when conducting bicycle and pedestrian counts.[4] Home-made poles (same with the Eco-counter) were used to allow portability of the two units for most of the trails where permanent poles are not available (Figure 8).

[4] Detailed instructions go to: http://www.chambers-electronics.com/bike-people-counter-rbbp.html.

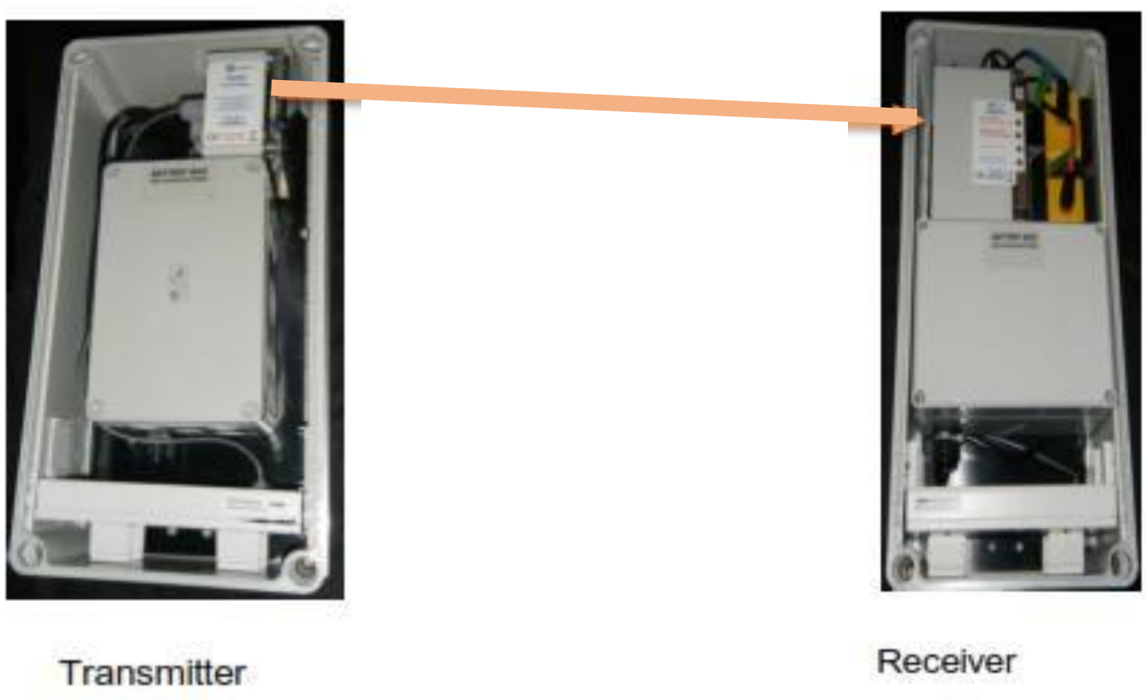


Figure 6. RadioBeam Bicycle-People Counter Units.

Figure 7. RadioBeam counter for continuous sites.

Figure 8. RadioBeam counter for short-duration sites.

3.2 Traffic count campaign

Using the technologies introduced above, I made use of a previously developed count campaign in Blacksburg, VA that included two types of count sites: (1) 4 continuous (permanent) reference sites and (2) 97 short-duration count sites. The continuous reference sites provide permanent (1-year) monitoring of bicycle and pedestrian traffic; the short-duration sites provide 1-week monitoring depending on the facility availability (i.e., pedestrians were not monitored on sites without sidewalks).

This research used 12 MetroCount, 10 Eco-counter, and 3 RadioBeam counters. Three MetroCount, 4 Eco-counter, and 1 RadioBeam counter were installed at the 4 continuous reference sites; the remaining counters were rotated on a weekly basis at the short-duration count sites.

3.2.1 Continuous reference sites

The continuous reference sites were selected based on (1) professional judgment (possible high/low bicycle/pedestrian volumes), (2) different road, trail, and facility type (roads with/without bike lane), (3) surrounding land use (i.e., proximity to the university, downtown and residential areas. More specifically, the sites included one off-street trail (Huckleberry Trail), one near campus and downtown road (College Avenue), one neighborhood local road without bike lanes (Giles Road), and one neighborhood local road with a bike lane (Draper Road) (Table 2; Figure 9). Traffic counts were collected for the full year-2015 at Huckleberry Trail and ~9 months (year-2015) at the other three continuous sites. The full year of counts allows for assessing traffic patterns in each consecutive month at the 4 reference sites. The traffic counts at the continuous reference sites can be used to generate scaling factors to estimate performance measures (i.e., AADT) at the short-duration count sites.

Table 2. Continuous reference sites installation

	Location Type	**Counter**	**Install Date**
Draper Road	neighborhood local road with a bike lane	1 MetroCount + 1 Eco-counter	April 18, 2015
College Avenue	local road near campus and downtown	1 MetroCount + 2 Eco-counter	March 19, 2015
Giles Road	neighborhood local road without bike lanes	1 MetroCount + 1 Eco-counter	April 18, 2015
Huckleberry Trail	off-street trails	1 RadioBeam	December 18, 2014

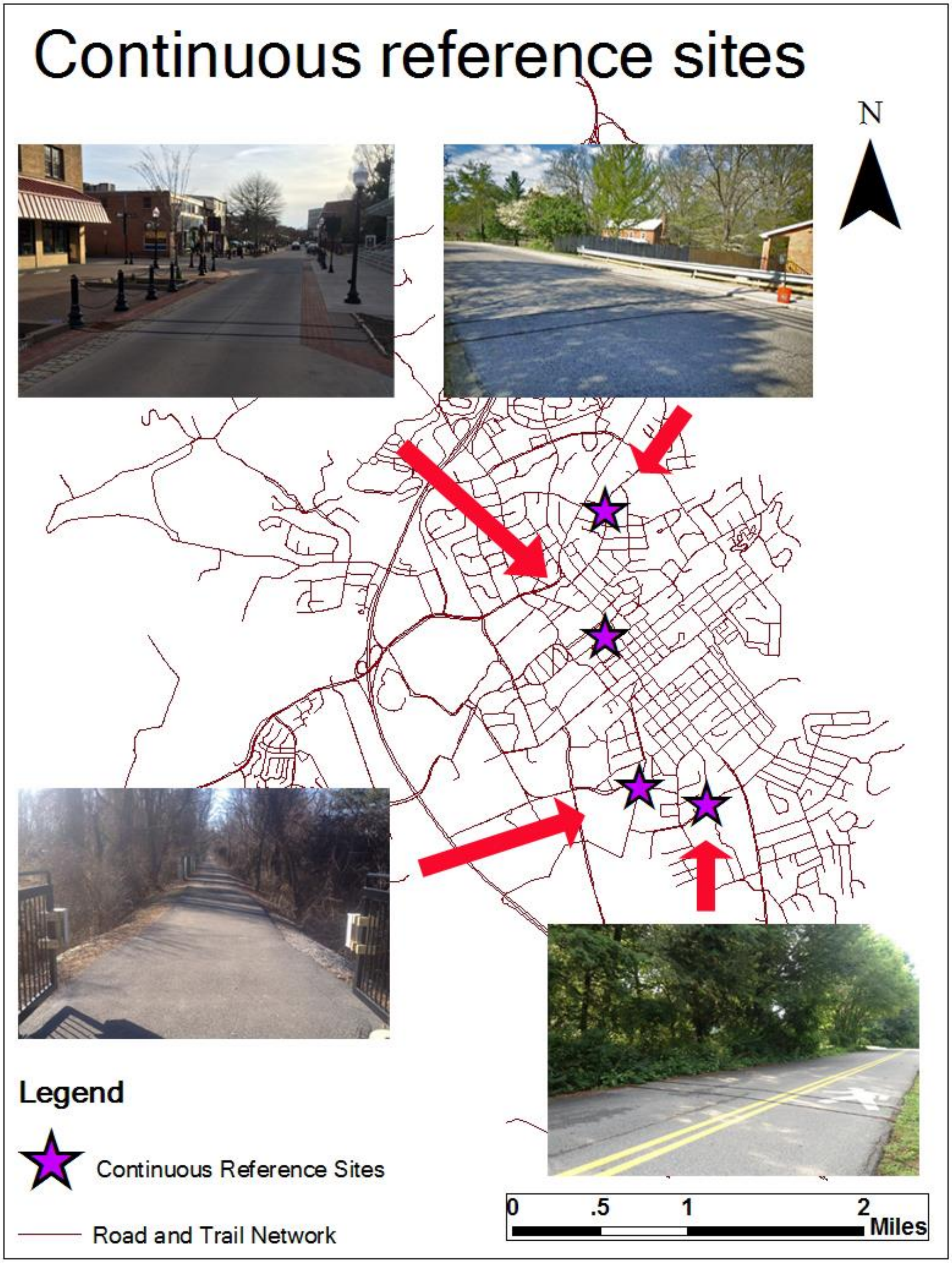


Figure 9. Continuous reference sites for bicycle and pedestrian monitoring.

3.2.2 Short-duration sites

Short-duration counting for at least 1 week between April and October has a satisfactory minimum AADT estimation error (Nordback et al., 2013). Hankey et al. (2012) found that street functional class (e.g., major road, local road) is associated with the bicycle and pedestrian volumes. Moreover, bicycle facilities (i.e., bike lanes and paths) are associated with increased levels of bicycle commuting (Krizek, Barnes, & Thompson, 2009; Nelson & Allen, 1997; Pucher & Buehler, 2006; Dill & Carr, 2003; Buehler & Pucher, 2012). Therefore, the 97 short-duration count sites were sampled from existing major roads, local roads and off-street trails using a combination of systematic and random selection in Blacksburg, VA. Briefly, all segments were grouped based on three criteria: (1) street functional class (i.e., major roads, local roads), (2) bicycle and pedestrian infrastructure (i.e., trails, bike lanes and sidewalks), and (3) centrality (i.e., magnitude of bicycle trip potential between a specific subset of O-D pairs that can be reasonably reached by cyclists; high centrality reveals high volume; McDaniel, Lowry, & Dixon, 2014). Count sites were then selected within those groups to represent the variability of bicycle and pedestrian traffic across the Town (Figure 10).

The major roads included 14 count sites with a bike lane and 15 sites without a bike lane (Figure 11). These sites cover the majority of major road segments in Blacksburg, VA. The local roads consist of 34 build-out (future planned bicycle facilities) sites and 14 random low volume sites (Figure 12). The bike build-out sites were chosen from the master plan for bicycle facilities in Blacksburg. The off-street trails include 10 transport trails (long distances or transport function) and 10 neighborhood trails (Figure 13). The off-street trails normally attract many users and play a key role in the non-motorized transportation system, therefore, apart from the on-street monitoring, the 20 sampling trails would convey valuable information to analyze the travel patterns of the entire transportation network. All sampled short-duration sites are shown in Table 23 and Table 24 (Appendix A).

To follow the research design, I installed the counters in a randomized order. The 4 continuous reference sites were installed permanently and all the short-duration sites were installed on a weekly basis from March-September based on weather condition (e.g., snow plowing) and counter availability. Generally, each site was monitored for at least one week (full 24-hour daily counts) and needed one extra day before and after for relocation. The sequence normally followed the randomized order as designated before counting began, however, some major roads needed the assistance of Town of Blacksburg to direct the traffic for deployment and so the order was adjusted slightly to accommodate these installations. I kept an event log for each site to validate traffic counts (Table 22, Appendix A).

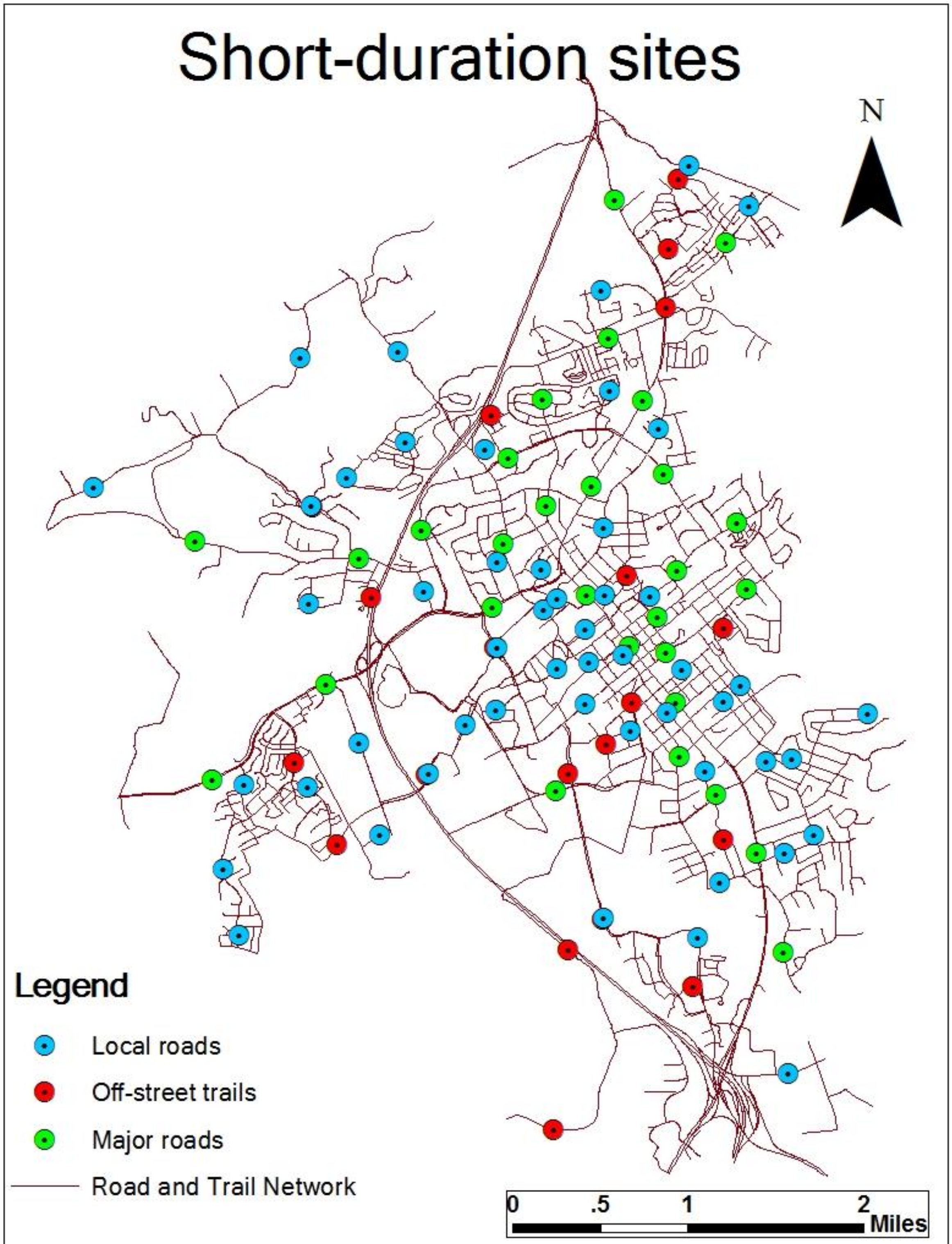


Figure 10. Short-duration sites for bicycle and pedestrian monitoring.

Figure 11. Major road short-duration site (South Main).

Figure 12. Local road short-duration site (Palmer Drive).

Figure 13. Off-street trail short-duration site (Research Center Drive).

3.3 Data extraction and processing

Data processing included extracting data from the automated counters and merging datasets among all counters (i.e., field-based count, MetroCount, Eco-counter, RadioBeam). Furthermore, I performed a set of quality assurance and quality control (QA/QC) measures to assemble a valid dataset.

The first step was to extract and assemble useful information (e.g., bicycle and pedestrian counts, time range, and corresponding sites and counters) from the existing manual field counts, and the three automated counters. Manual field counts are a source of validation data for specific sites to develop correction equations for the automated count data.

MetroCount data are extracted through a proprietary software called MetroCount Traffic Executive (Figure 48, Appendix A). The report profile settings include speed, separation, direction, class and scheme (e.g., ARX Cycle, BOCO, and Bicycle 15). The bicycle hourly data (24 hours) is in the corresponding class column based on the selected scheme, and exported into Excel format (Figure 49, Appendix A).

Eco-counter data are extracted using a field-based laptop (with activation magnetic key to wake up the counter and connect within 5-meter distance using Eco-Link) and sent to the online database provided by Eco-counter (Figure 50, Appendix A). Settings can be modified through the online dashboard (i.e., counting sites, attributes and period) and exported into Excel format.

RadioBeam data are stored in two separate data loggers (i.e., bicycle and pedestrian loggers, Figure 5 [in yellow]). The data loggers retrieve the counts every 5 minutes (default), and present the count rate and time stamp. All count data can be extracted from the proprietary software and exported into Excel format (Figure 51, Appendix A).

3.4 Adjusting and correcting count data

The second step is to adjust the output from the automated counters due to potential systematic undercounts. For example, when a bicycle and a vehicle pass the MetroCount pneumatic tubes at the same time, there is a chance to miss the bicycle count; when two or three pedestrians pass the Eco-counter at the same time, the counter may miss one or two counts due to occlusion. Similar occlusion may also happen for the RadioBeam counter when a cluster of pedestrians pass at the same time, however, bicycles sometimes are over-counted due to repeated detection of metal.

Counter errors are systematic and counts can be adjusted using correction equations. I developed correction equations for MetroCount, Eco-counter and RadioBeam counters to adjust all raw data from the counters. The goal is to apply the correction equations to adjust and replace all raw, hourly automated bicycle and pedestrian counts with new adjusted counts. Then, the adjusted counts can be used for further analysis.

3.4.1 MetroCount correction equations

MetroCount detects and classifies every vehicle using axle base and axle counts (i.e. raw axle counts, axle counts divided by 2, or gaps above a certain length). I compared three bicycle-based classification schemes provided by MetroCount (i.e., ARX Cycle, BOCO and Bicycle 15; Table 3).

The ARX Cycle scheme uses the Australian vehicle classification with an added bicycle scheme. The BOCO (Boulder County, CO) scheme revises the rules for truck classes based on ARX Cycle scheme and creates an extra bicycle class. The Bicycle 15 scheme adds an additional class for bicycles with the FHWA vehicle classification.

Table 3. Criteria for scheme classification

MetroCount Scheme	Axle Base	Axle Count
ARX Cycle	≤ 1.22 meters	2
BOCO	0.88 – 1.22 meters	Varies
Bicycle 15	≤ 1.16 meter	2

In this research, manual counts from selected locations were used to develop correction equations. To adjust the MetroCount data with different schemes, I compared manual bicycle counts with the automated bicycle count from each classification scheme. According to the *Traffic Monitoring Guide* (FHWA, 2013) and *NCHRP REPORT 797 Guidebook on Pedestrian and Bicycle Volume Data Collection* (Ryus et al., 2014) and other literature (Brosnan et al., 2015; Nordback et al., 2015), the common method to assess the accuracy of the MetroCount counters is as follows:

$$e_i = \frac{A_i - M_i}{M_i} \qquad \text{Equation 1}$$

Where

e_i = percent error = error for the count interval i

Ai = automated pneumatic counts for count interval i

Mi = manual counts for count interval i

Due to the possibility that individual observations may over- or under-count and offset each other, absolute error is also introduced to assess the accuracy of counters:

$$E_i = \left| \frac{A_i - M_i}{M_i} \right| \qquad \textit{Equation 2}$$

Where

E_i = absolute value of error = absolute value of error for the count interval i

Ai = automated pneumatic counts for count interval i

Mi = manual counts for count interval i

All the validation counts for bicycles were conducted at 8 locations (e.g., College Avenue, Patrick Henry Drive) in Blacksburg, VA (Figure 13) and 181 valid hours of manual counts were used (162 valid count hours were conducted by the graduate course of UAP 5864 Topics of Transport Policy). The selection criteria of the count locations are introduced in 3.1.1.

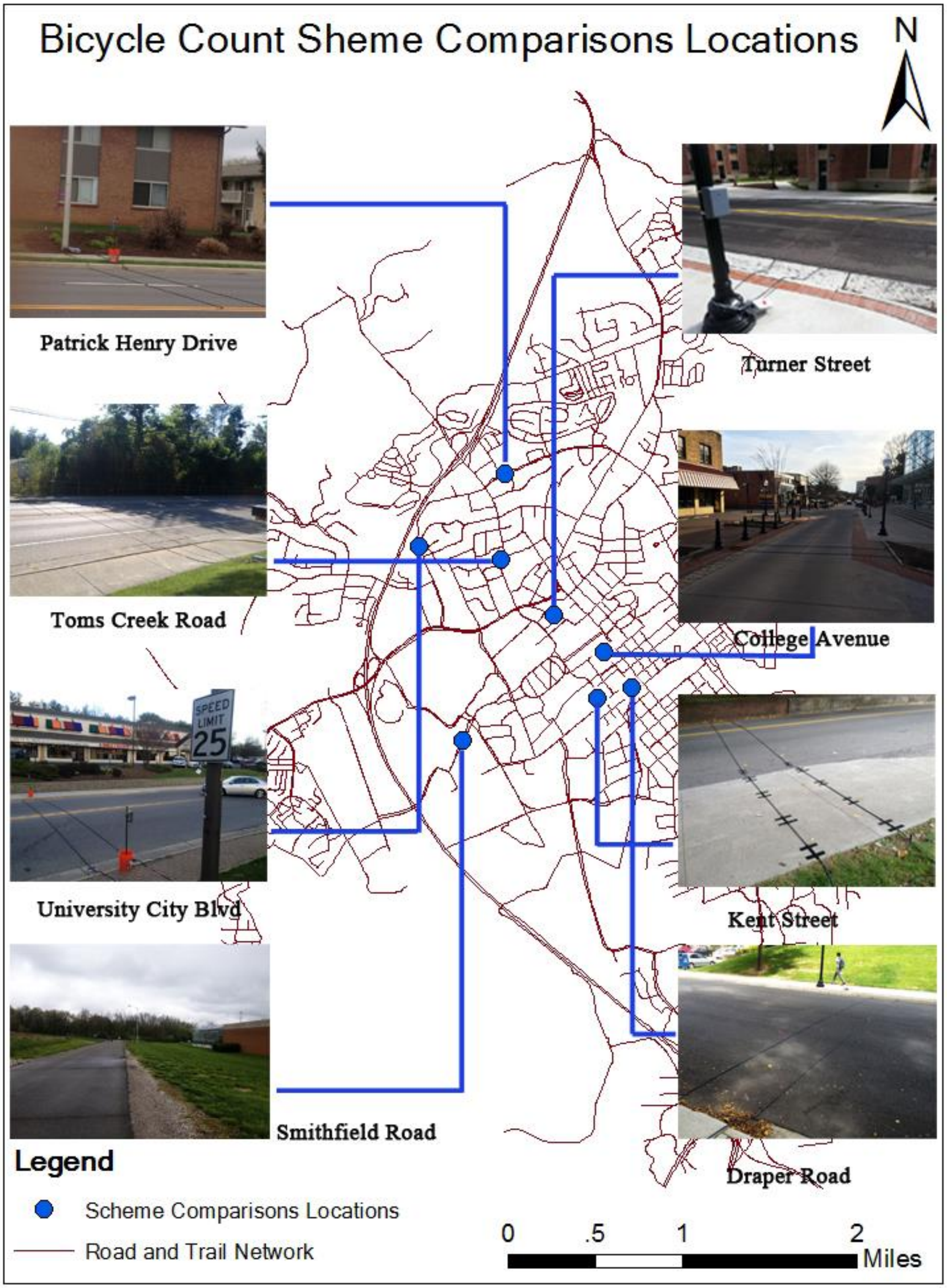


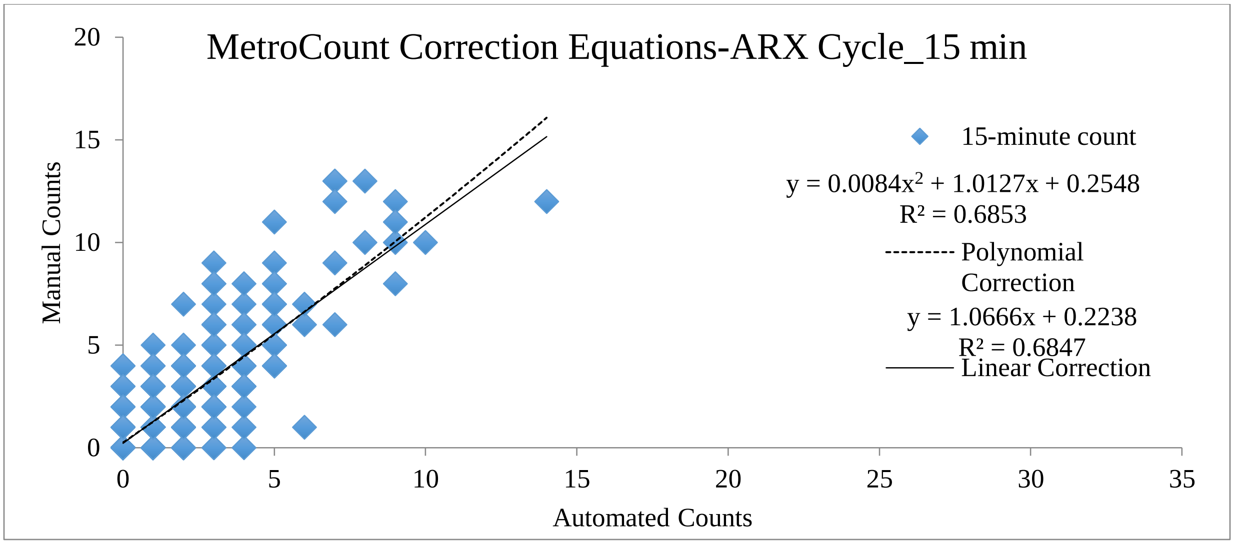
Figure 14. MetroCount bicycle count scheme comparisons location.

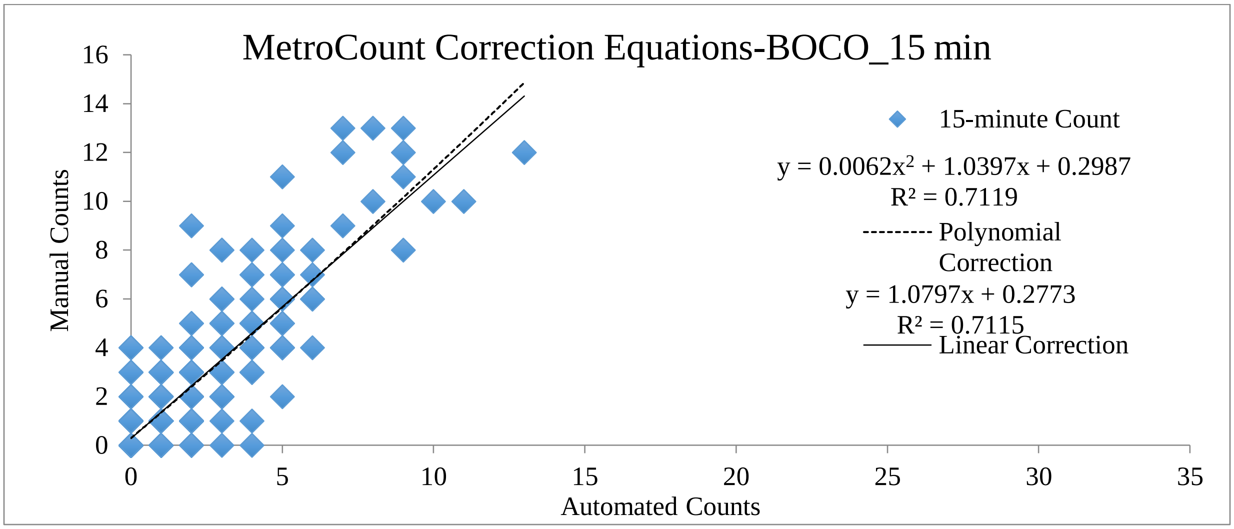
To fully compare each scheme, I calculated (1) the percent error and absolute value of error for 15-minute, 30-minute and 60-minute intervals and (2) the correction equations for 15-minute, 30-minute and 60-minute intervals (Figure 15, Figure 16, and Figure 17).

Table 4. Percent error and absolute error for each scheme

Time Interval	ARX Cycle		BOCO		Bicycle 15	
	Average Percent Error	Average Absolute Error	Average Percent Error	Average Absolute Error	Average Percent Error	Average Absolute Error
15-minute	-20.3%	43.5%	-25.7%	41.0%	-19.1%	47.7%
30-minute	-13.3%	42.2%	-19.8%	39.0%	-12.9%	42.9%
60-minute	-5.2%	40.2%	-17.5%	38.1%	-4.4%	40.4%

For average percent error, 60-minute time interval has the least error using all three schemes compared with other time intervals. Bicycle 15 scheme presents the least error with -4.4% for 60-minute interval among the three schemes. For the average absolute error, 60-minute time interval also has the least error using all three schemes. BOCO scheme shows the best accuracy with average absolute error 38.1% for 60-minute interval among the three schemes (Table 4). In this case, a 60-minute time interval is recommended for adjusting counts using correction equations.





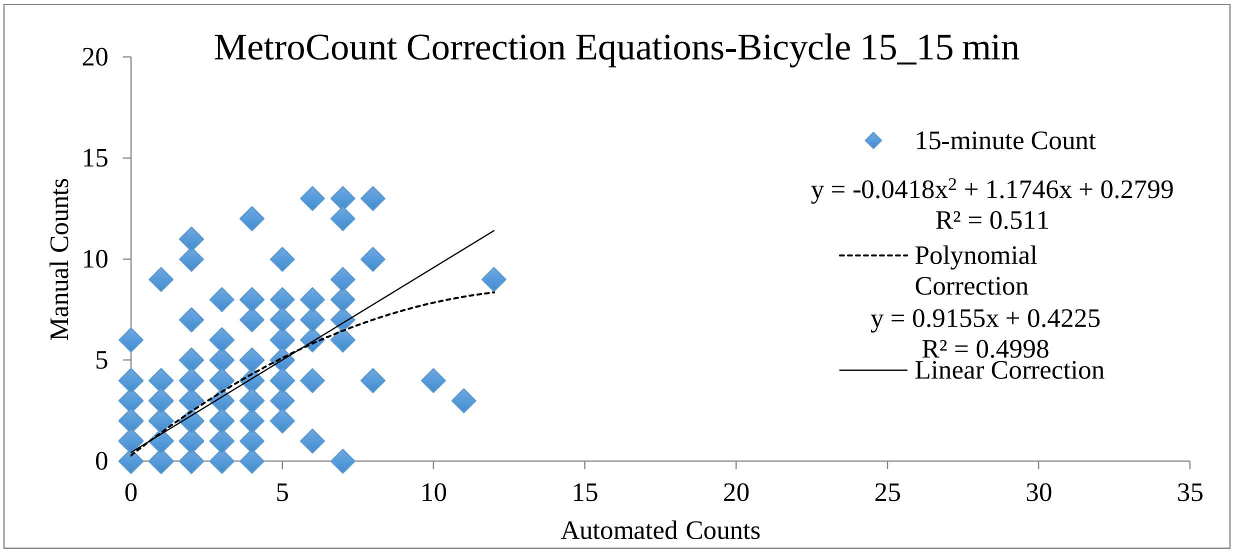
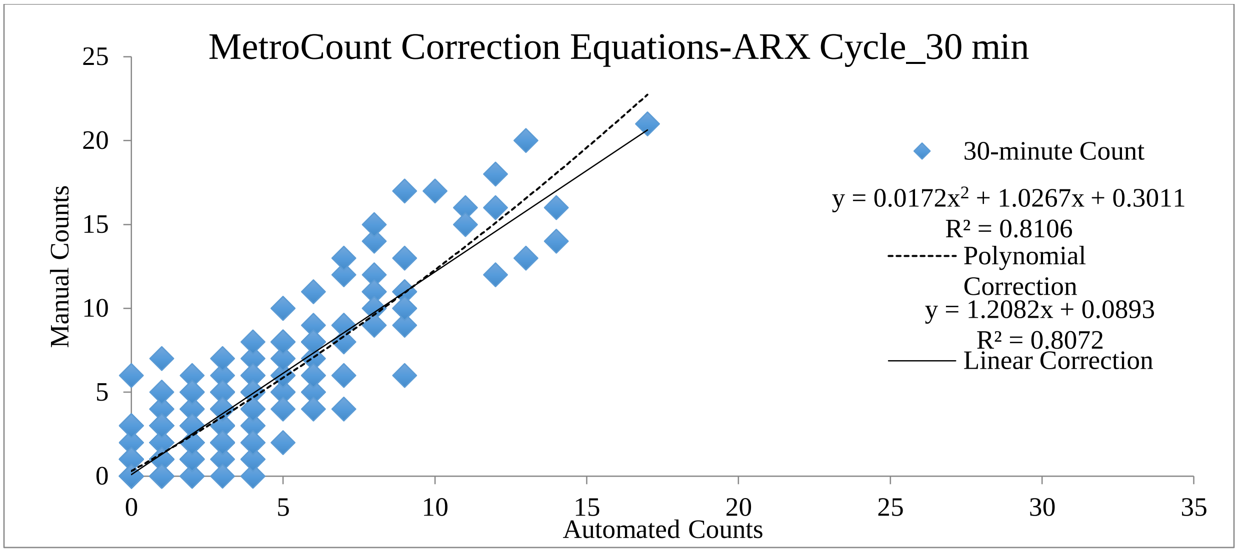
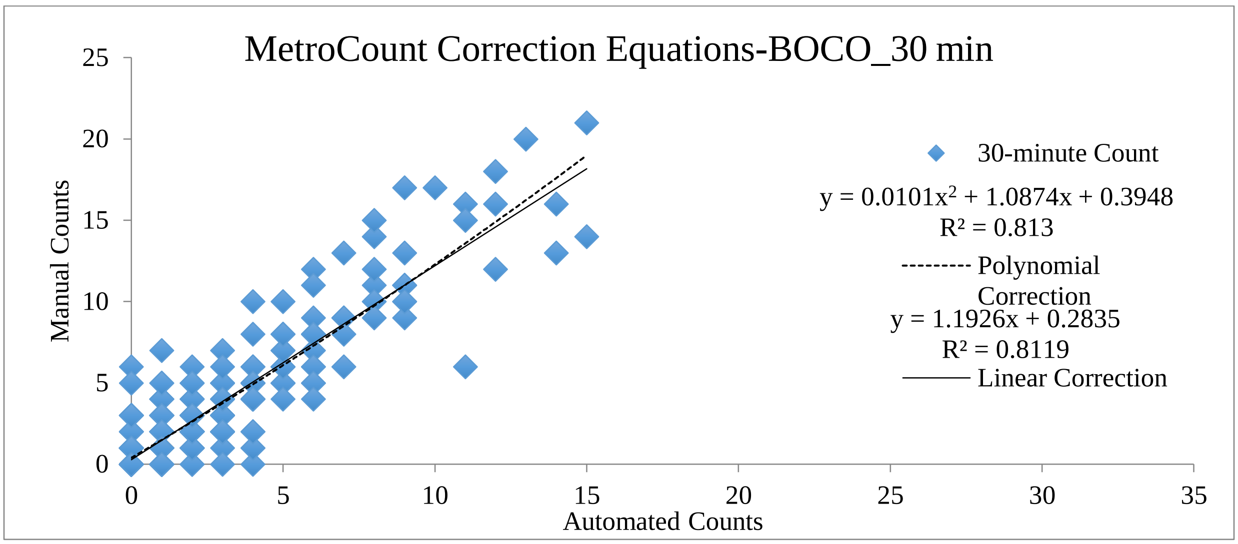


Figure 15. MetroCount correction equations-scheme comparisons_15-minute.





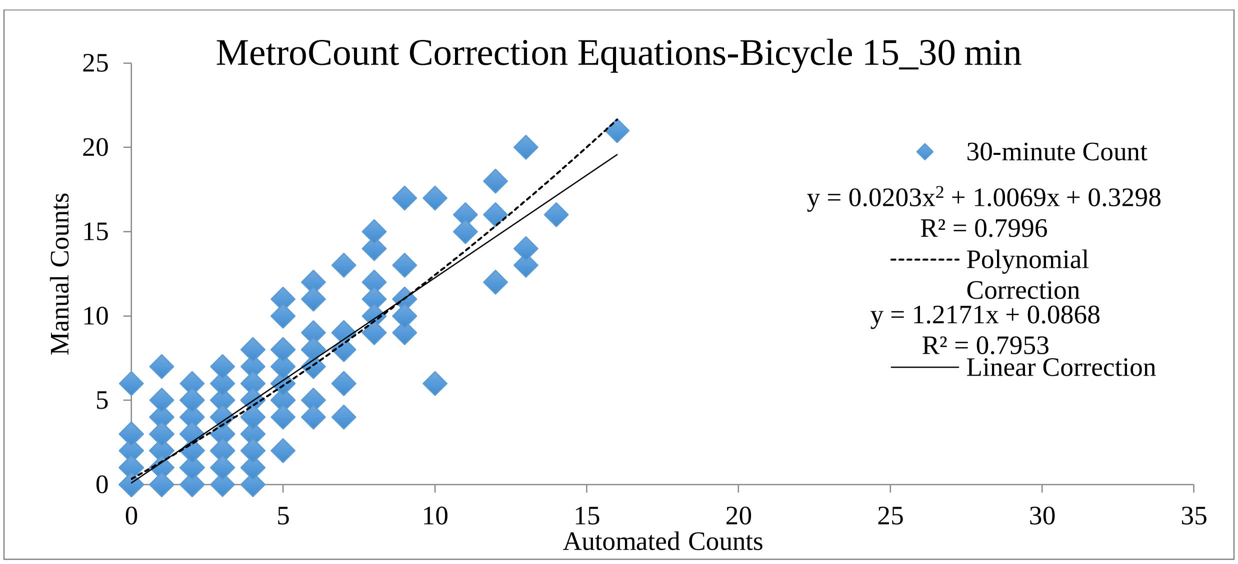


Figure 16. MetroCount correction equations-scheme comparisons_30-minute.

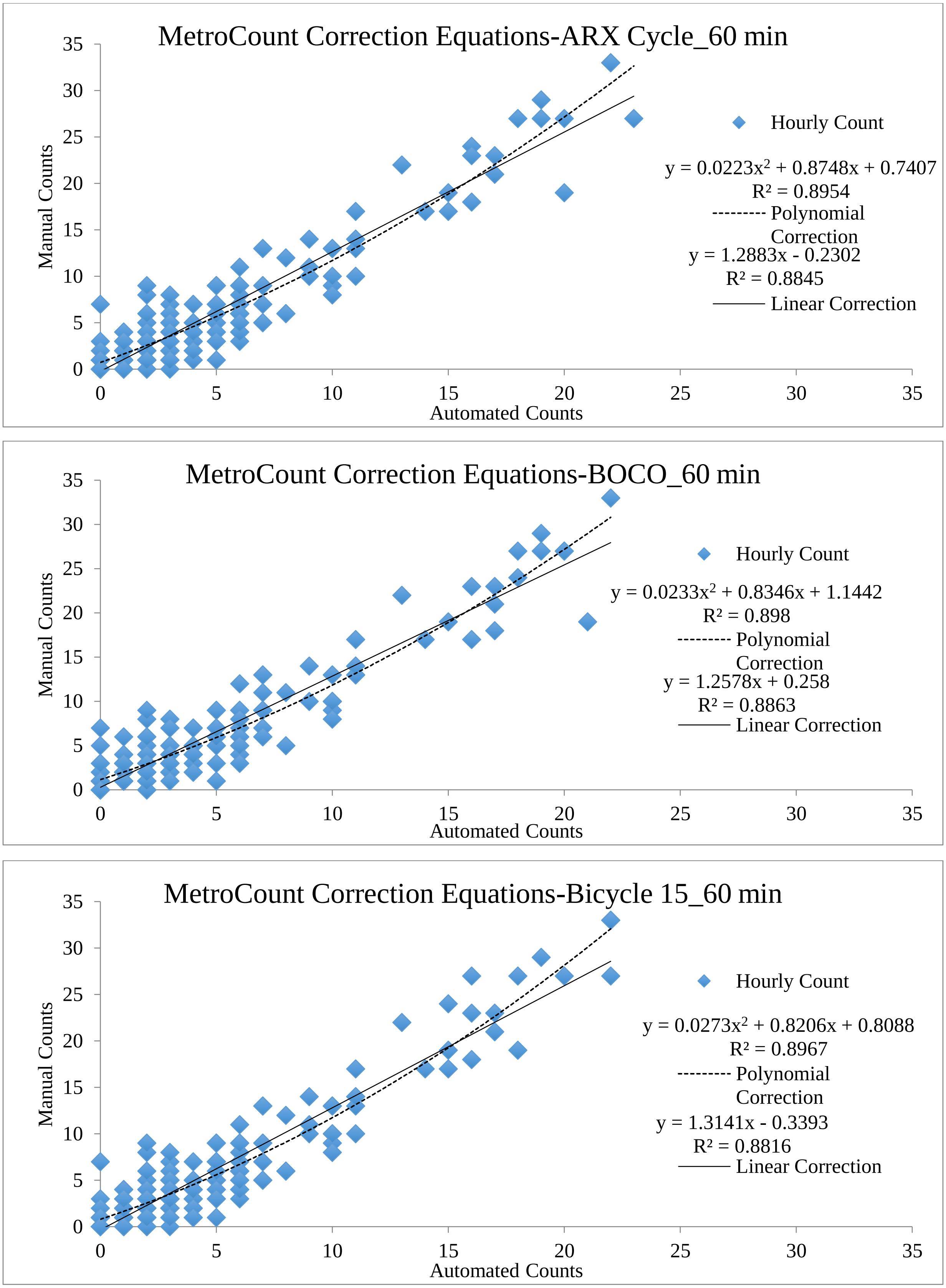


Figure 17. MetroCount correction equations-scheme comparisons_60-minute.

Table 5. Polynomial and linear correction equations for each scheme

Time Interval	ARX Cycle			BOCO			Bicycle 15		
	Polynomial Correction R^2	Linear Correction R^2	Linear Slope	Polynomial Correction R^2	Linear Correction R^2	Linear Slope	Polynomial Correction R^2	Linear Correction R^2	Linear Slope
15-minute	0.69	0.68	1.07	0.71	0.71	1.08	0.51	0.50	0.92
30-minute	0.81	0.81	1.21	0.81	0.81	1.19	0.80	0.80	1.22
60-minute	0.895	0.885	1.29	0.898	0.886	1.26	0.897	0.882	1.31

For the R^2 of polynomial and linear corrections comparisons, 60-minute time interval shows the highest value of R^2 for all three schemes (Table 5). ARX Cycle, BOCO and Bicycle 15 schemes share similar R^2 of polynomial correction equations, however, the BOCO scheme has lower linear slope (1.26) than ARX Cycle (1.29) and Bicycle 15 (1.31). In this case, the BOCO scheme is recommended, which is consistent with other similar studies (Brosnan et al., 2015; Hyde-wright, Graham, & Nordback, 2014; Nordback et al., 2015). Therefore, according to the percent error, absolute error and R^2 comparisons, I used BOCO scheme to validate bicycle traffic for hourly counts with polynomial correction equation.

3.4.2 Eco-counter correction equations

Similar to the MetroCount data I used field-based manual counts for counter validation. All of the validation counts for pedestrians were conducted at 5 locations with sidewalks (i.e., College Avenue [both sidewalks], Turner Street [both sidewalks], Country Club Drive, University City Blvd [east sidewalk] and Patrick Henry Drive [both sidewalks]).This process resulted in 274 valid hours of manual counts for use in developing correction equations.

When hourly pedestrian counts reached ~400, the correction curve demonstrated a polynomial pattern (Figure 18). This pattern supports Schneider et al. (2013) indicating that passive infrared undercounts more when pedestrian volumes increase. As such, this research applies the polynomial correction equations to adjust all the hourly counts retrieved from Eco-counter. The calculated average absolute error is 23.9%. Most likely because flow is constricted (i.e., more occlusion) when there are large volumes.

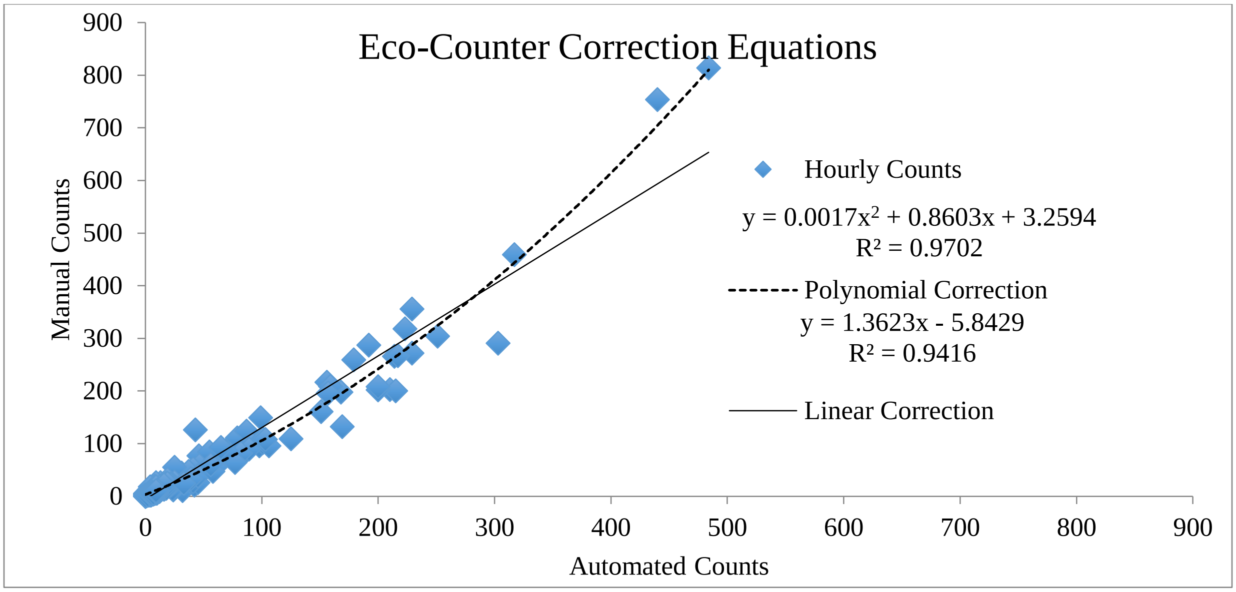


Figure 18. Eco-counter correction equations.

3.4.3 RadioBeam correction equations

I collected 29 hours of field-based manual counts at the Huckleberry Trail to validate both bicycle and pedestrian counts (Figure 19 and Figure 20). Since the count data reveals a linear pattern, I used linear equations to adjust the count data. The calculated average absolute errors for bicycles and pedestrians are 19.2% and 22.4%.

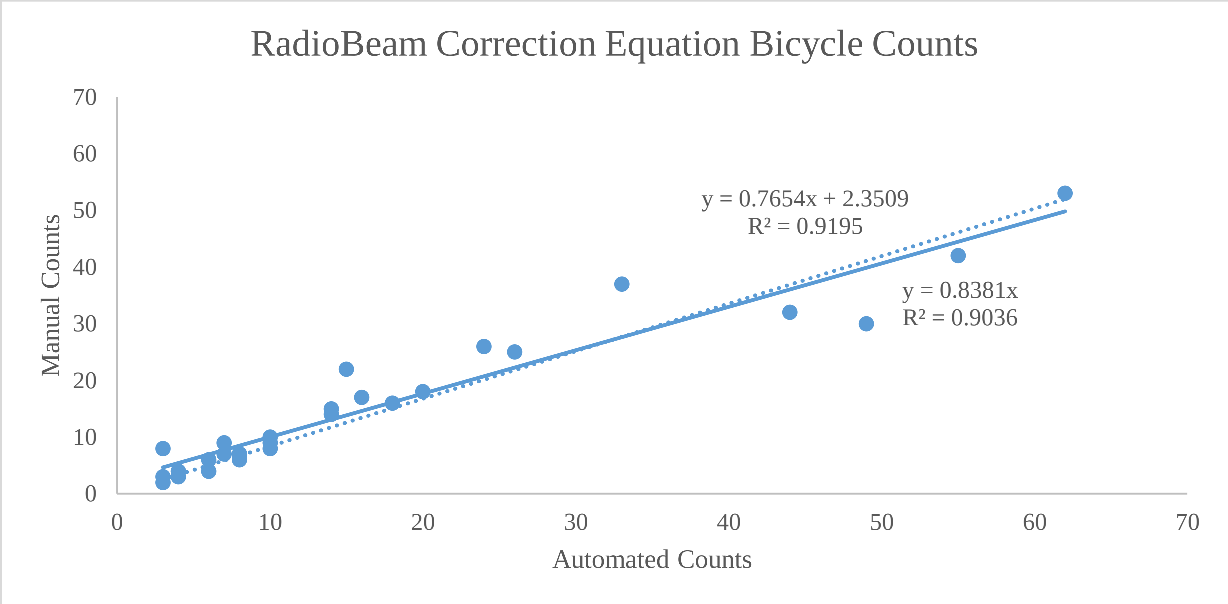


Figure 19. RadioBeam correction equation bicycle counts.

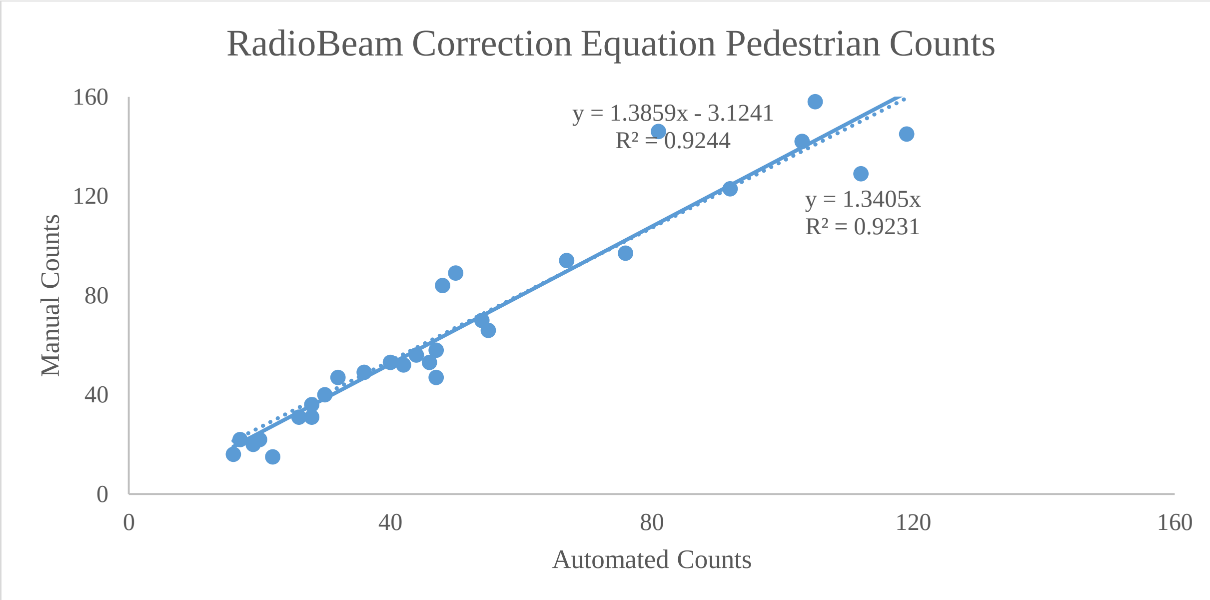


Figure 20. RadioBeam correction equation pedestrian counts.

Table 6. Comparisons of adjusted and raw counts of all counters

Counter	MetroCount		Eco-counter		RadioBeam			
Bicycle/Pedestrian	Bicycle		Pedestrian		Bicycle		Pedestrian	
Counts	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted
Results	5	6	10	12	5	6	5	4
	10	12	50	51	20	18	20	25
	20	27	400	619	50	41	150	205

Table 6 summarizes comparisons of adjusted and raw counts of all counters. The idea is to show how correction equations adjust the raw counts, and the hypothetic raw count values for each counter are selected based on each correction equation (i.e., 5, 10, 20, 50, 150 and 400). For example, MetroCount undercounts bicycles. Eco-counter undercounts pedestrians, especially when the raw count is 400, the adjusted count jumps to 619, which indicates polynomial curve when the pedestrian volume is very high. RadioBeam overcounts bicycles to some extent; however, it undercounts pedestrians.

3.5 Quality assurance and quality control

The next step was to clean the dataset and conduct quality assurance and quality control (QA/QC). This process was necessary due to some incidents that yielded gaps in count data (e.g., counter malfunction, data loss, battery loss, and counter vandalism). To justify the QA/QC process, I kept an event log of key information (e.g., battery loss, activity and events) that may influence data quality. The ultimate goal was to monitor the traffic patterns in normal cases (excluding events [i.e., activity] that may skew the final analysis; Table 7).

Two major methods were used to flag the suspicious data that should be cleaned: (1) direct cleaning based on the event log that identified suspect data and (2) statistical check based on the variability of the overall dataset. First, I flagged and censored all data (days) that have been noted in the data log. For example, there were weekly Friday afternoon concerts held at College Avenue during the summer months, which attracted a large number of people (compared with normal Fridays). Another example is battery loss or change for the RadioBeam counter at the Huckleberry Trail. Once all the data flagged from the event log were censored, I used statistical methods to flag and exclude other abnormal counts via the following process: (1) calculate the mean and standard deviation of the bicycle/pedestrian hourly counts within the monitoring period by day of week and month (i.e., calculate each parameter separately for weekend and weekday for each month), (2) flag bicycle outliers by using (mean bicycle ± 5*standard deviation) and flag pedestrian outliers by using (mean pedestrian ± 10*standard deviation), and (3) re-check the validity of flagged data and censor outlier data.

For the continuous reference sites, I summarized the valid monitoring days to show temporal coverage of the dataset (Table 8). Since some reference sites were not deployed for a full calendar year, the summary of valid percents is shown using both the calendar year (2015) and time the counter deployed as a basis. Due to an Eco-counter being stolen in September at Giles Road, only 102 valid days were monitored at that location for pedestrians. Giles Road was vulnerable to counter vandalism, so the valid pedestrian percent during counter deployed period was only 77% (102/133). Other sites had much higher percentage of valid counts for both bicycles and pedestrians: College Avenue experienced ~20 days of data loss for both bicycle and pedestrian monitoring while the Huckleberry Trail encountered 13 days of battery loss. Overall, the continuous reference sites demonstrated good temporal coverage during counter deployed (bicycles: 96%; pedestrians: 87%) and for the calendar year-2015 (bicycles: 75%; pedestrians: 87%). For short-duration sites, 98% and 94% of sites had at least 7 days of monitoring for bicycles and pedestrians, respectively; no sites experienced 5 days or less of counts (Table 9).

Table 7. Valid monitoring days of continuous reference sites

Valid monitoring days	Continuous reference sites							
	Bicycle				Pedestrian			
Sites	Draper	College	Giles	Huckleberry	Draper	College	Giles	Huckleberry
Valid days of calendar year (2015)	257/365	247/365	246/365	350/365	263/365	229/365	102/365	336/365
Valid percent of calendar year (2015)	70%	68%	67%	96%	72%	63%	28%	92%
Valid days during counter deployed	257/257	247/275	246/257	350/365	263/275	229/275	102/133	336/365
Valid percent during counter deployed	100%	90%	96%	96%	96%	83%	77%	92%
Short-duration count period	200							
Flagged data	N/A	No data retrieved; suspicious vehicle data	No data retrieved; abrupt bicycle change	No data retrieved; no battery	Abrupt bicycle change	No data retrieved; abrupt bicycle change	counter moved or vandalized	No data retrieved; no battery

Table 8. Total flagged days of continuous reference sites

Flagged days	Continuous reference sites							
	Bicycle				Pedestrian			
Sites	Draper	College	Giles	Huckleberry	Draper	College	Giles	Huckleberry
Counter malfunction/full data logger	0	22	8	2	0	18	0	1
No battery	0	0	0	13	0	0	0	13
Activity[5]	0	0	0	0	0	13	0	0
Road block	0	2	0	0	0	0	0	0
Counter move/vandalism	0	0	0	0	0	0	27	0
Statistical outlier	0	4	3	0	12	15	4	15
Total flagged days	0	28	11	15	12	46	31	29

Table 9. Valid monitoring days of short-duration sites

Valid monitoring days	Short-duration sites	
	Bicycle	Pedestrian
5 days or less	0.0%	0.0%
less than 7 days	2.1%	6.0%
7 days	75%	70%
7 days to 10 days	13%	15%
More than 10 days	11%	9.0%

[5] The activity means specifically the concert activities on Fridays during summer, which affects the pedestrian traffic.

4 ANALYSIS AND DISCUSSION OF TRAFFIC PATTERNS

4.1 Continuous reference sites

I analyzed the average daily traffic, mode share, weekend to weekday traffic ratio and hourly traffic patterns for all continuous reference sites. The goal is to illustrate seasonal, daily, and hourly traffic patterns for bicycles and pedestrians.

4.1.1 Average daily traffic and mode share

Here, I present the average daily traffic (adjusted using the correction equations from Chapter 3) and mode share to demonstrate the traffic patterns by month and mode share between bicycles and pedestrians. From February to August, the average daily bicycle volume increases gradually at the Huckleberry Trail and peaks approximately at 300 cyclists per day (Figure 21). The volume drops to ~100 cyclists per day from August to December. Bicycle traffic in February is lower than in January, which can be attributed to several days of heavy snow that obstructed cyclists. Draper Road decreases after May throughout the whole year. Both College Avenue and Giles Road increase from July to September and decrease gradually to December.

The average daily pedestrian volume is extremely high on College Avenue (~6,000 people per day), which decreases after April partly due to students leaving campus, and stabilizes from August when university is in session (Figure 22). Huckleberry Trail peaks at ~700 people per day in September, and increases ~200 people per day in March from January and February, which can be explained by warm weather in March and cold weather in January and February. Draper Road experiences two peaks in May and September. While on Giles Road, the volume plunges from April to July, and rises up to ~200 people per day in August (Giles Road stopped retrieving pedestrian data after September due to stolen Eco-counter).

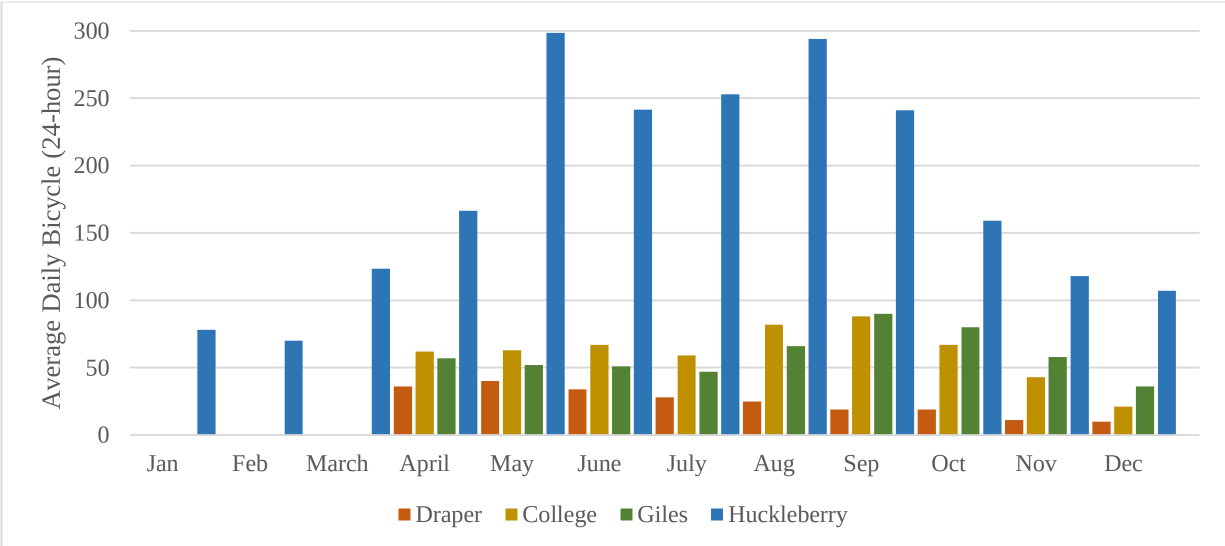


Figure 21. Average daily bicycle volume (24-hour) by month for continuous reference sites.

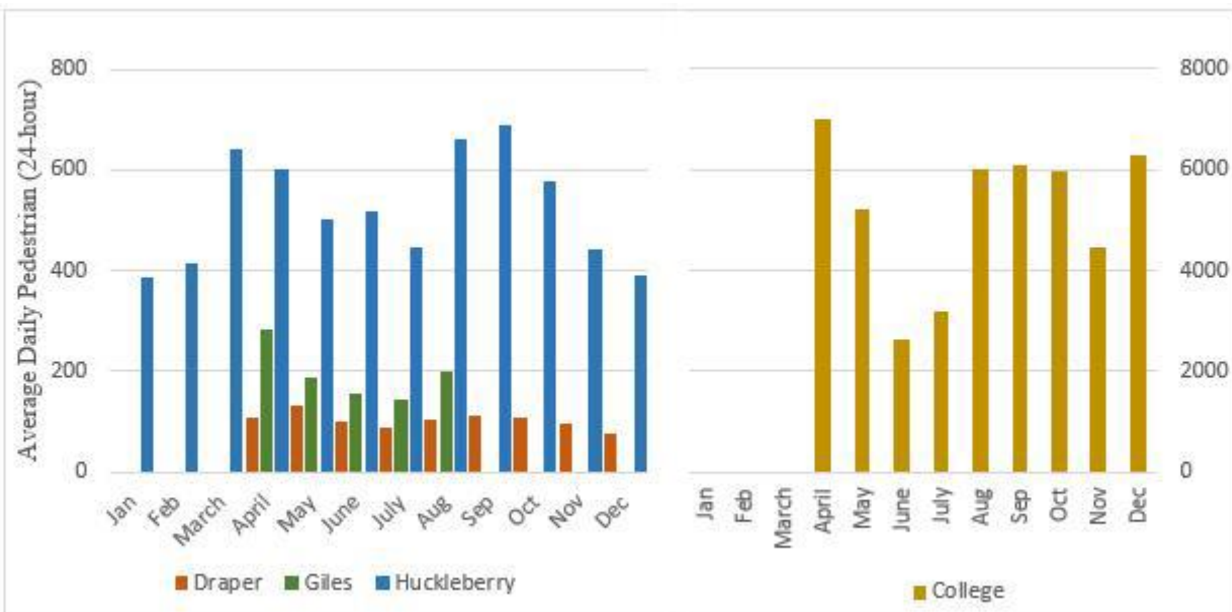


Figure 22. Average daily pedestrian volume (24-hour) by month for continuous reference sites.

The Huckleberry Trail location reveals a gradual increase of bicycle mode share until May, and all other sites gradually increase until June. All sites show decreasing bicycle share after July. Huckleberry jumps from 14.5% (February) to 37.2% (May), which may be explained by warm weather conditions for cyclists to use the trail. Huckleberry attracts an average of 24.6% bicycle share, and College Avenue has 98.7% pedestrian share (Figure 23 and Figure 24).

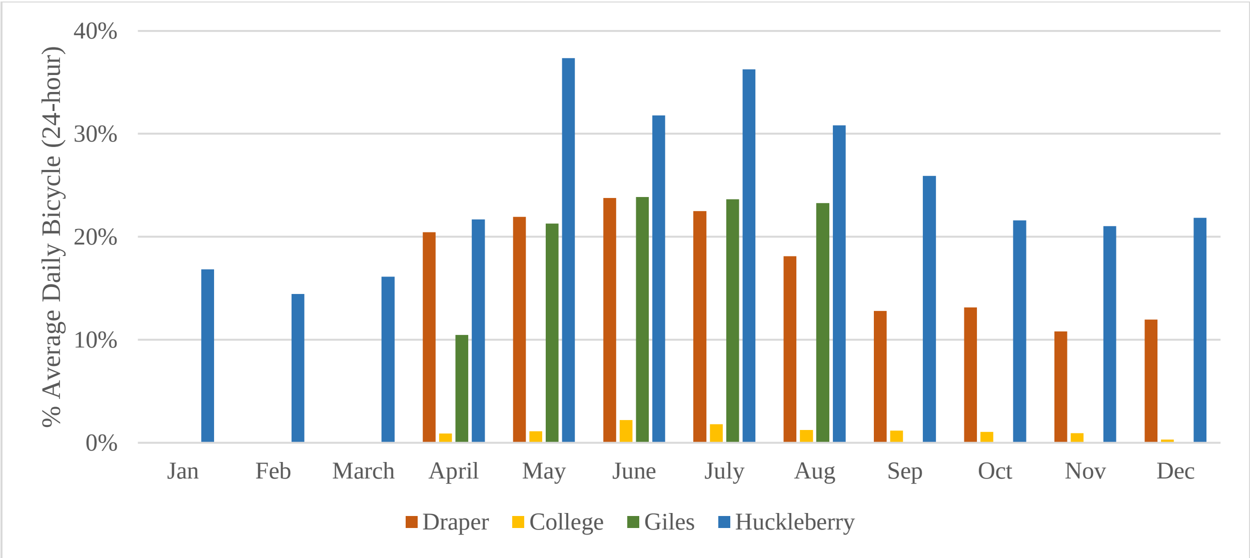


Figure 23. Percent Average Daily Bicycle volume by month for continuous reference sites.

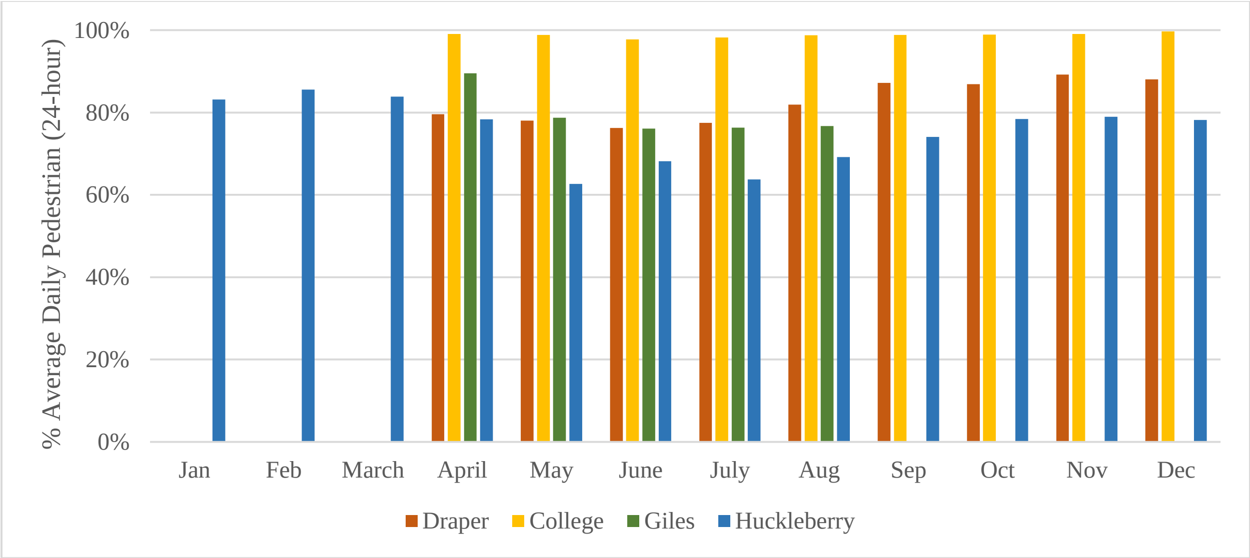


Figure 24. Percent Average Daily Bicycle volume by month for continuous reference sites.

Table 10. Descriptive statistics of average daily bicycle and pedestrian traffic volumes for the continuous reference sites

Mode	Site	Observations (days)	Mean	Median	IQR[6]	Standard Deviation
Bicycle	Draper	257	24	24	18	14
	College	247	62	62	36	30
	Giles	246	59	52	35	34
	Huckleberry	350	177	174	173	99
Pedestrian	Draper	263	103	96	47	41
	College	225	4,424	4,120	3,154	2,115
	Giles	102	168	156	45	51
	Huckleberry	336	514	502	321	244

[6] IQR (Interquartile Range) is a measurement of variability, based on dividing a data into quartiles. IQR = Q_3-Q_1 (Q_3=75th percentile, Q_1=25th percentile).

4.1.2 Weekend to weekday ratio

I summarized the daily average weekend to weekday count ratios (i.e., daily average weekend traffic divided by daily average weekday traffic) at each continuous reference site by month. These ratios are interpreted as follows: ratios greater than 1 indicate that the site would be more likely recreational users (i.e., daily average weekend traffic exceeds daily average weekday traffic) while ratios less than 1 may indicate more likelihood for commute users. However, there are still some commute users on weekends at sites with recreational pattern, and recreational users on weekdays at sites with commute pattern.

For bicycles on Giles Road, College Avenue, and Draper Road, the ratios are below 1, which suggests a commute pattern. Huckleberry Trail shows three ratio peaks in February, August and December; while Giles reveals the similar patterns with two ratio peaks in July and December (Figure 25).

For pedestrians, Draper Road maintains commute patterns from May to December, Giles Road also reveals commute patterns during May to July, and College Avenue indicates a recreational pattern from April to August. The Huckleberry Trail has a ratio above 1.2 during some months (except August to November), which shows a typical recreational pattern of use. From January to February, the ratio increases by 0.5, demonstrating stronger recreational pattern (Figure 26). Details of the daily average weekend to weekday bicycle and pedestrian ratio for continuous reference sites are shown in Table 26 (Appendix B).

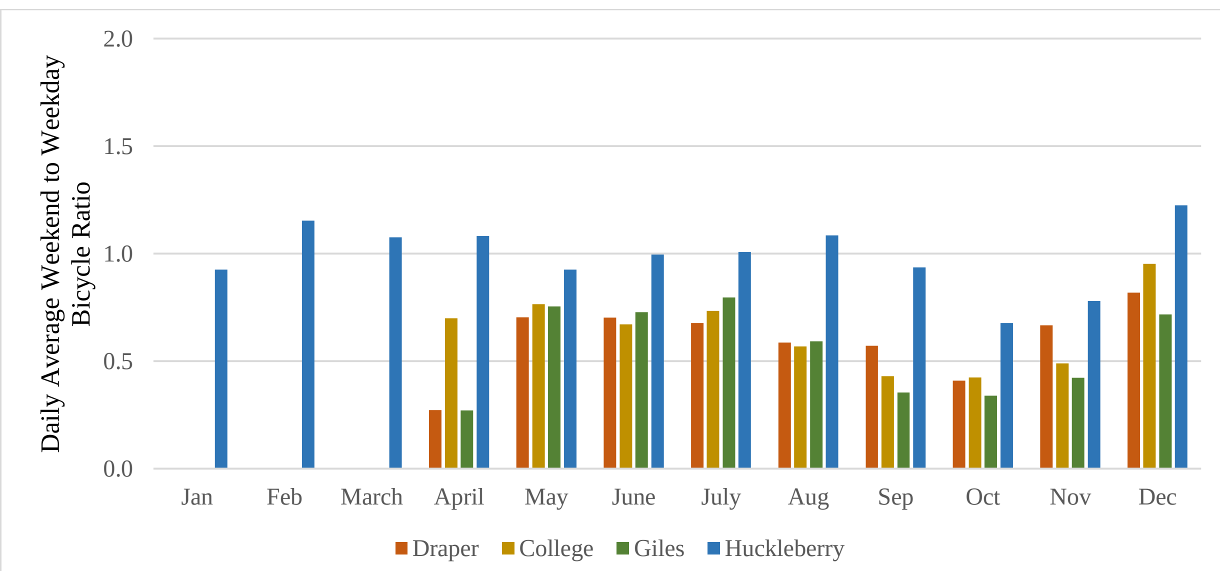


Figure 25. Continuous reference sites daily average weekend to weekday bicycle ratio.

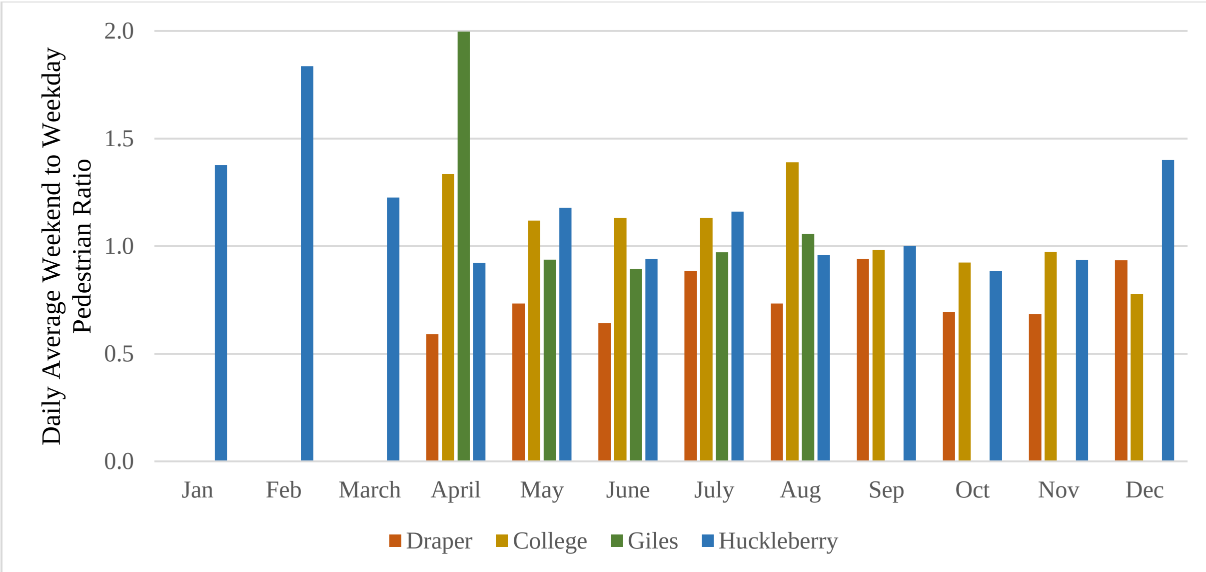


Figure 26. Continuous reference sites daily average weekend to weekday pedestrian ratio[7].

4.1.3 Hourly traffic patterns

Figure 27 and Figure 28 display the hourly traffic patterns of the continuous reference sites. For bicycle hourly patterns on weekends, Draper Road generally increases from 6:00 a.m. to 11:00 a.m., and drops down later the day. College Avenue and Giles Road share roughly similar pattern during the middle of the day (6:00 a.m. to 6:00 p.m.) with a bell-shape curve. The Huckleberry Trail presents a very strong recreational pattern and reaches the 12% peak at around 4:00 p.m. While on weekdays, College Avenue and Giles Road show a commute pattern in the morning, but with lower volumes in the afternoon on College Avenue. Draper Road and Huckleberry show mixed recreational and commute use with peak hour at around 5:00 p.m.

For pedestrian hourly traffic patterns on weekends, Giles Road experiences a high ratio (~5.2%) during late night hours, and College Avenue doubles that ratio (~10.7%) presumably due to proximity to bars and restaurants around downtown. The Huckleberry Trail shows a mixed pattern with peak ratio at 10% around 10:00 a.m. and 4:00 p.m. While on weekdays, Giles Road indicates slight commute pattern, and Draper Road and Huckleberry Trail display recreational pattern. However, College Avenue peaks at 12% at 12:00 p.m., which may be explained by a lunch time rush-hour. Details of the weekend and weekday average hourly volume at each site are shown in Figure 50-Figure 53 (appendix B).

[7] Neither Giles Road nor Draper Road has a full month dataset of April. Pedestrian data from September at Giles Road is not available due to stolen Eco-counter.

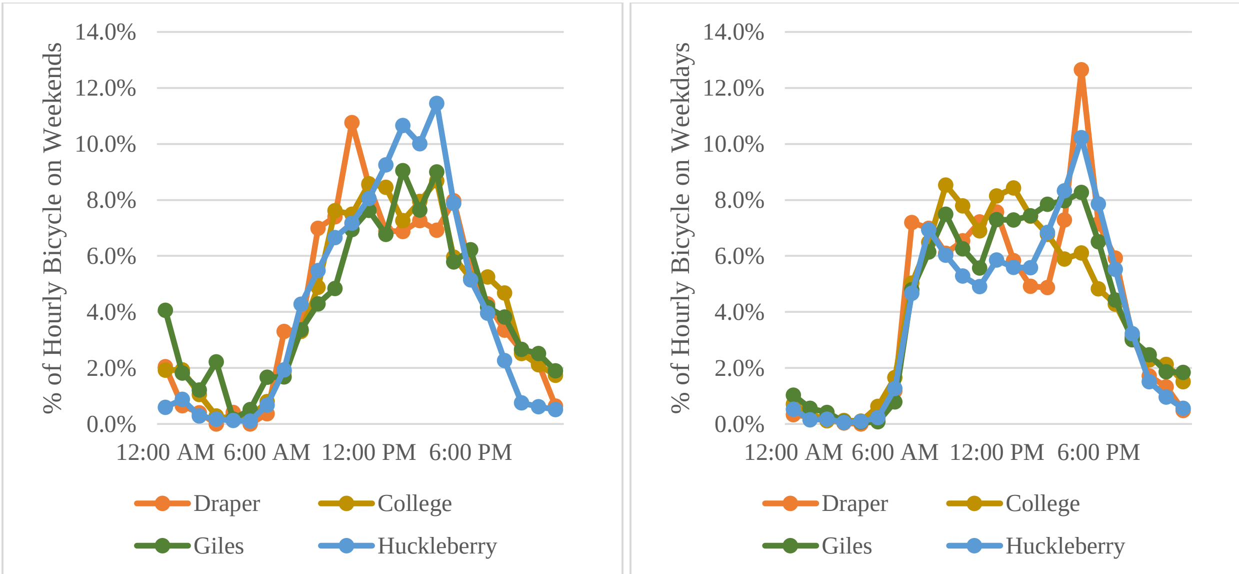


Figure 27. Continuous reference sites average weekend and weekday hourly bicycle ratio.

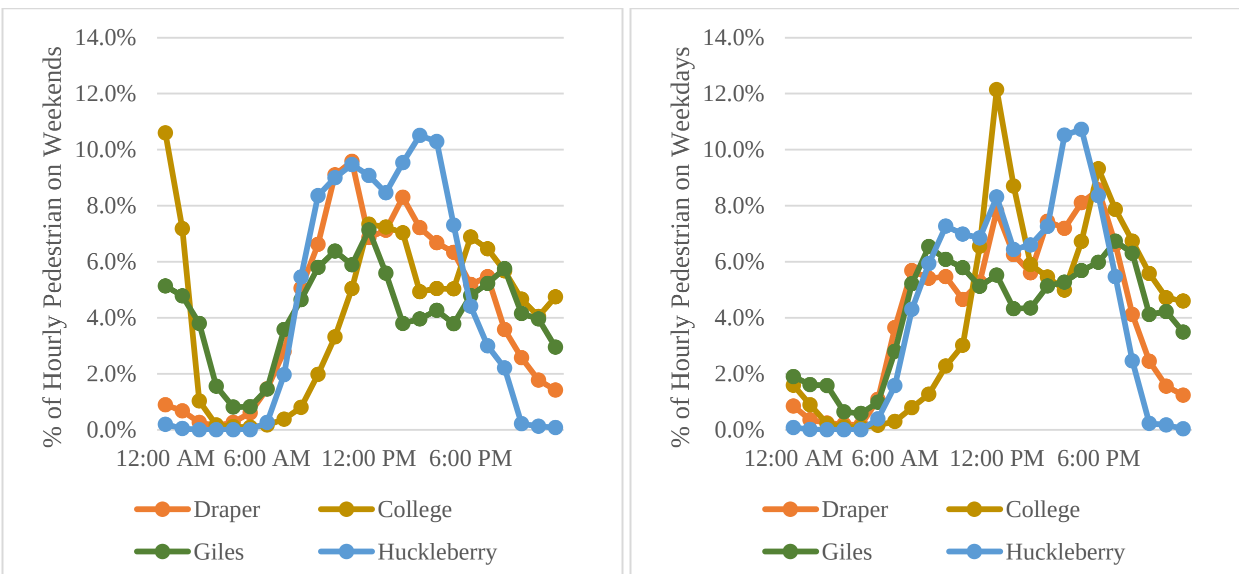


Figure 28. Continuous reference sites average weekend and weekday hourly pedestrian ratio.

4.2 Short-duration sites

4.2.1 Factor groups

Based on the metrics used by Miranda-Moreno et al. (2013) and Hankey et al. (2014), I use similar methods to classify all short-duration sites into potential factor groups. The purpose is to categorize the short-duration sites into factor groups (i.e., commute, recreational and mixed patterns) to generate scaling factors by location type. The factor groups are normally used for corresponding continuous reference sites with the same patterns to apply scaling factors (details of scaling factors will be introduced later in this Chapter). For example, continuous reference sites labeled as commute pattern only serve to scale short-duration sites with the commute pattern. However, due to limitations of the number (n=4) of continuous reference sites, this research will not separately apply scaling factors based on different factor groups. Instead, all reference sites will be pooled to estimate scaling factors to scale all short-duration sites. The factor groups of short-duration sites here serve as reference information for future research.

To categorize count sites into factor groups, two indices are introduced: (1) relative index of weekend vs. weekday traffic (WWI) and (2) relative index of morning (7:00 a.m. to 9:00 a.m.) to midday (11:00 a.m. to 1:00 p.m.) traffic (AMI) for weekdays. Miranda-Moreno et al. (2013) derived four classifications: (1) utilitarian, (2) mixed-utilitarian, (3) mixed-recreational, and (4) recreational. To simplify this process, I define only three factor groups: Commute, Recreation, and Mixed (Table 11). The goal is to calculate WWI and AMI for each site and classify them into factor groups.

$$WWI = \frac{Average\ Weekend\ Traffic}{Average\ Weekday\ Traffic} \qquad \text{Equation 3}$$

$$AMI = \frac{Average\ Weekday\ Traffic\ from\ 7\ a.m.\ to\ 9\ a.m.}{Average\ Weekday\ Traffic\ from\ 11\ a.m. to\ 1\ p.m.} \qquad \text{Equation 4}$$

Table 11. Factor groups definitions

Travel Pattern	**WWI and AMI**
Commute	WWI ≤ 1.0 AMI > 1.0
Recreation	WWI > 1.0 AMI ≤ 1.0
Mixed	Other

I generated box plots to display the distribution of bicycle and pedestrian WWI and AMI among the short-duration sites based on 5 number summary: 5th percentile, 25th percentile, 50th percentile, 75th percentile, and 95th percentile. The commute pattern shows lower WWI and higher AMI, while the recreation pattern presents higher WWI and lower AMI, and the mixed pattern is in the middle. The box plots show exactly this pattern for both bicycles and pedestrians (Figure 29 and Figure 30). To explain the distribution of the travel patterns across Blacksburg, VA, I mapped the factor groups for bicycles and pedestrians (Figure 31). Most sites demonstrate a mixed pattern for bicycles and pedestrians, which indicates that these sites reveal no dominant (i.e., recreational or commute) traffic pattern. Due to zero count values during some periods of time (i.e., weekend/weekday, morning/midday traffic), some sites are not mapped (n=12).

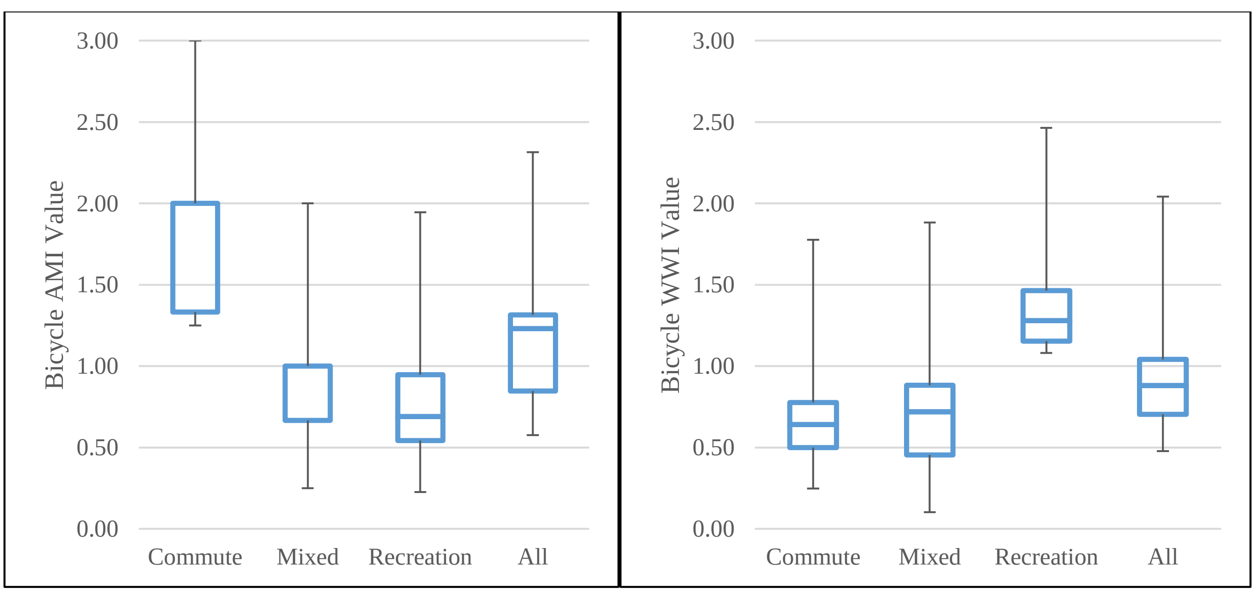


Figure 29. Bicycle WWI and AMI box plot for short-duration sites.

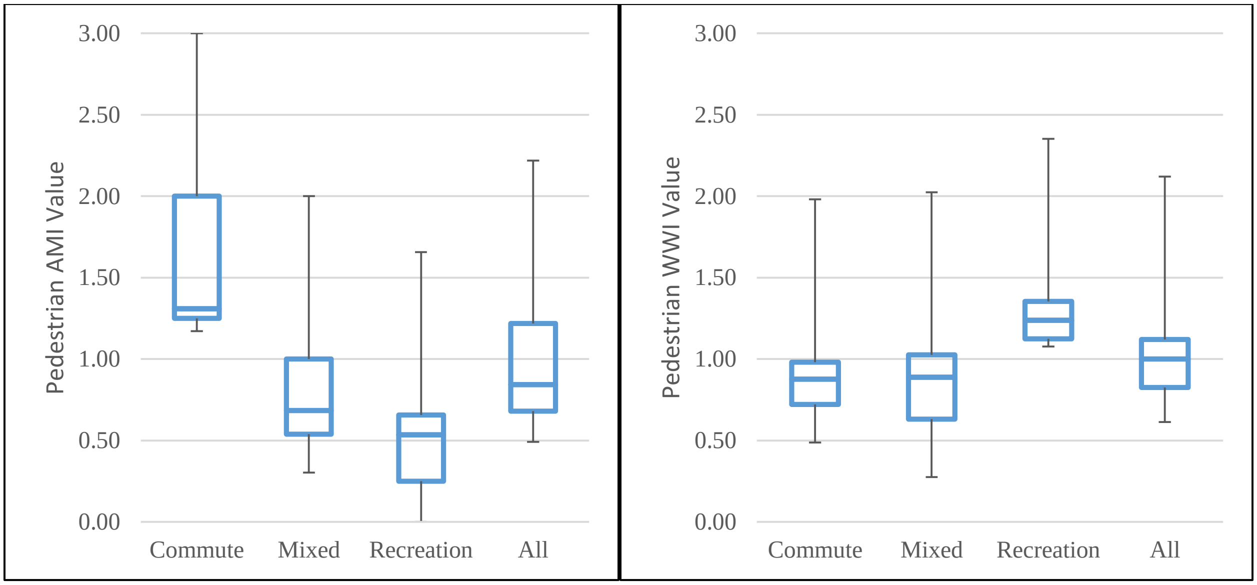


Figure 30. Pedestrian WWI and AMI box plot for short-duration sites.

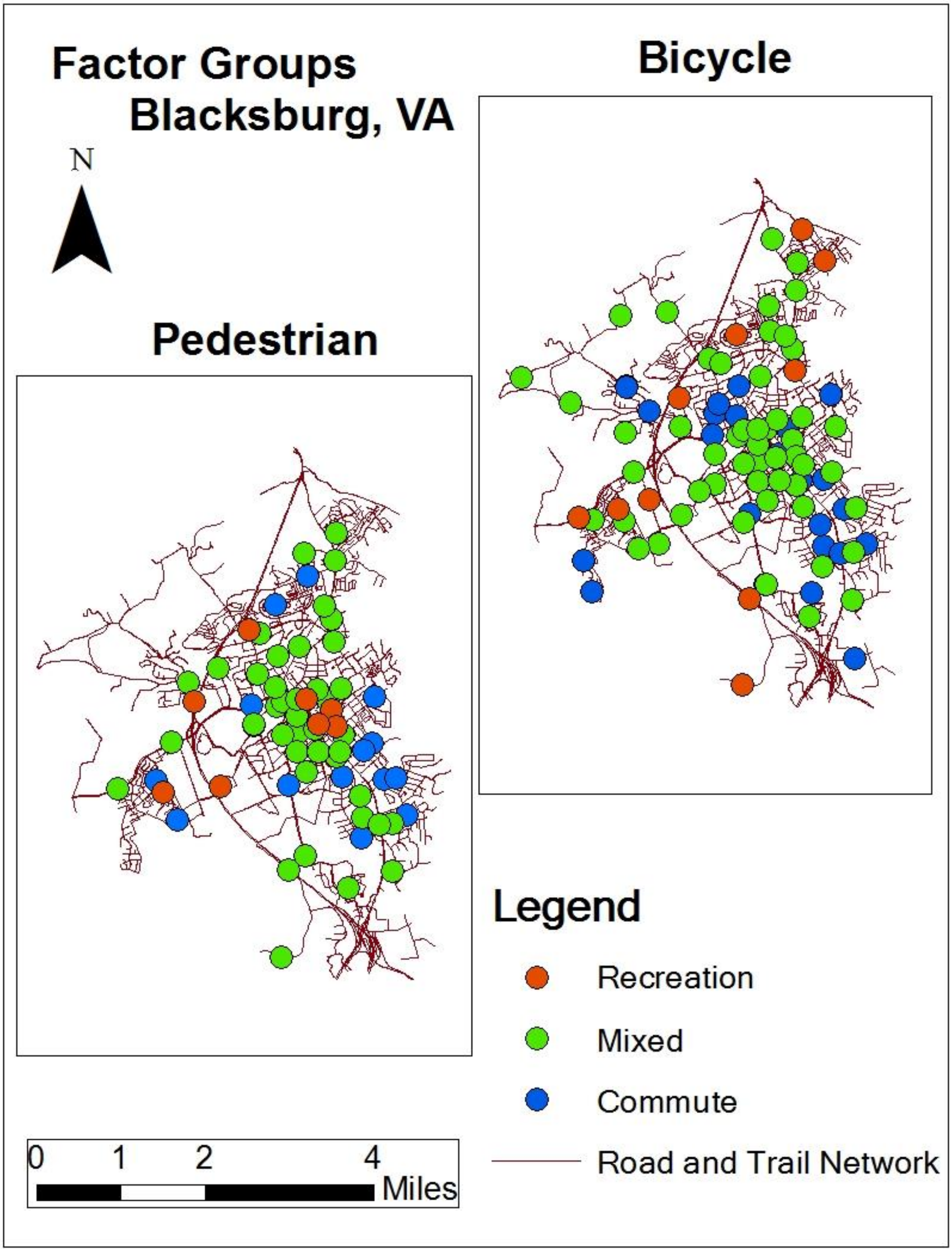


Figure 31. Factor groups (i.e., commute, recreational, and mixed) of traffic count sites in Blacksburg, VA.

4.2.2 Weekend and weekday traffic patterns

To further explore the bicycle and pedestrian traffic patterns for short-duration sites on weekends and weekdays, I plotted the average hourly traffic patterns for all of the short-duration sites that are classified by the three factor groups (i.e., commute, mixed, recreation). For weekend bicycle patterns, recreation pattern presents a 12% peak in the afternoon, and mixed pattern is a bell-shaped curve. For weekday bicycle traffic, the commute locations show the typical two peaks in the morning and afternoon (morning peak is higher than the afternoon); recreation locations show a 10% peak in the afternoon, which matches with the expected recreational pattern (Figure 32).

For weekend pedestrian traffic, recreation locations demonstrate two peaks at 11:00 a.m. and 8:00 p.m. For weekday pedestrian traffic, commute locations show the typical two peaks in the morning and afternoon; recreation locations show an afternoon peak at around 8% of the daily pedestrian traffic (Figure 33).

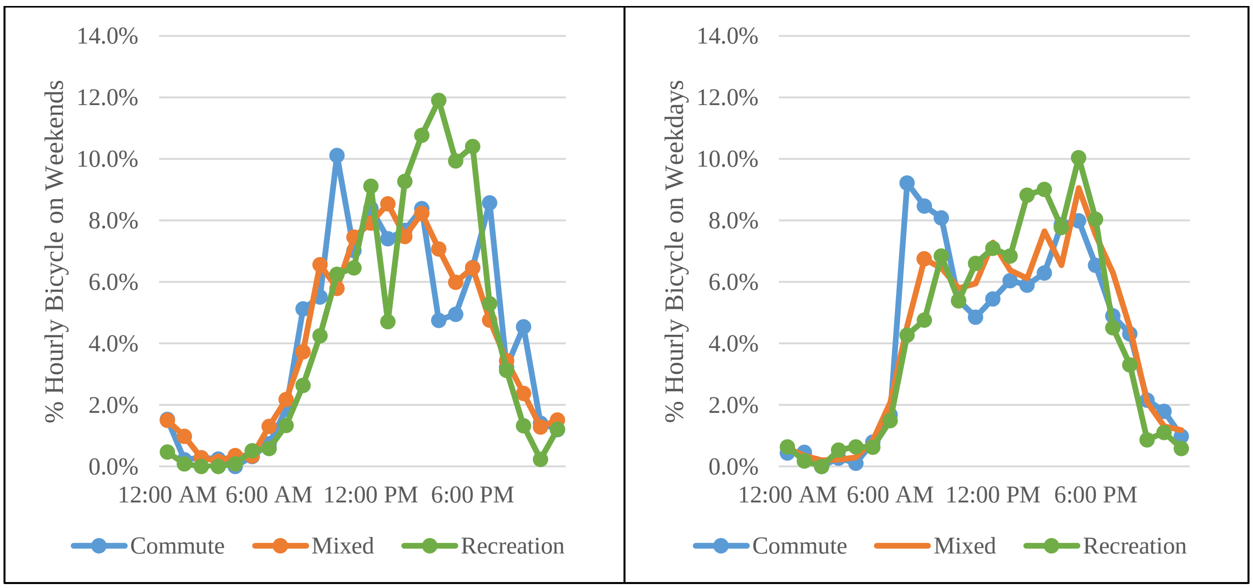


Figure 32. Short-duration sites average weekend and weekday hourly bicycle ratio.

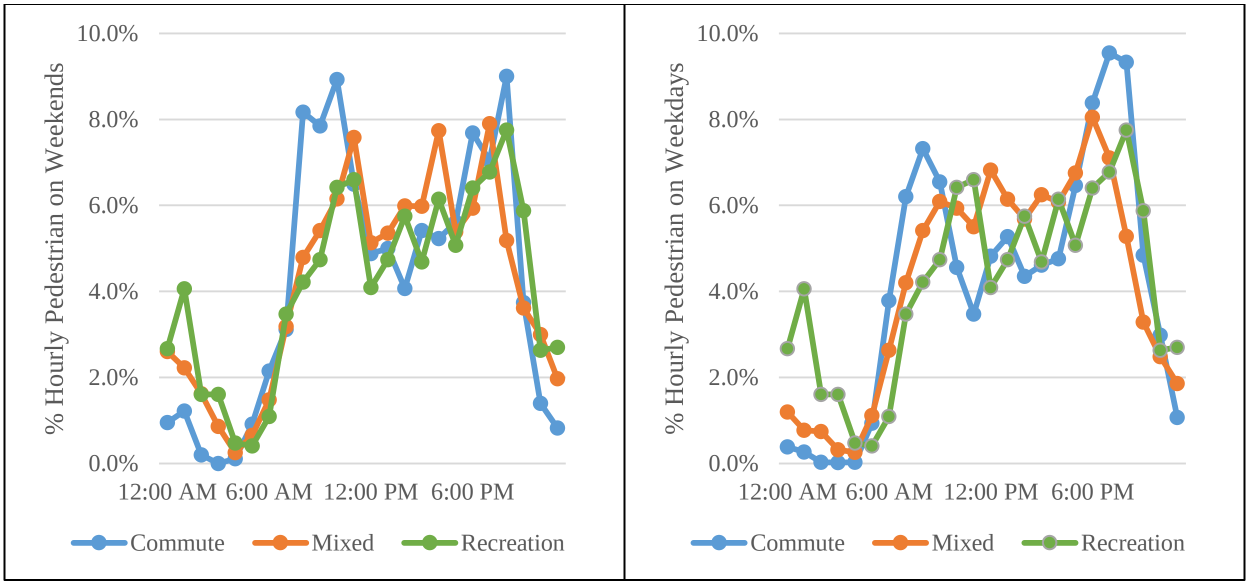


Figure 33. Short-duration sites average weekend and weekday hourly pedestrian ratio.

4.2.3 Traffic patterns by road and street type

Descriptive statistics of average daily bicycle and pedestrian traffic for the short-duration sites is shown in Table 12.

Table 12. Descriptive statistics of average daily bicycle and pedestrian for short-duration sites

		Observations (sites)	Mean	Median	IQR	Standard Deviation
Bicycle	Total	97	46	31	39	58
	Major Road	29	37	33	31	18
	Local Road	48	38	22	33	51
	Off-street Trail	20	79	42	102	92
Pedestrian	Total	68	306	124	158	670
	Major Road	24	198	156	138	151
	Local Road	24	593	161	423	1066
	Off-street Trail	20	92	50	136	108

To further divide the factor groups by road/trail type, I also generated bar charts to analyze number of sites showing the relevant factor groups (Figure 34). Bicycles on local roads present the largest proportion among all road/trail types in commute pattern or mixed pattern, which may due to the suitable environment for cycling (e.g., low vehicle volumes, fewer traffic lights). A similar pattern is shown for pedestrians; pedestrians on local roads demonstrate the largest proportion in commute pattern, however, major roads also serve similar proportion with local roads in mixed pattern, which may be explained by available sidewalk facilities.

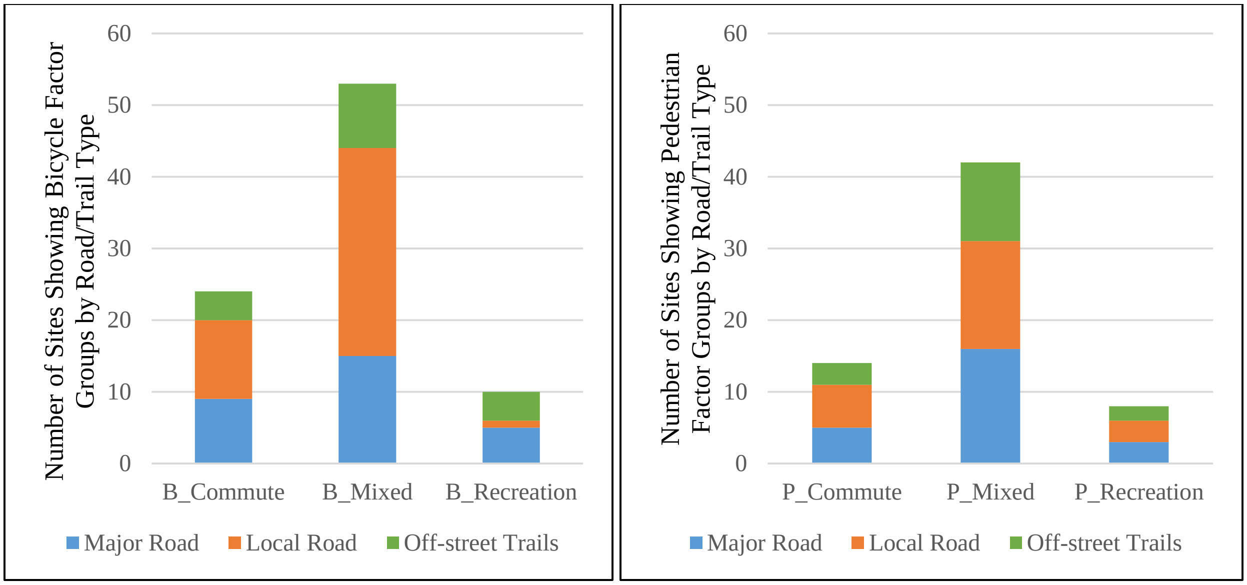


Figure 34. Bicycle and pedestrian factor groups by road and street type.

4.3 Imputing missing days and estimating AADT for the continuous reference sites

Apart from understanding the traffic patterns of all sites, another important outcome of this research is to estimate performance measures (e.g., AADT). Figure 35 shows the flow chart of estimating AADT. As mentioned earlier, the idea is to (1) use observed dataset from continuous reference sites to impute missing data by negative binomial regression models, (2) combine observed and estimated dataset to estimate AADT for continuous reference sites, and (3) use average day-of-year scaling factors extrapolated from AADT and observed dataset at continuous reference sites, and estimate AADT for short-duration sites.

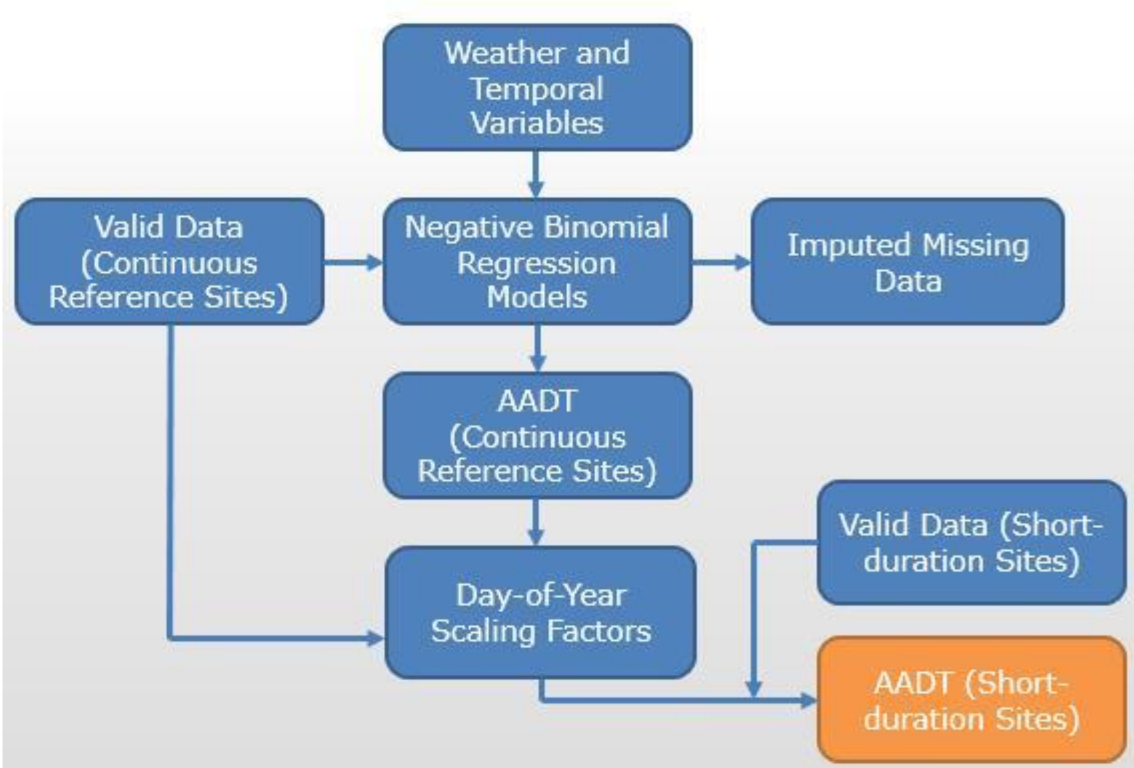


Figure 35. Flow chart of estimating AADT.

In this part, this research first estimates AADT for the continuous reference sites. Previous research indicates that negative binomial regression models outperform ordinary least squares regression for imputing missing count days (Wang et al., 2014; Lindsey et al., 2013; Cao et al., 2006; Kim & Susilo, 2013). Therefore, I used negative binomial regression models to impute missing days and estimate AADT for bicycles and pedestrians at all 4 continuous reference sites in Blacksburg, VA. Also, I compared the model estimates with observed (automated) counts and calculated scaling factors to estimate AADT for all short-duration count sites.

4.3.1 Negative binomial regression models

Normally, negative binomial regression takes into account the issue of overdispersion in the data (variance exceeds the mean), and it is appropriate to use when the data is a non-negative integer (e.g., counts). If overdispersion is not an issue, then a Poisson regression may be appropriate. The probability of y is expressed as follows:

$$P(y = m|\lambda, x_1, x_2 \cdots) = \frac{e^{-\lambda}\lambda^m}{m!} \qquad \text{Equation 5}$$

I used a type 2 negative binomial regression (Cameron, Trivedi, Journal, Jan, & Cameron, 2016), which assumes that the mean is λ, and the variance is $\lambda + \alpha \lambda^2$. Maximum likelihood estimation (MLE) is used in the STATA package to estimate the parameters as follows in this research:

$$ln\, \lambda = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \qquad \text{Equation 6}$$

With the estimated parameters, *y* can be estimated as:

$$E\,(y\ / x_1, x_2, \cdots) = \hat{\lambda} = exp\,(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots) \qquad \text{Equation 7}$$

However, the MLE does not have traditional R^2 to evaluate goodness-of-fit due to the nonlinear form of the negative binomial regression. Instead, McFadden's Pseudo-R^2 (from 0 to 1) is introduced to be consistent with previous literature:

$$R^2_{McFadden} = 1 - \frac{ln(L_{Full})}{ln(L_{Intercept})} \qquad \text{Equation 8}$$

Where L_{Full} denotes the estimated likelihood value from the model with predictors, and $L_{Intercept}$ denotes the corresponding value from the model without predictors. McFadden's Pseudo-R^2 represents a proportional reduction in "error variance" (Allison, 2014).

I developed 8 site-specific negative binomial regression models to estimate both the bicycle and pedestrian traffic on each day (year-2015) for each continuous reference site. The models incorporate weather and temporal variables (e.g., max temperature, precipitation, and wind speed). All the models are estimated using STATA 14 (StataCorp LP, College Station, Texas) and its extension, SPost 9 (Long & Freese, 2006).

The following weather variables are used during model-building (Table 13): *tmax* denotes the daily max temperature in Blacksburg, VA, which is expected to promote bicycle and pedestrian activities except under extremely high temperatures. *Tmaxdev* describes the daily variation compared to the normal 30 years' averages (1980-2010) with either positive or negative signs. *Precipitation* is treated as a natural barrier for outdoor activities with a negative sign. All data were retrieved from the national Climate Data Center of the national Oceanic and Atmospheric Administration (NOAA). *Windspeed* generally reduces the preference to bike or walk, and the data was retrieved from the national Weather Service Forecast Office. Since Virginia Tech is expected to influence the traffic volumes, I incorporated dummy variables (i.e., *weekend* and *university in session*) into the analysis. *Weekend* indicates whether it was weekend (1) or weekday (0); and *university in session* denotes whether the university was in session (1) or not (0).

Variables	Definition	Mean	Expected signs
tmaxdev	High temperature deviation from the 30-year (1980-2010) temperature	0.91	+/-
tmax	Recorded high temperature (Celsius)	18	+
precipitation	Precipitation (mm)	3.4	-
windspeed	Average wind speed (mph)	4.3	-
weekend	Saturday or Sunday (equals 1, otherwise 0)	0.29	+/-
university in session	University in session (equals 1, otherwise 0)	0.44	+

Table 13. Selected variables for bicycle and pedestrian models and expected signs

Table 14. Negative binomial regression results of the bicycle and pedestrian models

	Bicycle Model				Pedestrian Model			
	Draper	College	Giles	Huckleberry	Draper	College	Giles	Huckleberry
Observation	257	247	246	350	263	225	102	336
Pseudo R^2	0.067	0.11	0.12	0.082	0.026	0.031	0.055	0.022
Constant	1.9	2.6	3.01	4.03	4.2	7.4	6.05	5.5
Weather and temporal variables								
tmaxdev	-0.052***	-0.051***	-0.030***	-0.021***	-0.017***	-0.0054	0.017*	-0.0064
tmax	0.062***	0.062***	0.038***	0.059***	0.021***	0.018***	-0.036***	0.030***
precipitation	-0.0081***	-0.0031	-0.0064***	-0.0080***	-0.0035*	-0.0015	-0.0018	-0.0044*
windspeed	-0.0069	-0.020	-0.039***	-0.028***	-0.0028	0.0085	-0.019*	-0.018*
weekend	-0.36***	-0.097*	-0.090*	0.11**	-0.14***	0.62***	0.64	0.41***
university in session	0.22***	0.66***	0.92***	0.18***	0.21***	0.83***	0.25***	0.38***

Note: dispersion factor *p* of each model is smaller than 0.05. Chi-square tests ($p < 0.05$). *** denotes p-value < 0.01; ** denotes p-value < 0.05; *denotes p-value < 0.10.

4.3.2 Model results

The overall results of the site-specific negative binomial regression models are as expected (Table 14). The likelihood ratio (LR) test compares negative binomial regression models with Poisson models. In this case, the dispersion factor p in the LR test for each model is smaller than 0.05, which suggests that there is significant evidence of overdispersion and negative binomial regression models are more appropriate than the Poisson models. Higher values of McFadden's Pseudo-R^2 (from 0 to 1) indicates a better overall fit (Long & Freese, 2006). Also, McFadden (1979) suggested that Pseudo-R^2 values between 0.2 and 0.4 could be considered to represent a very good fit. The Chi-square tests ($p < 0.05$) also indicates good performance of the goodness–of-fit of the models. Almost all sites show correlations with the included variables. However, some sites are not sensitive to some variables. For example, the bicycle and pedestrian traffic at College Avenue are not significantly influenced by precipitation or wind speed, which may be explained by the necessary needs to pass by (e.g., eating, attending class, meeting friends). Draper Road is also not significantly influenced by wind speed. Pedestrians at Giles Road do not demonstrate correlation with precipitation or whether it's weekends or weekdays. Based on previous research, sensitivity to weather and temporal variables at similar sites, and the satisfied Chi-square tests ($p < 0.05$), I incorporated all the selected variables into the models for consistency. The results show that cyclists are more sensitive to weather conditions than pedestrians, which echoes the research of Hankey et al. (2012).

For bicycles at the continuous reference sites, *tmax* is significant with an expected positive sign: 1 °C increase in temperature is associated with an average 5.5% increase of bicycles. The variable *tmaxdev* is significant with a negative sign, which means for 1 °C more deviation from the 30-year (1980-2010) averages, bicycles decrease by average 3.7%. The coefficient of *precipitation* is negative as expected: 1 mm increase of precipitation associates with average 0.7% decrease of bicycles. Similar to *precipitation*, *windspeed* is also significant for 2 sites and has a negative sign: The percent change in bicycles is a 2.4% decrease for every 1 mph increase of wind speed.

The site-specific bicycle traffic also depends on whether it's weekend or weekday, and university is in session or not. The variable *weekend* is significant with mixed signs. More specifically, Huckleberry Trail has estimated 11% higher traffic on weekends than weekdays controlling for other variables in the models, while on average, other three sites experience estimated 18% drop. The variable *university in session* has significantly positive sign, which indicates that when university is in session, Giles Road shows estimated 91% higher traffic compared to other time. College Avenue is also sensitive to this variable with a 66% difference, however, the other two sites only change by 20% in this case.

For pedestrians at the continuous reference sites, *tmax* is significant at the 1% level with an expected positive sign for sites except Giles Road: 1°C increase in temperature is associated with average 3% pedestrian increase for most sites, however, Giles Road reacts 3% decrease instead. This may be explained by comparatively less valid pedestrian count days (102 days on a yearly basis). The variable *tmaxdev* is significant with a negative sign for sites except Giles Road, and 1 °C more deviation from the 30-year (1980-2010) averages, pedestrians decrease averagely 1.1%, however, similar to the situation for *tmax*, Giles Road reveals opposite direction of effect. The coefficient of *precipitation* is negative: 1 mm increase of precipitation is significantly associated with 0.3% decrease of pedestrians at Draper Road and Huckleberry Trail, which suggests slight disturbance from precipitation, while College Avenue and Giles Road are not significantly associated with precipitation. This may due to College Avenue's proximity to downtown restaurant and Giles Road's lack of valid monitoring days. Similar to precipitation, *windspeed* reveals negative signs: average 1.8% pedestrians decrease for 1 mph increase of wind speed at Giles Road and Huckleberry Trail, while it is not significant at Draper Road or College Avenue.

The variable *weekend* is significant with mixed signs. College Road and Huckleberry Trail have 50% more pedestrian on weekends than on weekdays controlling all other variables in the models, while Draper Road experiences 13% decrease (this may be explained by party groups to downtown and recreational use on Huckleberry Trail on weekends, while Draper Road reveals a commute pattern). *University in session* is also significant at less than 1% level with a positive sign. This indicates that when university is in session, College Avenue has 83% more pedestrian traffic, while other sites also increase by 27% in average.

4.3.3 Model validation and imputing missing counts at the continuous reference sites

Applying the negative binomial regression models to estimate missing counts, I compared the estimated (model-generated) counts with existing observed (automated) counts (Figure 36-Figure 39). The left panel of the figures show comparisons between full-year estimated counts and existing observed (automated) counts; the right figures show correlations between estimated counts and observed counts. The goal is to estimate a full 365-day dataset for use in developing scaling factors (i.e., to impute missing days).

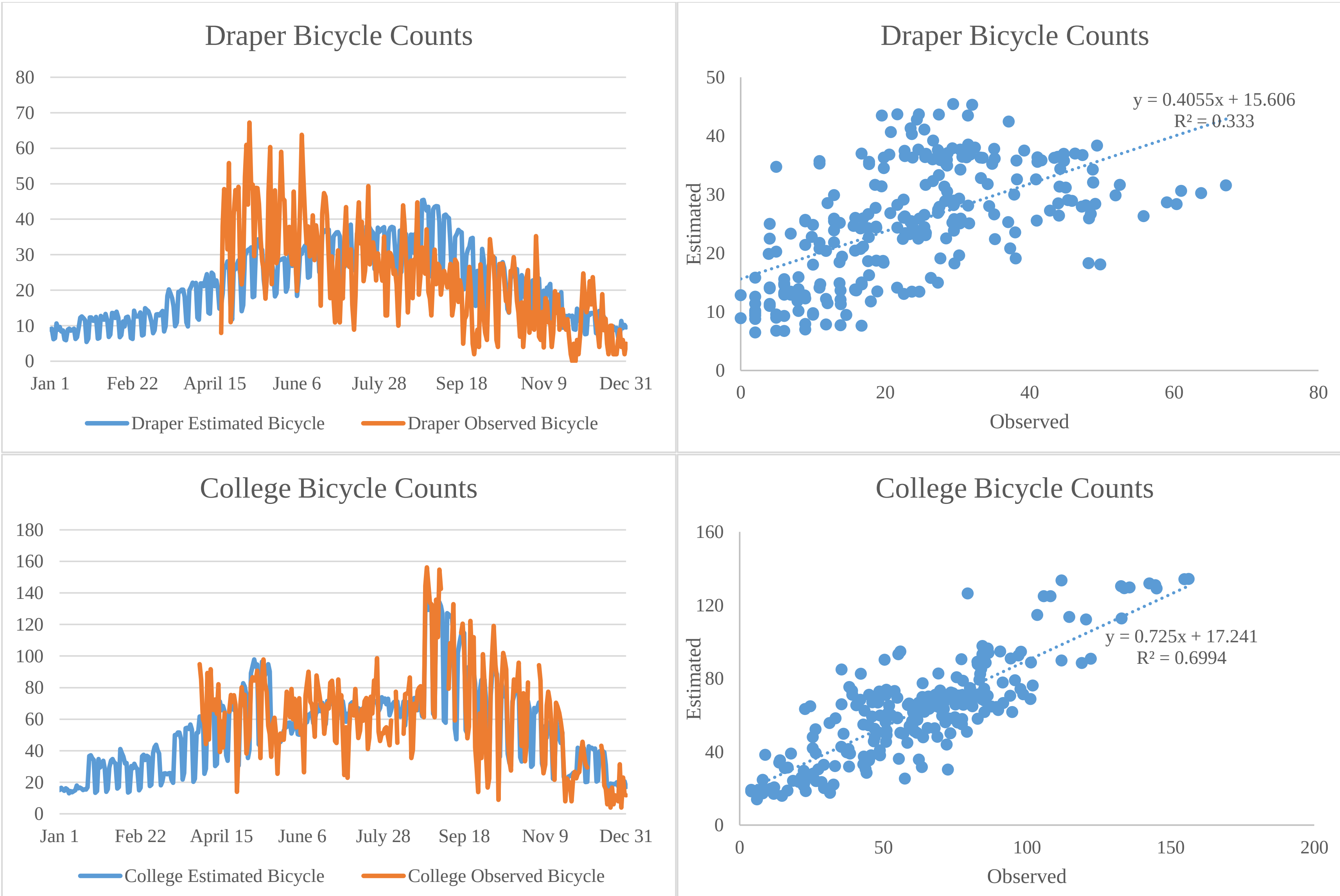


Figure 36. Observed and estimated daily bicycle traffic at Draper Road and College Avenue.

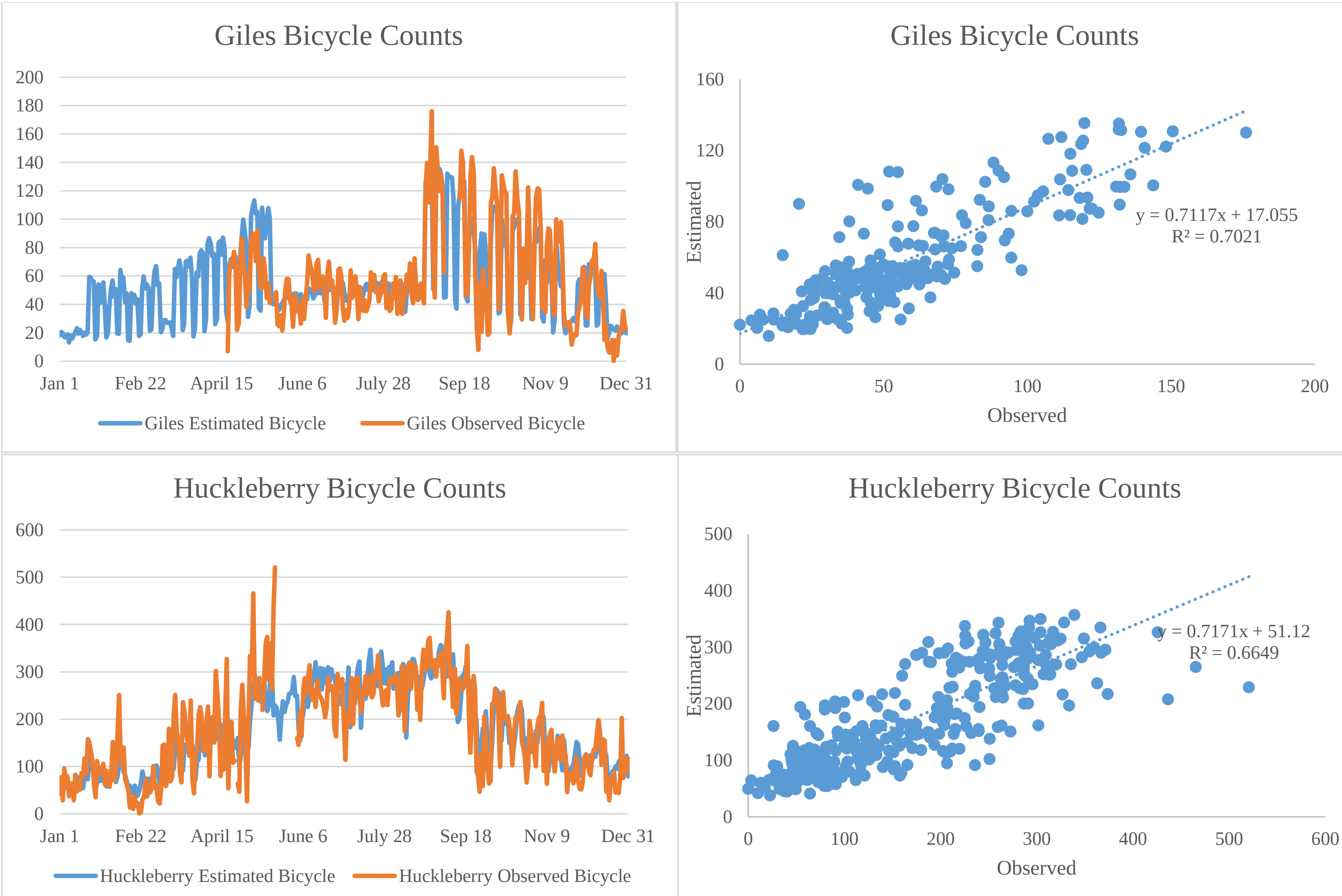


Figure 37. Observed and estimated daily bicycle traffic at Giles Road and Huckleberry Trail.

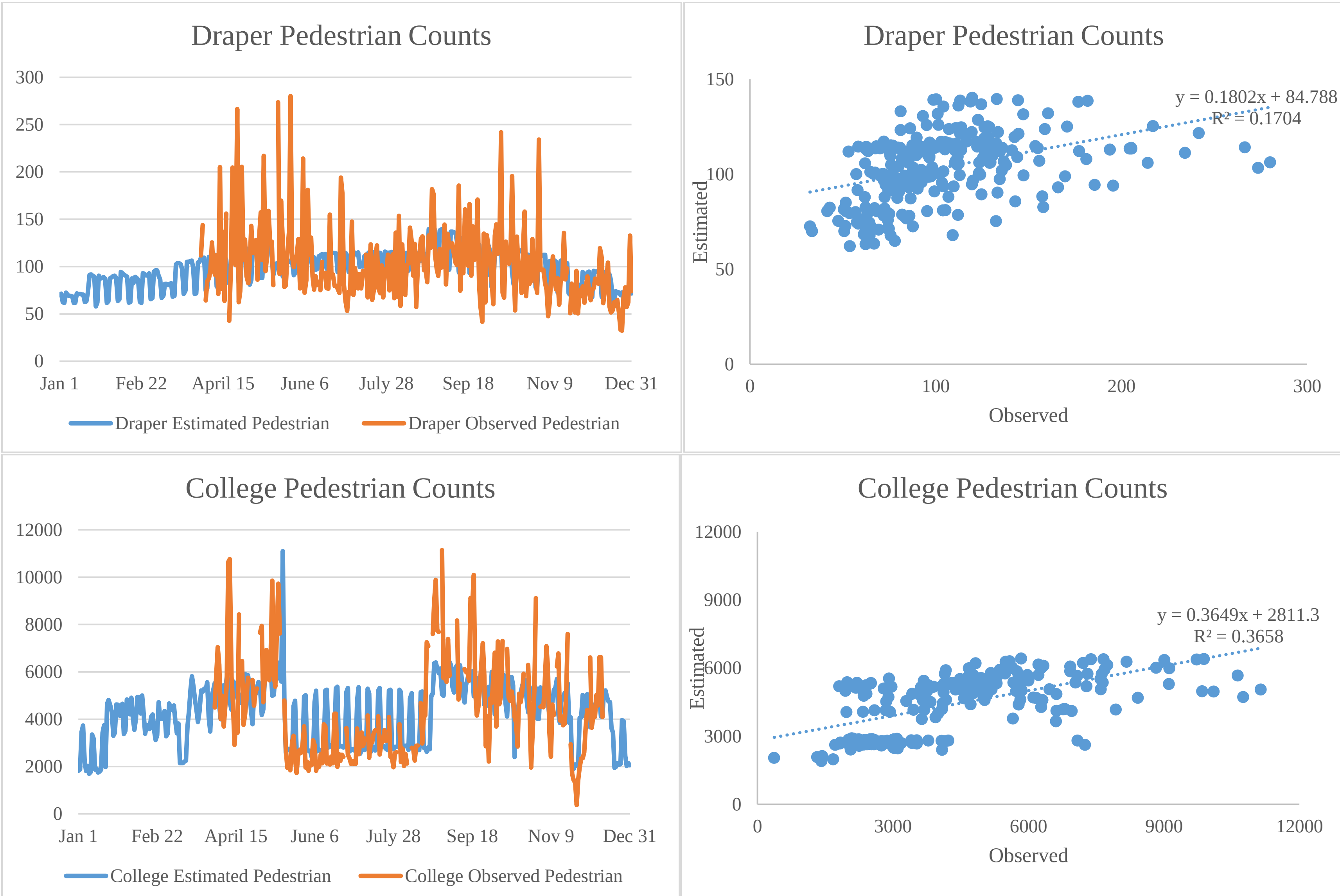


Figure 38. Observed and estimated daily pedestrian traffic at Draper Road and College Avenue.

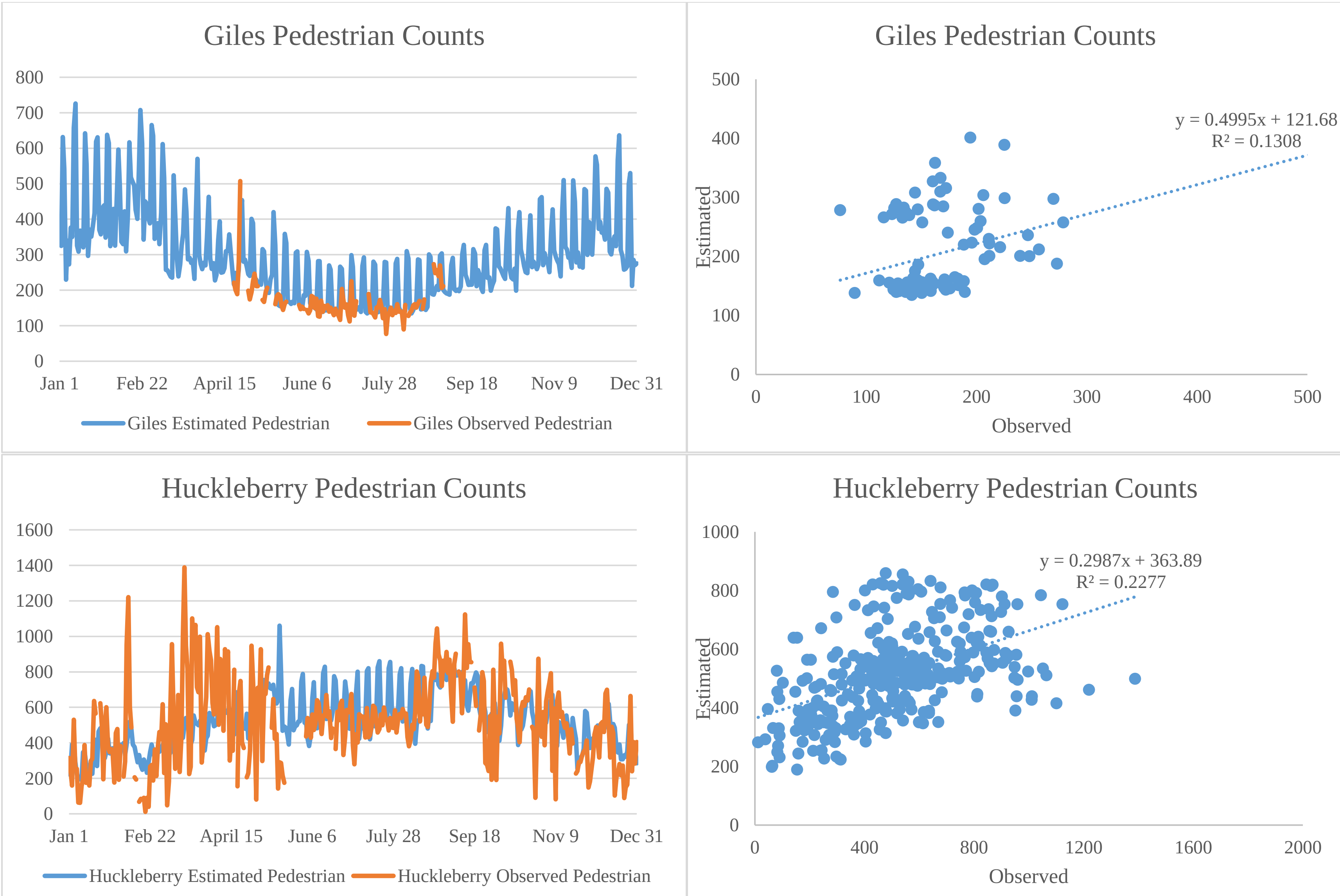


Figure 39. Observed and estimated pedestrian traffic at Giles Road and Huckleberry Trail.

Overall, the bicycle traffic perform more reliably (validation R^2 = ~0.70) as compared to the pedestrian traffic models (validation R^2 = ~0.30). This is likely because some variables (i.e., windspeed, precipitation) are not significantly associated with pedestrian traffic at some sites (i.e., College Avenue, and Giles Road) or that other important factors are not included in the models. However, as mentioned above in terms of previous literature and chi-squared test results ($p < 0.05$), this research incorporates all listed weather and temporal variables into pedestrian models.

For the bicycle models, College Avenue, Giles Road and Huckleberry Trail all show reasonable validation R^2 (0.70, 0.70 and 0.67). However, Draper Road has relatively low validation R^2 = 0.33. The estimated bicycle traffic (blue line) tracks well with the observed line (orange) at College Avenue, Giles Road and Huckleberry Trail; however, during April 15 to June 6, Draper Road doesn't fit that well. For the pedestrian estimation models, College Avenue has validation R^2 = 0.37, and other sites reveal low validation R^2 at around 0.20. Draper Road underestimates between April 15 and June 6; College Avenue, Giles Road and Huckleberry Trail overestimate during June to August. Above all, the eight site-specific models work reasonably well to estimate the bicycle and pedestrian traffic for the minority of days that are missing data.

I combined the observed values with the model-generated values for missing days to develop a full year-2015 dataset for each site. The purpose is to use the full year of bicycle and pedestrian dataset (observed days and estimated missing days) instead of only using observed days to calculate the AADT (Table 15). This AADT can then be used during the development of the day-of-year scaling factors for extrapolating the short-duration counts to long-term averages. The combined datasets are shown in Figures 40 and 41. Details of all the weather and temporal variables are shown in Table 26 (Appendix C).

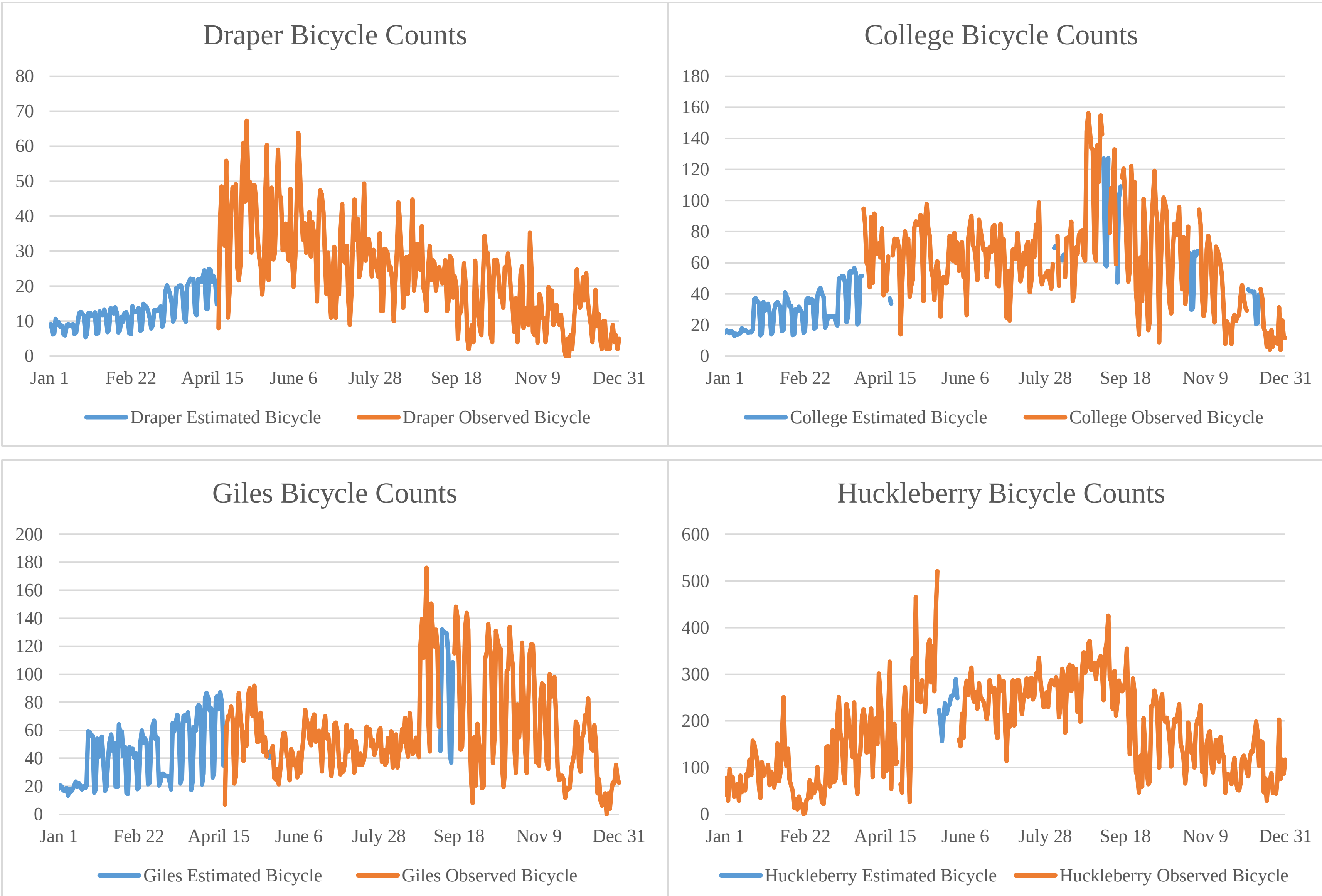


Figure 40. Full year-2015 bicycle traffic at all continuous reference sites.

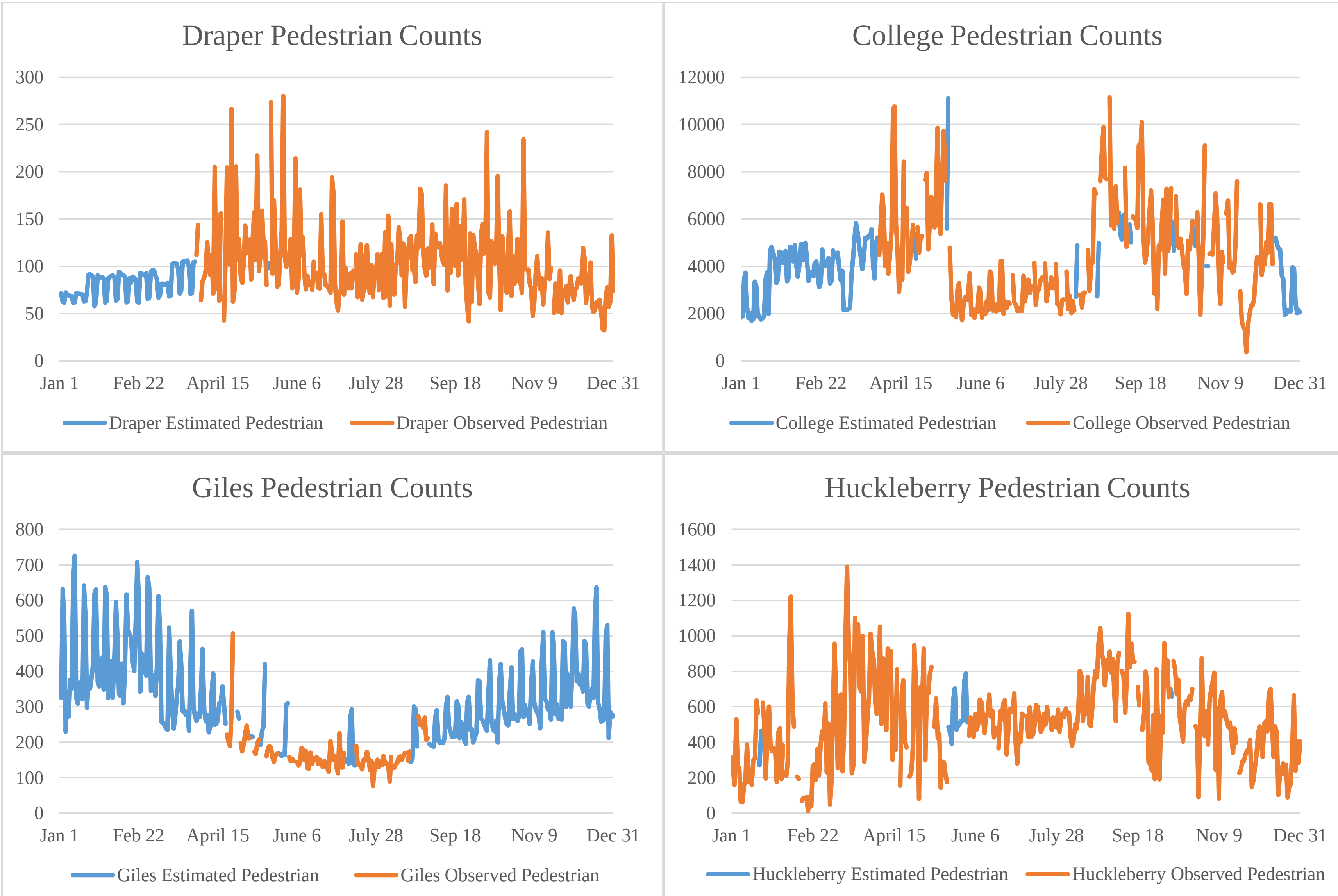


Figure 41. Full year-2015 pedestrian traffic at all continuous reference sites.

Table 15. AADT for continuous reference sites

		Draper	College	Giles	Huckleberry
AADT using estimated missing days and observed (automated) days (full year)	Bicycle AADT	21	54	55	179
	Pedestrian AADT	98	4232	289	518
AADT using observed (automated) days only	Bicycle AADT	24	62	59	177
	Pedestrian AADT	103	4424	168	514

4.4 Estimating AADT for short-duration count sites

4.4.1 Scaling factors

This part mainly uses average day-of-year scaling factors extrapolated from AADT (using estimated missing days and observed days) and observed dataset at continuous reference sites, and estimates AADT for short-duration sites. As mentioned in Chapter 2, Hankey et al. (2014) and Nosal et al. (2014) introduced a day-of-year scaling factor approach to produce AADT estimates with smaller error than the day-of-week (ratio of average day of week traffic to AADT) and month-of-year (ratio of average monthly traffic to AADT) methods. I used a similar method to calculate the 365 average day-of-year scaling factors from the 4 continuous reference sites for both bicycles and pedestrians[8].

$$Scaling\ factor = \frac{Average\ traffic\ on\ a\ specific\ day}{AADT} \qquad \text{Equation 9}$$

[8] Due to 8 days invalid data at all reference sites, 8 day-of-year average pedestrian scaling factors are not available.

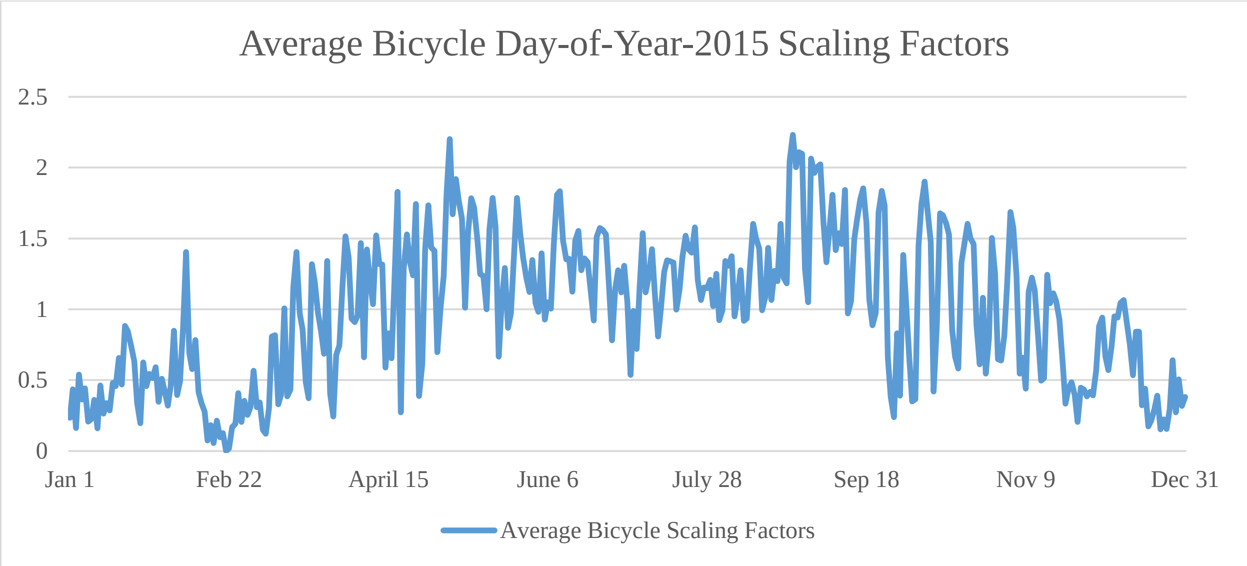


Figure 42. Average Bicycle Day-of-Year-2015 Scaling Factors.

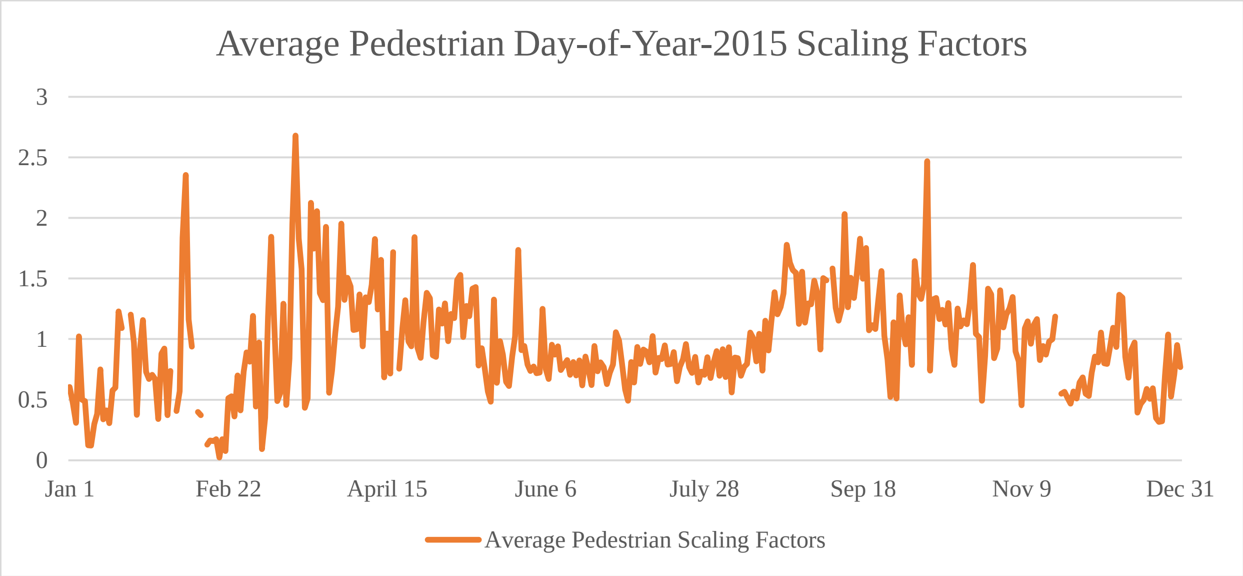


Figure 43. Average Pedestrian Day-of-Year-2015 Scaling Factors.

The overall pattern of the bicycle and pedestrian scaling factors is an "M" shape, which reveals the general traffic patterns throughout the year-2015 (Figure 42 and Figure 43). More specifically, weather and temporal factors have an influence, i.e., less traffic in winter because of weather and less in summer because students leave. These figures only show all data as an illustration but during implementation I use only the observed data and AADT at the continuous reference sites.

4.4.2 AADT estimation at short-duration count sites

I used the average bicycle and pedestrian day-of-year scaling factors to estimate the site-specific AADT for each day of the short-duration count period (~7 days per location), and then averaged the AADT estimates to calculate a final AADT estimate for each short-duration site. For example, at 2-Sunridge, the monitoring period is from May 5 to May 11 (May 9 and May 10 are weekends; Table 16 and Table 17). The scaling factors are retrieved from the average day-of-year-2015 scaling factors. The number of reference sites provides additional reference information on the number of sites that are used to calculate the average of scaling factors, 48 (142) days for bicycles (pedestrians) have 4 reference sites, and 205 (79) days have 3 reference sites.

$$AADT\ Estimate = \frac{1}{n} \sum_{i=1}^{n} \frac{AdjC_i}{SF_i} \qquad \text{Equation 10}$$

Where,

$AdjC_i$ is the adjusted count on day i,

n equals the number of days for short-duration counts,

SF_i denotes scaling factors retrieved from observed data.

Table 16. Example bicycle AADT estimate for a short-duration count site

2-SUNRIDGE		**Bicycle**		
Data	**Adj count**	**Scaling factor**	**AADT Estimate**	**Number of reference sites**
May 5	42	2.20	19	4
May 6	28	1.67	17	4
May 7	34	1.92	18	4
May 8	49	1.77	28	4
May 9	37	1.64	23	4
May 10	34	1.01	34	3
May 11	41	1.54	27	4
Average	**38**	**1.68**	**24**	**4**

Table 17. Example pedestrian AADT estimate for a short-duration count site

2-SUNRIDGE		**Pedestrian**		
Data	**Adj count**	**Scaling factor**	**AADT Estimate**	**Number of reference sites**
May 5	119	0.98	121	3
May 6	95	1.21	79	4
May 7	101	1.17	86	3
May 8	92	1.49	62	3
May 9	122	1.53	79	4
May 10	106	1.02	104	3
May 11	123	1.27	96	4
Average	**108**	**1.24**	**90**	**3**

4.4.3 Re-sample of a subset of the short-duration count sites

Since most of the short-duration counts were conducted from April to July (some when university was in session, some when it was not), I also selected 16 sampled sites from the existing short-duration sites to conduct a re-sample of some 1-week short-duration count sites from July to October (some when university was in session, some when it was not). The goal of this resample was to compare the estimated AADT when university was in session (students were here) to when it was not in session. The estimated AADT when university was in session or when it was not is shown in Table 18. The average percent error between university not in session and university in session of estimated bicycle (pedestrian) AADT is 16% (11%), and median percent error is 3% (9%). Most sites show low percent error, however, some sites show a much higher percent error for bicycle AADT (e.g., 96-COUNTRY CLUB). This may be due to the low number (only 1 continuous reference site available) of reference sites when university was in session for that particular site, while the second trial relies on the average scaling factor of 4 continuous reference sites. The details of estimated AADT for all sites in the re-sample are shown in Table 28 (Appendix C).

Table 18. Comparison of first and second trial of estimated AADT for short-duration sites (university was in session or not)

Sites	AADT_University not in session		AADT_University in session		Percent error		Absolute error		Error	
	Bicycle	**Pedestrian**	**Bicycle**	**Pedestrian**	**Bicycle**	**Pedestrian**	**Bicycle**	**Pedestrian**	**Bicycle**	**Pedestrian**
2-SUNRIDGE	25	74	24	90	-7%	21.8%	7%	22%	-2	16
6-HARDWOOD	3	N/A	3	N/A	-4%	N/A	4%	N/A	0	N/A
8-GROVE	6	N/A	4	N/A	-41%	N/A	41%	N/A	-2	N/A
19-PLANTATION	34	N/A	24	N/A	-28%	N/A	28%	N/A	-10	N/A
20-SMITHFIELD	114	N/A	125	N/A	9%	N/A	9%	N/A	11	N/A
27-TURNER	27	1126	53	1223	96%	8.6%	96%	9%	26	97
31-WILLARD	5	72	11	86	120%	19.5%	120%	20%	6	14
32-PALMER	21	91	37	128	76%	41.0%	76%	41%	16	37
33-EHEART	13	132	7	122	-47%	-7.7%	47%	8%	-6	-10
39-RESEARCH CENTER	25	N/A	34	N/A	34%	N/A	34%	N/A	9	N/A
46-TOMS CREEK	22	N/A	21	N/A	-7%	N/A	7%	N/A	-1	N/A
47-PROGRESS	36	286	67	249	86%	-13.0%	86%	13%	31	-37
48-GILES	38	142	33	153	-13%	7.6%	13%	8%	-5	11
85-PROGRESS	42	224	48	N/A	15%	N/A	15%	N/A	6	N/A
96-COUNTRY CLUB	78	120	20	88	-74%	-27.0%	74%	27%	-58	-32
99-NORTH MAIN	35	219	50	323	41%	47.1%	41%	47%	14	103
Average	**33**	**249**	**35**	**273**	**16%**	**11%**	**44%**	**21%**	**2**	**22**
Median	**26**	**137**	**29**	**128**	**3%**	**9%**	**37%**	**20%**	**3**	**14**

4.4.4 Mapping and analysis of estimated AADT

I estimated the bicycle and pedestrian AADT for all short-duration sites and mapped all sites (including continuous reference sites; Figure 44 and Figure 45). The graduated symbols are classified into 5 categories. The graduated symbols show that more bicycles are found along the Huckleberry Trail, Smithfield Trail and around the university campus (in the center area). Pedestrians gather around the campus and some major neighborhood areas (e.g., Foxridge). To have a better look at the land use patterns and the estimated bicycle and pedestrian AADT, I add the major land use components (i.e., university, commercial, and residential) in the map.

Chapter 2 mentions that mixed use of land containing convenience stores, offices, or restaurants can increase bicycle activities (Cervero, 1996; Cervero & Duncan, 2003; Jones et al., 2010; Pucher & Buehler, 2006; Moudon et al., 2005; Pikora et al., 2003; Cui, Mishra, & Welch, 2014; Faghih-Imani et al., 2014). As Figure 43 shows, downtown (central) areas (with stores, offices and restaurants) have higher traffic volumes of cyclists. Bicycle volumes are higher on existing off-street trails (e.g., Huckleberry Trail) or segmented trails attached to local roads near the university (e.g., Smithfield Road).

The largest pedestrian volumes (~500/hour) are within the University area (Virginia Tech) and pedestrians cluster along Main Street with commercial uses. In some neighborhood areas (i.e., Foxridge in the west) and off-street trails (i.e., Huckleberry Trail), walking activity is also higher compared to outer lying areas.

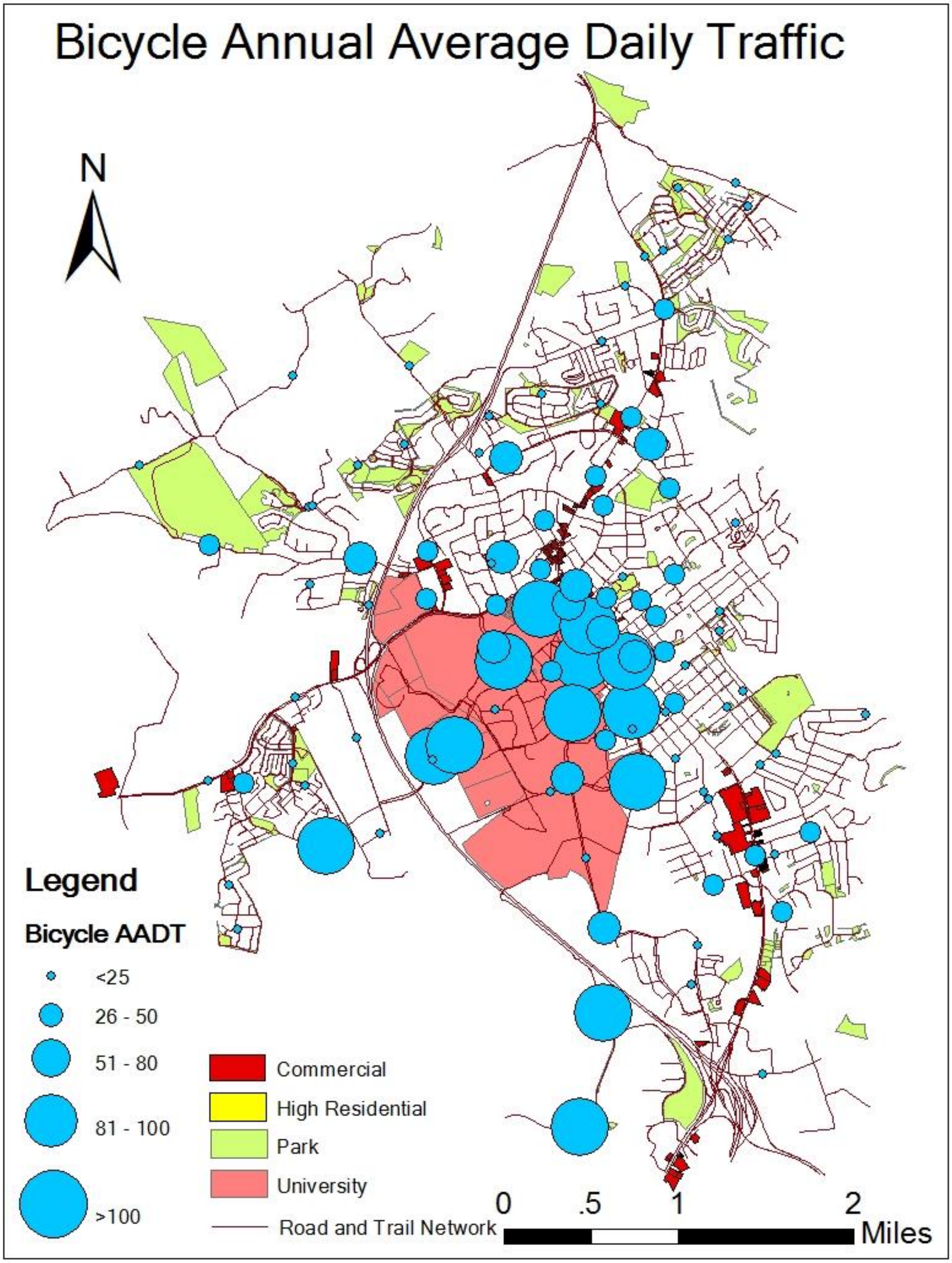


Figure 44. Estimated AADT for bicycles at all monitoring sites.

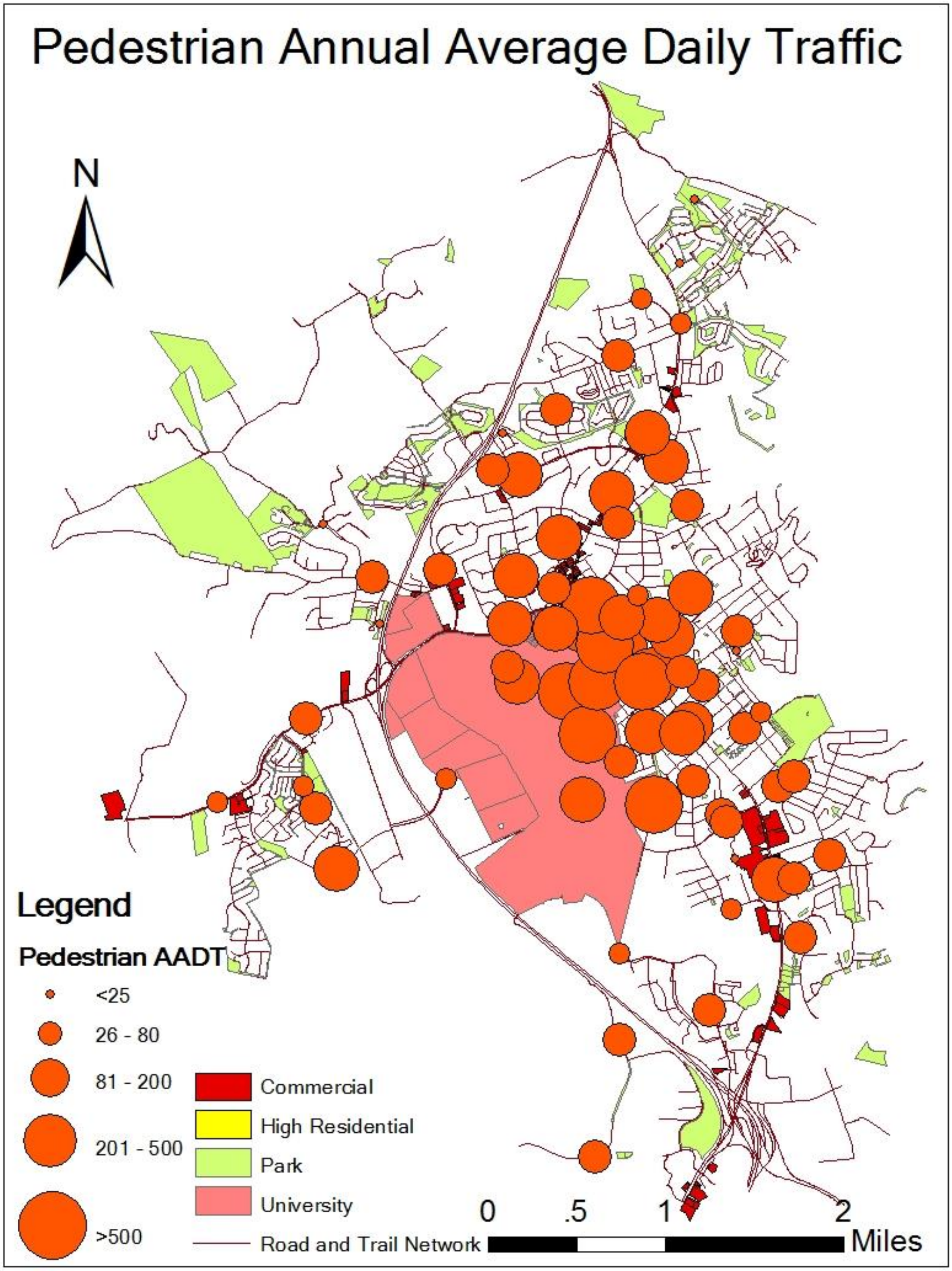


Figure 45. Estimated AADT for pedestrians at all monitoring sites.

Figure 46 and Figure 47 display the distribution of bicycle and pedestrian AADT among road and street type (street functional class) and bike facility (i.e., bike lane) based on 5 number summary: 5th percentile, 25th percentile, 50th percentile, 75th percentile, and 95th percentile. As mentioned in literature review in Chapter 2, bicycle facilities (i.e., bike lanes and paths) are associated with increased levels of bicycle commuting (Krizek, Barnes, & Thompson, 2009; Nelson & Allen, 1997; Pucher & Buehler, 2006; Dill & Carr, 2003; Buehler & Pucher, 2012), and cyclists show a preference to bicycle facilities compared to roads without (Hunt & Abraham, 2007; Wardman, Hatfield, & Page, 1997; Brand et al., 2014; Buehler, 2012; Fishman et al., 2014; Sanders & Cooper, 2013; Kang & Fricker, 2013; Winters et al., 2011).

To reflect the literature, for bicycle AADT, an independent-sample t-test is conducted to compare AADT for roads with a bike lane and roads without. The results show that bicycle AADT is significantly higher ($p < 0.01$) on roads with a bike lane (mean: 72) compared to roads without (mean: 30). Similarly, a t-test also found that bicycle AADT is significantly higher ($p < 0.01$) on off-street trails (mean: 72) compared to major roads (mean: 33). The results are consistent with the research reference above.

Pedestrian AADT is significantly higher ($p < 0.01$) on local roads (mean: 693) as compared to off-street trails (mean: 111); this finding is likely owing to the fact that most roads on the Virginia Tech campus are classified as local roads.

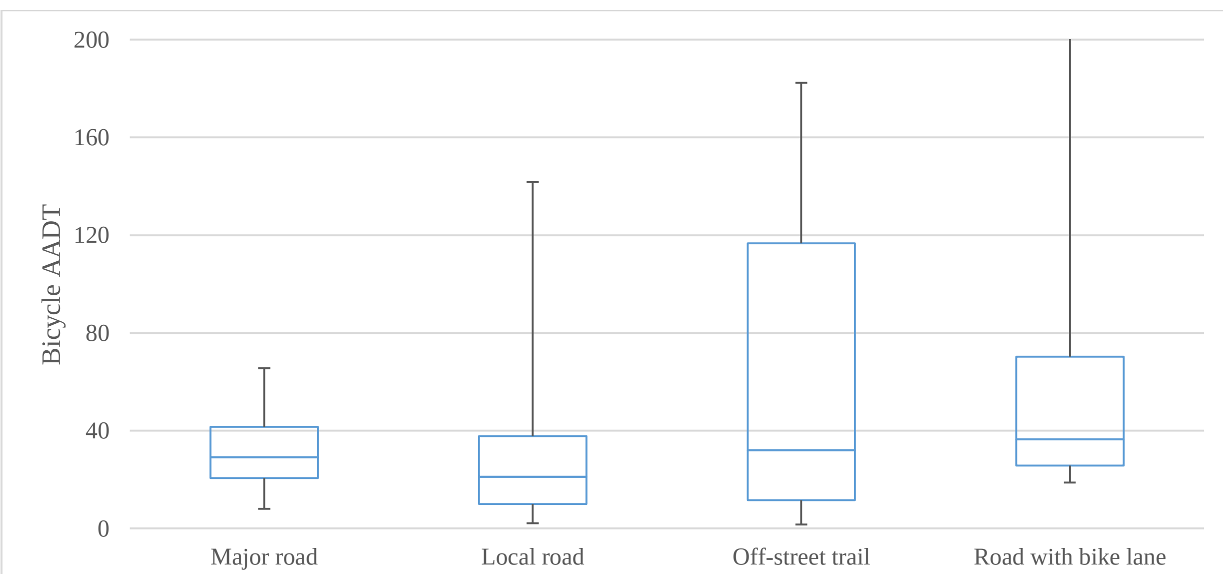


Figure 46. Bicycle AADT by road/trail type and bike lane.

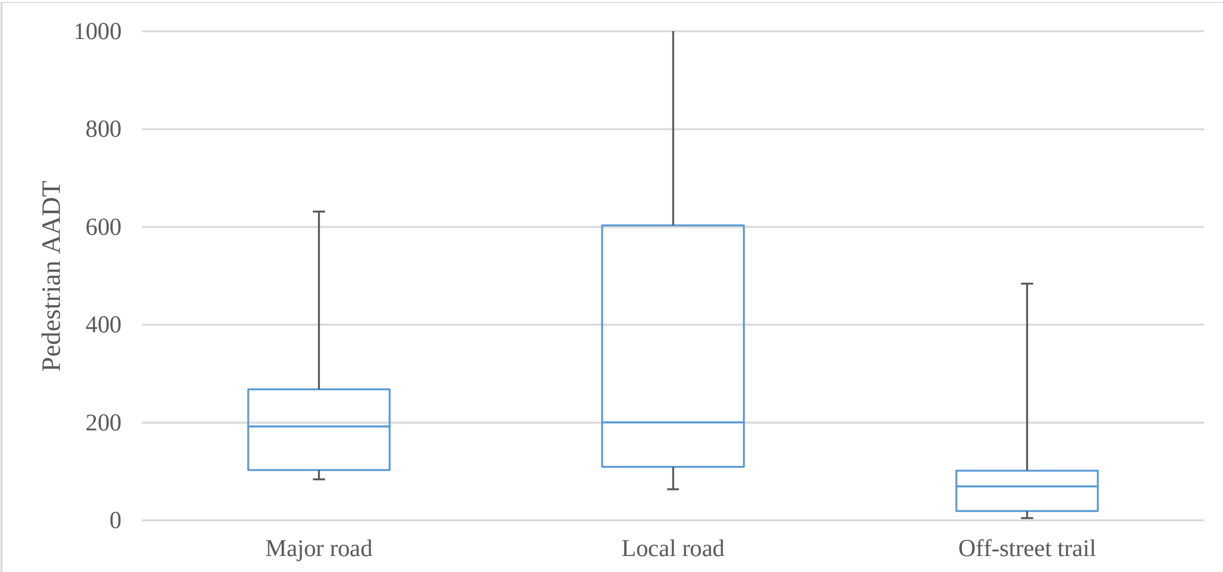


Figure 47. Pedestrian AADT by road/trail type.

5 CONCLUSIONS

This research describes a bicycle and pedestrian count campaign and use of the resulting temporal and spatial data to analyze and assess non-motorized traffic patterns in Blacksburg, VA. In this final chapter, I summarize the main conclusions in three areas: (1) recommendations for implementation (e.g., counter installation and data analysis), (2) key findings of the bicycle and pedestrian traffic analysis in Blacksburg and (3) strengths, limitations, and directions for future research.

5.1 Recommendations for implementation

5.1.1 Count campaign and counter installation

I collected ~40,000 hours of bicycle and pedestrian counts using a previously developed count campaign, which included 4 continuous reference sites (~full year-2015 counts) and 97 short-duration sites (≥ 1-week counts) that covered different road and trail types (i.e., major road, local road, and off-street trails). While all automated counters (i.e., MetroCount, Eco-counter, and RadioBeam) demonstrated good performance, my research recommends some key considerations for future count campaigns. For example, MetroCount counter should be installed at proper road segments to catch passing cyclists. Additionally, proximity to intersections or drive-through entrances can cause disturbance of vehicle flows required for accurate counting. The Eco-counter has specific criteria for monitoring direction (i.e., pointing towards sidewalks) and temporary stanchions used to deploy the counter units are vulnerable to vandalism. RadioBeam requires side-by-side installation with periodic battery/data check (see Table 19 for specific counter-related recommendations). Therefore, a combination of counter selections (i.e., MetroCount counts bicycles on the roads, Eco-counter counts pedestrians on sidewalks, and RadioBeam counts bicycles and pedestrians on the off-street trails) ensures coverage of entire transportation network rather than only focus on off-street trail systems or specific transportation corridors.

I validated automated counts with field-based manual counts for all counters (210 total hours of valid counts) due to systematic counter errors (e.g., occlusion). All automated counters were well correlated with the manual counts (MetroCount R^2 [absolute error]: 0.90 [38%]; Eco-counter: 0.97 [24%]; RadioBeam bicycle: 0.92 [19%], RadioBeam pedestrian: 0.92 [22%]). I compared three bicycle-based classification schemes provided by MetroCount (i.e., ARX Cycle, BOCO and Bicycle 15). Based on the validation counts the BOCO (Boulder County, CO) classification scheme (hourly counts) had similar R^2 using a polynomial correction equation (0.898) as compared to ARX Cycle (0.895) and Bicycle 15 (0.897). Using a linear fit, the slope was smallest for BOCO (1.26) as compared to ARX Cycle (1.29) and Bicycle 15 (1.31). Therefore, BOCO classification scheme is recommended to adjust the automated hourly bicycle counts from MetroCount for future practices.

Table 19. Automated counter installation recommendations for bicycle and pedestrian monitoring

Counter	Do	Do not
MetroCount	Choose the proper road segments where no alternative route is nearby for cyclists	Install the counters too close to intersections, exits or drive-through entrances
	Install the counters parallel to nearby poles (e.g., lights, signs) and lock the unit system with chains	Install the pneumatic tubes within the parking spot
	Around 10% length of each one tube need to be pulled through the cleats to be fixed with nails and tape	Install the unit system too lower than the road surface (e.g., ditch, drain)
	Check the unit storage if longer period of monitoring is needed (>10 days)	Hammer the nails too hard to puncture the pneumatic tubes
Eco-counter	Maintain at least 25 feet distance away from parking lots or alternative paths	Install the counters too near to the bus stop or intersections
	Attach the counters to permanent poles (e.g., lights, signs) or temporary stanchions	Point the counters to waving leaves or glass windows
	Check the monitoring direction and ensure it points to the sidewalk rather than the road	Install the counters with too low height (lower than the waist of an adult)
	Tag and check the counters periodically on the unit and data	Incidentally shut off the counter unit with too long time activating it with the key
RadioBeam	Install the counters on both sides of the trail/narrow road with 65 cm above ground level	Install the receivers and transmitters with wrong side
	Check the counters periodically on the battery and data	Leave the data logger for longer time without any boot/check
	Stabilize the counters with any available materials (e.g., wood pack)	Install the units near electrical or signal disturbance
	Install the counters side-by-side instead of face-to-face	Unplug the data logger while counting/connecting to a computer

5.1.2 Bicycle and pedestrian data analysis

Data quality is important to build the credibility and usability, and periodic summary check can help better understand the bicycle and pedestrian traffic patterns. First, since suspected data with abrupt changes in hourly counts (e.g., events, road block, and battery loss) may skew the daily traffic summaries, quality assurance and quality control (QA/QC) protocols are recommended to flag these outliers and yield a cleaned dataset for further analysis. Two steps are necessary: (1) direct cleaning based on the event log that identified suspect data and (2) statistical check based on the variability of the overall dataset. Second, periodic site visits and count analysis during the monitoring period are recommended to ensure a better validity of the analysis. For example, monthly analysis at the continuous references sites and weekend/weekday analysis at the short-duration sites would inform analysts/operators of timely feedback of traffic patterns through each month/week.

5.2 Key findings of bicycle and pedestrian traffic analysis

I summarized the traffic patterns (e.g., mode share, weekend to weekday ratio and hourly traffic curves) to explore seasonal, daily and hourly patterns for bicycles and pedestrians at the continuous reference sites and short-duration sites. The results from the continuous reference sites suggested that pedestrian traffic started to decrease when the university is not in session during the summer (May to August), while bicycle traffic continued to increase with warmer weather. I also found that peak-hour pedestrian traffic was in the evening (7:00 p.m. to 8:00 p.m. [6:00 p.m. to 7:00 p.m.] for weekdays [weekends]) and that peak-hour bicycle traffic was in the afternoon (5:00 p.m. to 6:00 p.m. [3:00 p.m. to 4:00 p.m.] for weekdays [weekends]).

The 8 site-specific negative binomial regression models I built (4 for bicycles and 4 for pedestrians) used temporal and weather variables (i.e., daily max temperature, daily temperature variation compared to the normal 30-year averages [1980-2010], precipitation, wind speed, weekend, and university in session). In general, the goodness-of-fit for the models was better for the bicycle traffic models (validation R^2 = ~0.70) as compared to the pedestrian traffic models (validation R^2 = ~0.30). The independent variables were correlated with traffic counts and cyclists are more sensitive to weather conditions than pedestrians. For example, daily max temperature was positively correlated with bicycle and pedestrian traffic; daily temperature variation was negatively correlated with bicycle traffic at all sites and pedestrian traffic at most sites. Precipitation was negatively correlated with bicycle and pedestrian traffic as expected.

Wind speed was negatively correlated with bicycle and pedestrian traffic at some sites, which may be explained by land use factors (e.g., eating, attending class, meeting friends) at some sites. Day of week (i.e., weekend or weekday) was significantly correlated with mixed signs; this may indicate that some sites show recreational or commute patterns. University being in session had a consistently positive effect on traffic, however, the effect size varied (18% to 92%).

Adding model-generated estimates of missing days into the existing observed reference site counts allowed for calculating AADT for each continuous reference site (bicycles volumes ranged from 21 to 179; pedestrian volumes ranged from 98 to 4,232). Therefore, these reference sites have provided representative variabilities of daily traffic for a small town. Since a full year of data was not available at the short-duration sites, I developed day-of-year scaling factors from the 4 continuous reference sites to apply to the short-duration counts. The scaling factors were used to estimate site-specific AADT for each day of the short-duration count sites (~7 days of counts per location). Exploring the spatial relationships among bicycle and pedestrian AADT, road and trail types, and bike facility (i.e., bike lane), I found that bicycle AADT is significantly higher ($p < 0.01$) on roads with a bike lane (mean: 72) as compared to roads without (mean: 30); bicycle AADT is significantly higher ($p < 0.01$) on off-street trails (mean: 72) as compared to major roads (mean: 33). Pedestrian AADT is significantly higher ($p < 0.01$) on local roads (mean: 693) as compared to off-street trails (mean: 111); this finding is likely owing to the fact that most roads on the Virginia Tech campus are classified as local roads.

5.3 Strengths, limitations and directions for future research

This research offers a proof-of-concept for a count campaign conducted in a small rural college town (Blacksburg, VA) to be used to estimate the bicycle and pedestrian. It offers evidence that non-motorized traffic can be monitored on a routine basis and annual estimates (i.e., AADT) are possible to obtain using continuous reference sites and short-duration sites in future endeavors.

5.3.1 <u>Strengths and limitations</u>

This research aims to assess best practices for conducting bicycle and pedestrian traffic monitoring and may be useful to practitioners. First, all the bicycle and pedestrian counters are commercially available and installation operations are easy-to-apply. Second, following the count campaign of this research can allow you to acquire bicycle and pedestrian traffic patterns, especially the useful and commonly accepted AADT. One can imagine that the methodologies and AADT estimates could be assimilated into state and regional databases to raise awareness of monitoring non-motorized traffic. Third, this research could guide local government (i.e., Town of Blacksburg) or other organizations (i.e., Virginia Tech) to conduct bicycle and pedestrian traffic monitoring on a routine basis. For example, AADT estimates for consecutive years could be compared to prioritize projects and measure infrastructure performance.

However, some questions remain. First, due to limitations of the counters and budget, the count campaign only uses 4 continuous reference sites; furthermore, 3 of the 4 reference sites did not have a complete year of data (due to vandalism or the inability to deploy during snow season) and only one site was deployed in the first three months of the sampling campaign. Questions remain on how increasing the number of reference sites would influence the development of day-of-year scaling factors and error in AADT estimates. Second, some monitoring sites in this small town have low bicycle volumes (~25/day); as such, error rates for the MetroCount are comparatively high. A little-studied area is whether and how bicycle volumes influence the MetroCount errors. Third, pedestrians could only be monitored where walking facilities (i.e., sidewalks) are available, which limits the number of sites that could be used to obtain pedestrian AADT in this research. Lastly, the negative binomial regression models demonstrated modest performance for pedestrians (validation R^2 = ~0.30). Spatial factors including other variables (e.g., land use variables) may be useful to study pedestrian volumes in future research.

5.3.2 Directions for future research

This work points to several factors that could be improved in future research. First, to develop more robust day-of-year scaling factors, more continuous reference sites are recommended in future research. Additional reference sites may capture more comprehensive temporal information for estimating long-term averages. Second, more field-based manual counts are recommended for sites where bicycle volumes are high to measure the performance of MetroCount and develop more robust correction equations. Third, more research could be conducted on monitoring sites where sidewalks are not available. For example, how to best monitor these sites? Could pedestrian traffic be estimated in this situation? Fourth, whether built environment (i.e., land use variable) and socio-economic variables (i.e., gender, income) should be considered to procedures to estimate bicycle and pedestrian AADT.

Collecting bicycle and pedestrian counts and estimating their AADT is the first step, however, there is great potential for using these data in other analyses. For example, how to effectively use the AADT (e.g., crash analysis, air quality exposure, and bicycle and pedestrian route choices) for future research and practical guidance. The ultimate goal is to take advantage of these spatial and temporal traffic patterns into decision-making processes for non-motorized traffic to encourage healthy, safe, and harmonious communities.

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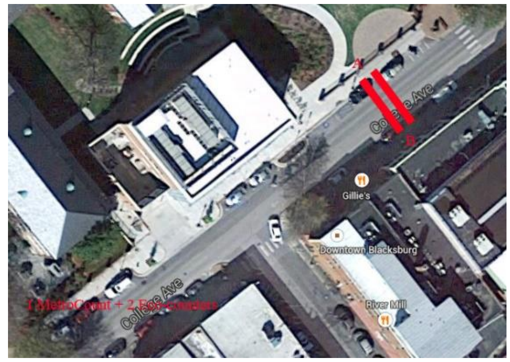

APPENDIX A COUNT CAMPAIGN

Table 20. Standard Screenline Count Form Sample 1

Name:____________Location_______________Direction_____________________________
Date:_____________Start Time:________________End Time:_________________________
Weather_____________
Please fill in your name, count location, date, time period, and weather conditions (fair, rainy, very cold). Count all bicyclists and pedestrians crossing your screen line under the appropriate categories. People in the Bicycles do not count as Pedestrians.

1 Count for two hours in 15 minute increments.
2 People using equipment such as skateboards or rollerblades should be included in the "Other" category.

East↔West

Time	Bicycles on the road		Bicycles on the sidewalk		Pedestrians		Other	
Every 15 minutes	E→W	W→E	A	B	A	B	E→W	W→E
00-15								
15-30								
30-45								
45-1:00								
00-15								
15-30								
30-45								
45-2:00								
Total								

Table 21. Standard Screenline Count Form Sample 2

Name:____________Location_______________Direction______________________________
Date:_____________Start Time:________________End Time:_________________________
Weather_____________
Please fill in your name, count location, date, time period, and weather conditions (fair, rainy, very cold). Count all bicyclists and pedestrians crossing your screen line under the appropriate categories. People in the Bicycles do not count as Pedestrians.

1 Count for two hours in 15 minute increments.

2 People using equipment such as skateboards or rollerblades should be included in the "Other" category.

North↔South

Time	Bicycles on the road		Bicycles on the sidewalk		Pedestrians		Other	
Every 15 minutes	N→S	S→N	A	B	A	B	N→S	S→N
00-15								
15-30								
30-45								
45-1:00								
00-15								
15-30								
30-45								
45-2:00								
Total								

Table 22. Example of the Short-duration schedule and event log sample (10 of 97 sites shown here)

Random Order	**FID**	**LocType**	**Name**	**Facility**	**Start Time**	**End Time**	**Lanes**	**Sidewalk**	**MetroCount**	**Eco-counter**	**Incident**
S1	48	Bike Build Out	GILES	Local Street	4/18/15 12:00	5/4/15 12:00	2	1	1	1	Eco-counter was moved before 4/20, also moved on 4/29.
S2	98	Major Rd	MAIN	Minor Arterial	5/21/15 14:00	5/29/15 9:00	4	2	2	2	
S3	22	Bike Build Out	TALL OAKS	Local Street	5/4/15 11:00	5/12/15 11:00	2	1	2	1	
S4	31	Bike Build Out	WILLARD	Local Street	4/18/15 12:00	5/4/15 10:00	2	1	1	1	Eco-counter effective from 4/21
S5	92	Major Rd	MAIN	Minor Arterial	5/21/15 14:00	5/29/15 14:00	3	2	1	2	Eco-counters were moved on 5/18, 299(W) was moved on 5/23, 5/25
S6	76	Major Rd	CLAY	Collector	5/29/15 11:00	6/5/15 11:00	2	1	1	1	
S7	32	Bike Build Out	PALMER	Local Street	4/18/15 12:00	4/28/15 11:00	2	1	1	1	Eco-counter effective from 4/21,No data till 04302015, effective from 5/1
S8	47	Bike Build Out	PROGRESS	Local Street	4/26/15 12:00	5/10/15 10:00	2	2	1	0	Eco-counters were moved on 4/29, before 4/29 data weird
S9	20	Bike Build Out	SMITHFIELD	Local Street	4/26/15 12:00	5/10/15 11:00	2	0	1	0	
S10	94	Major Rd	MOUNT TABOR	Collector	5/27/15 12:00	4/15/05 11:00	2	0	1	0	

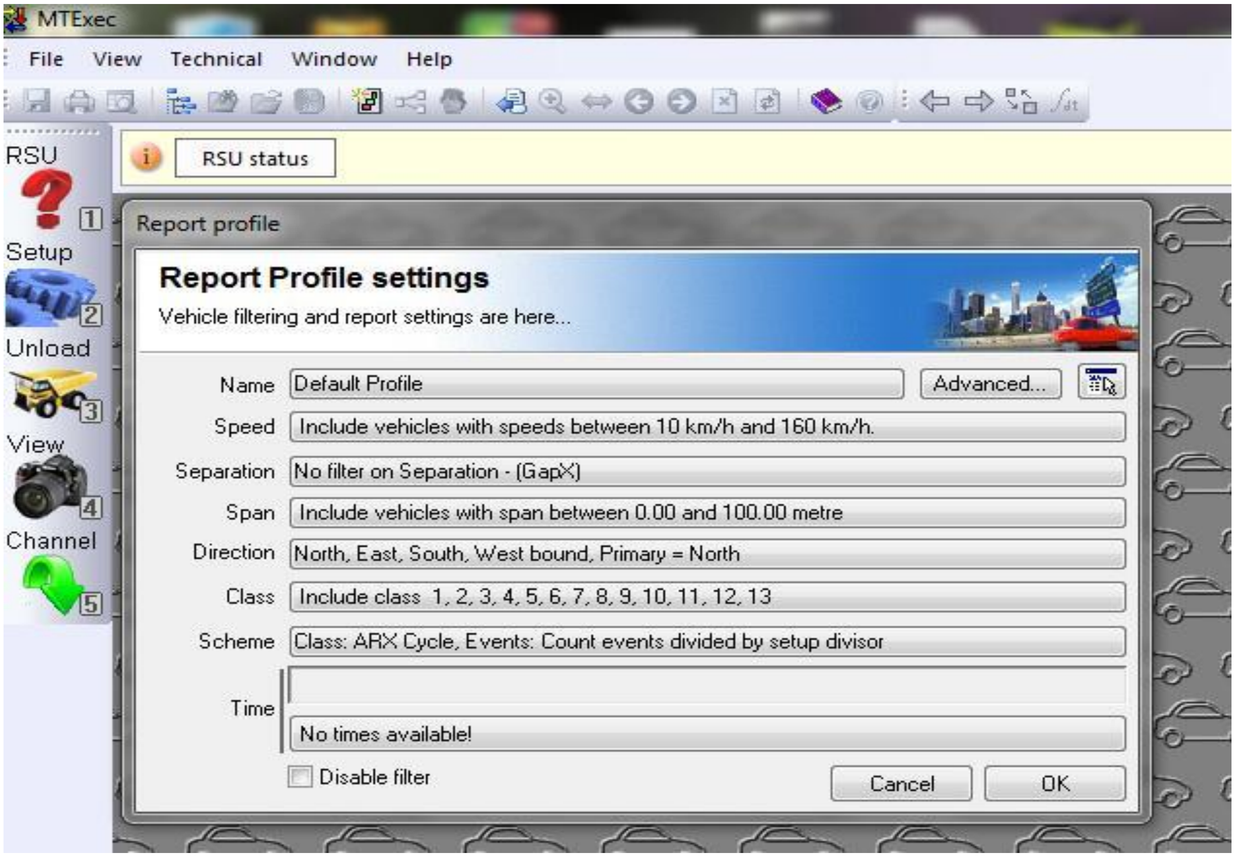

Figure 48. MetroCount Traffic Executive report profile settings.

Tuesday, May 05, 2015

Time	Total	Cls 1	Cls 2	Cls 3	Cls 4	Cls 5	Cls 6	Cls 7	Cls 8	Cls 9	Cls 10	Cls 11	Cls 12	Cls 13	Mean	Vpp 85
0000	51	0	0	0	0	1	49	0	0	1	0	0	0	0	24.4	27.5
0100	47	1	0	0	0	0	44	0	2	0	0	0	0	0	24.5	27.7
0200	29	1	0	0	0	0	28	0	0	0	0	0	0	0	24.4	28.2
0300	10	0	0	0	0	0	10	0	0	0	0	0	0	0	26.4	-
0400	7	0	0	0	0	0	6	0	1	0	0	0	0	0	24	-
0500	16	0	0	0	0	0	14	0	2	0	0	0	0	0	27.6	32.7
0600	40	1	0	0	0	0	31	0	8	0	0	0	0	0	25	28.9
0700	161	3	0	0	0	0	136	0	20	2	0	0	0	0	26.3	30
0800	151	0	0	0	0	1	142	0	7	1	0	0	0	0	27	30.9
0900	160	2	0	0	0	0	149	0	9	0	0	0	0	0	24.1	28.4
1000	145	1	0	0	0	0	133	0	9	1	1	0	0	0	25.6	29.3
1100	131	0	0	0	0	2	119	0	6	3	0	0	0	1	25.8	29.3
1200	177	2	0	0	0	0	160	0	15	0	0	0	0	0	25.6	29.1
1300	177	2	0	0	0	1	163	0	8	2	0	0	1	0	25.6	28.9
1400	181	2	0	0	0	0	157	1	21	0	0	0	0	0	25.7	28.9
1500	231	1	0	0	0	1	210	0	18	0	1	0	0	0	24.8	28.6
1600	281	2	0	0	0	0	254	0	21	2	0	0	2	0	24.8	28.4
1700	336	3	0	0	0	3	302	0	23	3	0	0	2	0	23.5	28.2
1800	268	0	0	0	0	0	250	0	15	3	0	0	0	0	25	28
1900	220	2	0	0	0	2	208	0	7	0	0	0	1	0	24.9	27.7
2000	180	2	0	0	0	1	158	0	16	3	0	0	0	0	25.1	28
2100	145	1	0	0	0	0	135	0	7	2	0	0	0	0	25.1	28.6
2200	112	1	0	0	0	0	104	0	6	1	0	0	0	0	25.2	28.9
2300	89	0	0	0	0	0	85	0	3	1	0	0	0	0	24.8	28.4

Figure 49. MetroCount data report sample.

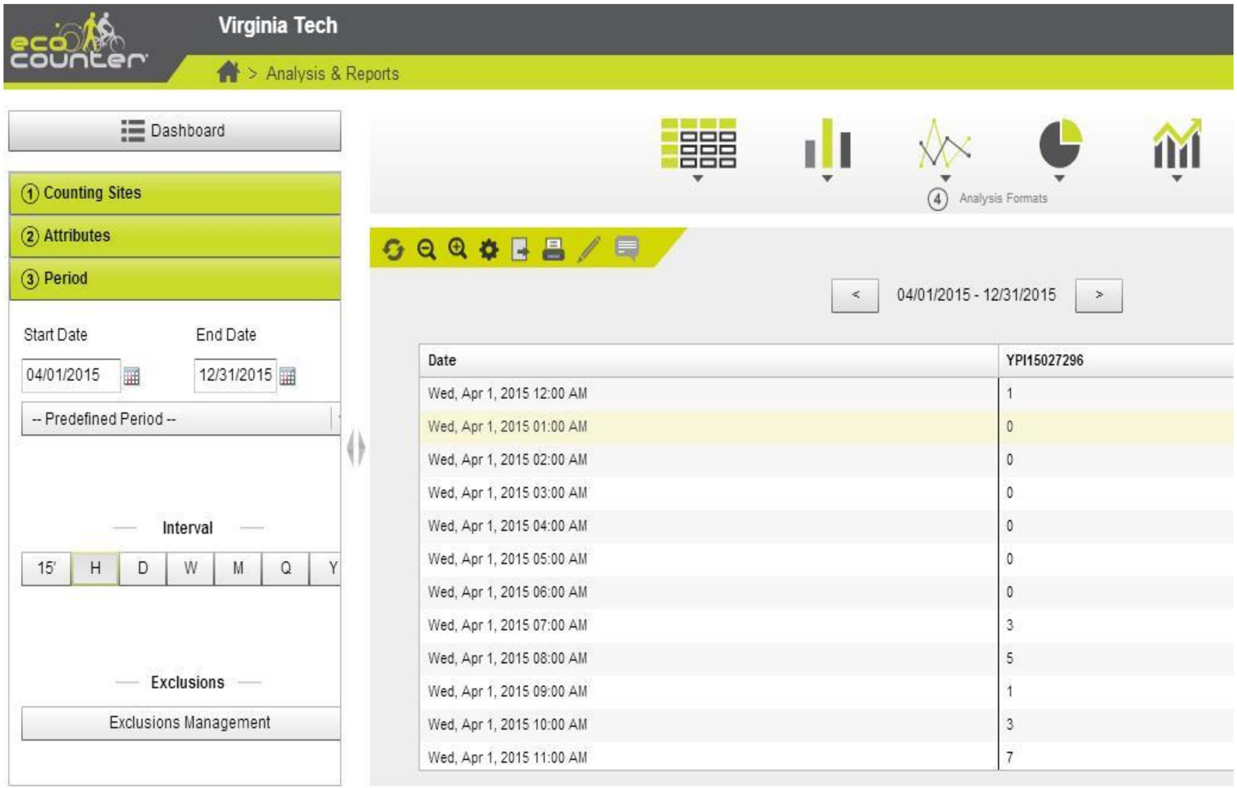

Figure 50. Eco-counter data report sample.

	Time	1
S/N		674612
Type		TGC-0032
Description		Bike logger
Property		Count Rate
1	11/01/2015 17:20	0.0 / minute
2	11/01/2015 17:25	0.0 / minute
3	11/01/2015 17:30	0.0 / minute
4	11/01/2015 17:35	0.0 / minute
5	11/01/2015 17:40	0.2 / minute
6	11/01/2015 17:45	0.0 / minute
7	11/01/2015 17:50	0.0 / minute
8	11/01/2015 17:55	0.0 / minute
9	11/01/2015 18:00	0.0 / minute
10	11/01/2015 18:05	0.0 / minute
11	11/01/2015 18:10	0.2 / minute
12	11/01/2015 18:15	0.0 / minute

Figure 51. RadioBeam data report sample.

Table 23. Random selection order of monitoring major roads and local roads of short-duration sites

Order	RandSelection	FID	LocType	NAME	FacilityS0	BikeS0	Lanes	Sidewalk	Metro Count	Eco-counter
S1	0.004948259	48	Bike Build Out	GILES	Local Street		2	1	1	1
S2	0.017875218	98	Major Rd	MAIN	Minor Arterial		4	2	2	2
S3	0.02767981	22	Bike Build Out	TALL OAKS	Local Street		2	1	2	1
S4	0.033558695	31	Bike Build Out	WILLARD	Local Street		2	1	1	1
S5	0.041850203	92	Major Rd	MAIN	Minor Arterial		3	2	1	2
S6	0.04266721	76	Major Rd	CLAY	Collector	Bike Lane	2	1	1	1
S7	0.052655064	32	Bike Build Out	PALMER	Local Street		2	1	1	1
S8	0.058821051	47	Bike Build Out	PROGRESS	Local Street		2	2	1	0
S9	0.069987581	20	Bike Build Out	SMITHFIELD	Local Street		2	0	1	0
S10	0.077207558	94	Major Rd	MOUNT TABOR	Collector		2	0	1	0
S11	0.079727733	21	Bike Build Out	TALL OAKS	Local Street		2	0	1	0
S12	0.088736084	79	Major Rd	PATRICK HENRY	Minor Arterial	Bike Lane	4	2	2	2
S13	0.090471203	99	Major Rd	MAIN	Minor Arterial		3	2	2	2
S14	0.128727217	51	Bike Build Out	ALUMNI MALL	Local Street		2	2	2	2
S15	0.137839759	81	Major Rd	TOMS CREEK	Minor Arterial	Bike Lane	2	2	1	2
S16	0.166902904	82	Major Rd	UNIVERSITY CITY	Minor Arterial	Bike Lane	2	2	1	2
S17	0.173760465	39	Bike Build Out	RESEARCH CENTER	Local Street		2	0	1	0
S18	0.183210935	84	Major Rd	PRICES FORK	Minor Arterial	Bike Lane	4	2	2	2
S19	0.183392278	19	Bike Build Out	PLANTATION	Local Street		2	0	1	0
S20	0.189337685	8	Rand Low Centrality	GROVE	Local Street		2	0	0	0
S21	0.233510815	88	Major Rd	SOUTHGATE	Collector		2	0	1	0

S22	0.240782156	85	Major Rd	PROGRESS	Collector		2	1	1	1
S23	0.253817682	6	Rand Low Centrality	HARDWOOD	Local Street		2	0	1	0
S24	0.264800815	33	Bike Build Out	EHEART	Local Street		2	0	1	0
S25	0.272005133	46	Bike Build Out	TOMS CREEK	Local Street		2	0	1	0
S26	0.274185596	86	Major Rd	GLADE	Collector		2	0	1	0
S27	0.285376395	30	Major Rd	CLAY	Collector		2	1	1	1
S28	0.296698808	2	Rand Low Centrality	SUNRIDGE	Local Street		2	1	1	1
S30	0.3154743	16	Major Rd	PROGRESS	Collector		2	1	1	1
S31	0.323444466	5	Rand Low Centrality	SHADOW LAKE	Local Street		2	0	1	0
S32	0.330211288	78	Major Rd	HARDING	Minor Arterial	Bike Lane	2	1	1	1
S33	0.393859875	87	Major Rd	PRICES FORK	Minor Arterial		4	2	2	2
S34	0.396132532	23	Bike Build Out	HETHWOOD	Local Street		4	0	2	0
S35	0.424879481	37	Bike Build Out	MARLINGTON	Local Street		2	1	1	1
S36	0.426978842	36	Bike Build Out	GRISSOM	Local Street		2	1	1	1
S37	0.429851415	27	Bike Build Out	TURNER	Local Street		2	2	1	2
S38	0.453702395	12	Rand Low Centrality	KELSEY	Local Street		2	0	1	0
S39	0.462534239	3	Rand Low Centrality	VILLAGE WAY NORTH	Local Street		2	0	1	0
S40	0.464703902	91	Major Rd	MAIN	Minor Arterial		4	2	2	2
S41	0.468779589	52	Bike Build Out	WASHINGTON	Local Street	Bike Lane	2	2	1	2
S42	0.477912229	13	Rand Low Centrality	PRIMROSE	Local Street		2	0	1	0
S43	0.495337842	80	Major Rd	PRICES FORK	Minor Arterial	Bike Lane	5	2	2	2
S44	0.505326637	25	Bike Build Out	DRILLFIELD	Local Street		1	1	1	1

S45	0.506406478	83	Major Rd	GLADE	Collector	Bike Lane	2	1	2	1
S46	0.51351847	0	Rand Low Centrality	COTTONWOOD	Local Street		1	0	1	0
S47	0.528687258	53	Bike Build Out	DRAPER	Local Street		2	2	1	2
S48	0.534421629	14	Rand Low Centrality	TALL OAKS	Local Street		2	0	1	0
S49	0.535424154	89	Major Rd	AIRPORT	Collector		2	2	1	2
S50	0.537192862	17	Major Rd	MAIN	Minor Arterial		2	0	1	0
S51	0.572858673	29	Major Rd	ROANOKE	Minor Arterial		2	0	1	1
S52	0.598704078	97	Major Rd	MAIN	Minor Arterial		3	2	1	2
S53	0.607227669	38	Bike Build Out	HUBBARD	Local Street		2	0	1	0
S54	0.615733112	50	Bike Build Out	HARDING	Local Street	Bike Lane	2	2	1	1
S55	0.616010785	41	Bike Build Out	DRAPER	Local Street		2	2	1	2
S56	0.665595082	42	Bike Build Out	INDUSTRIAL PARK	Local Street		2	0	1	0
S57	0.666816648	1	Rand Low Centrality	JANIE	Local Street		1	0	1	0
S58	0.706465695	24	Bike Build Out	KENT	Local Street		2	2	1	2
S59	0.7117157	11	Rand Low Centrality	INVENTIVE	Local Street		2	0	1	0
S60	0.717223302	15	Bike Build Out	BISHOP	Local Street		2	0	1	0
S61	0.732788235	77	Major Rd	HARDING	Minor Arterial	Bike Lane	2	1	1	1
S62	0.74483533	96	Major Rd	COUNTRY CLUB	Collector		2	1	1	1
S63	0.746367569	45	Bike Build Out	MEADOWBROOK	Local Street		2	0	1	0
S64	0.7487014	4	Rand Low Centrality	VILLAGE WAY SOUTH	Local Street		2	0	1	0
S65	0.778622448	9	Rand Low Centrality	WARREN	Local Street		2	0	1	0
S66	0.780583782	35	Bike Build Out	PALMER	Local Street		2	1	1	1

S67	0.781977062	18	Bike Build Out	OLD GLADE	Local Street		2	0	1	0
S68	0.785428891	90	Major Rd	GIVENS	Collector		2	0	1	0
S69	0.798155243	43	Bike Build Out	RESEARCH CENTER	Local Street		2	0	1	0
S70	0.801333066	93	Major Rd	ELLETT	Collector		2	1	1	1
S71	0.805635452	28	Bike Build Out	WEBB	Local Street		2	1	1	0
S73	0.824992456	75	Major Rd	MAIN	Minor Arterial	Bike Lane	5	2	2	2
S74	0.855843861	54	Bike Build Out	WEST CAMPUS	Local Street	Bike Lane	4	1	2	1
S75	0.86403087	34	Bike Build Out	COUNTRY CLUB	Local Street		2	1	1	0
S77	0.92585009	44	Bike Build Out	MEADOWBROOK	Local Street		2	0	1	0
S78	0.927953467	10	Rand Low Centrality	CUPP	Local Street		2	0	1	0
S79	0.97416777	26	Bike Build Out	STANGER	Local Street	Bike Lane	2	2	1	2
S80	0.982995204	95	Major Rd	PATRICK HENRY	Minor Arterial		4	2	2	2

Table 24. Random selection order of monitoring off-street trails of short-duration sites

Order	RandSelection	FID	LocType	NAME	FacilityS0
T1	0.012823965	55	Trail Transport	Existing Trail	Multi use Trail
T2	0.185159576	66	Trail Neighborhood	Existing Trail	Multi use Trail
T3	0.188817765	64	Trail Transport	Existing Trail	Multi use Trail
T4	0.198109228	69	Trail Neighborhood	Existing Trail	Multi use Trail
T5	0.215304325	68	Trail Neighborhood	Existing Trail	Multi use Trail
T6	0.258185975	61	Trail Transport	Existing Trail	Multi use Trail
T7	0.308100138	60	Trail Transport	Existing Trail	Multi use Trail
T8	0.341928427	63	Trail Transport	Existing Trail	Multi use Trail
T9	0.490051103	67	Trail Neighborhood	Existing Trail	Multi use Trail
T10	0.49663045	72	Trail Neighborhood	Existing Trail	Multi use Trail
T11	0.500623925	59	Trail Transport	Existing Trail	Multi use Trail
T12	0.561286634	62	Trail Transport	Existing Trail	Multi use Trail
T13	0.561523651	74	Trail Neighborhood	Existing Trail	Multi use Trail
T14	0.650362607	57	Trail Transport	Existing Trail	Multi use Trail
T15	0.724524688	65	Trail Neighborhood	Existing Trail	Multi use Trail
T16	0.808371846	70	Trail Neighborhood	Existing Trail	Multi use Trail
T17	0.817616937	56	Trail Transport	Existing Trail	Multi use Trail
T18	0.858769635	71	Trail Neighborhood	Existing Trail	Multi use Trail
T19	0.913449771	58	Trail Transport	Existing Trail	Multi use Trail
T20	0.987130686	73	Trail Neighborhood	Existing Trail	Multi use Trail

APPENDIX B TRAFFIC ANALYSIS FOR CONTINUOUS REFERENCE SITES

Table 25. Average weekend and weekday bicycle and pedestrian traffic for continuous reference sites

Draper	Weekend Average Bicycle	Weekday Average Bicycle	Weekend:Weekday Average Bicycle Ratio	Weekend Average Pedestrian	Weekday Average Pedestrian	Weekend:Weekday Average Pedestrian Ratio
Jan	N/A	N/A	N/A	N/A	N/A	N/A
Feb	N/A	N/A	N/A	N/A	N/A	N/A
March	N/A	N/A	N/A	N/A	N/A	N/A
April	12	44	0.27	81	137	0.59
May	31	44	0.70	113	154	0.73
June	26	37	0.70	79	123	0.64
July	21	31	0.68	84	95	0.88
Aug	17	29	0.59	88	120	0.73
Sep	12	21	0.57	109	116	0.94
Oct	9	22	0.41	84	121	0.69
Nov	8	12	0.67	67	98	0.68
Dec	9	11	0.82	71	76	0.93
College	Weekend Average Bicycle	Weekday Average Bicycle	Weekend:Weekday Average Bicycle Ratio	Weekend Average Pedestrian	Weekday Average Pedestrian	Weekend:Weekday Average Pedestrian Ratio
Jan	N/A	N/A	N/A	N/A	N/A	N/A
Feb	N/A	N/A	N/A	N/A	N/A	N/A
March	N/A	N/A	N/A	N/A	N/A	N/A
April	49	70	0.70	7428	5568	1.33
May	52	68	0.76	5625	5031	1.12
June	49	73	0.67	2861	2531	1.13
July	47	64	0.73	3222	2850	1.13
Aug	54	95	0.57	6814	4903	1.39
Sep	43	100	0.43	6015	6124	0.98
Oct	34	80	0.43	5073	5490	0.92
Nov	25	51	0.49	3944	4053	0.97
Dec	20	21	0.95	5242	6733	0.78

Giles	Weekend Average Bicycle	Weekday Average Bicycle	Weekend:Weekday Average Bicycle Ratio	Weekend Average Pedestrian	Weekday Average Pedestrian	Weekend:Weekday Average Pedestrian Ratio
Jan	N/A	N/A	N/A	N/A	N/A	N/A
Feb	N/A	N/A	N/A	N/A	N/A	N/A
March	N/A	N/A	N/A	N/A	N/A	N/A
April	19	70	0.27	507	254	2.00
May	43	57	0.75	179	191	0.94
June	40	55	0.73	143	160	0.89
July	39	49	0.80	140	144	0.97
Aug	45	76	0.59	205	194	1.06
Sep	38	107	0.36	N/A	N/A	N/A
Oct	34	100	0.34	N/A	N/A	N/A
Nov	30	71	0.42	N/A	N/A	N/A
Dec	28	39	0.72	N/A	N/A	N/A
Huckleberry	Weekend Average Bicycle	Weekday Average Bicycle	Weekend:Weekday Average Bicycle Ratio	Weekend Average Pedestrian	Weekday Average Pedestrian	Weekend:Weekday Average Pedestrian Ratio
Jan	75	81	0.93	446	324	1.38
Feb	75	65	1.15	536	292	1.84
March	128	119	1.08	707	577	1.23
April	173	160	1.08	577	626	0.92
May	287	310	0.93	542	460	1.18
June	241	242	1.00	502	534	0.94
July	254	252	1.01	478	412	1.16
Aug	306	282	1.09	646	674	0.96
Sep	233	249	0.94	689	688	1.00
Oct	128	189	0.68	540	611	0.88
Nov	103	132	0.78	427	456	0.94
Dec	120	98	1.22	455	325	1.40

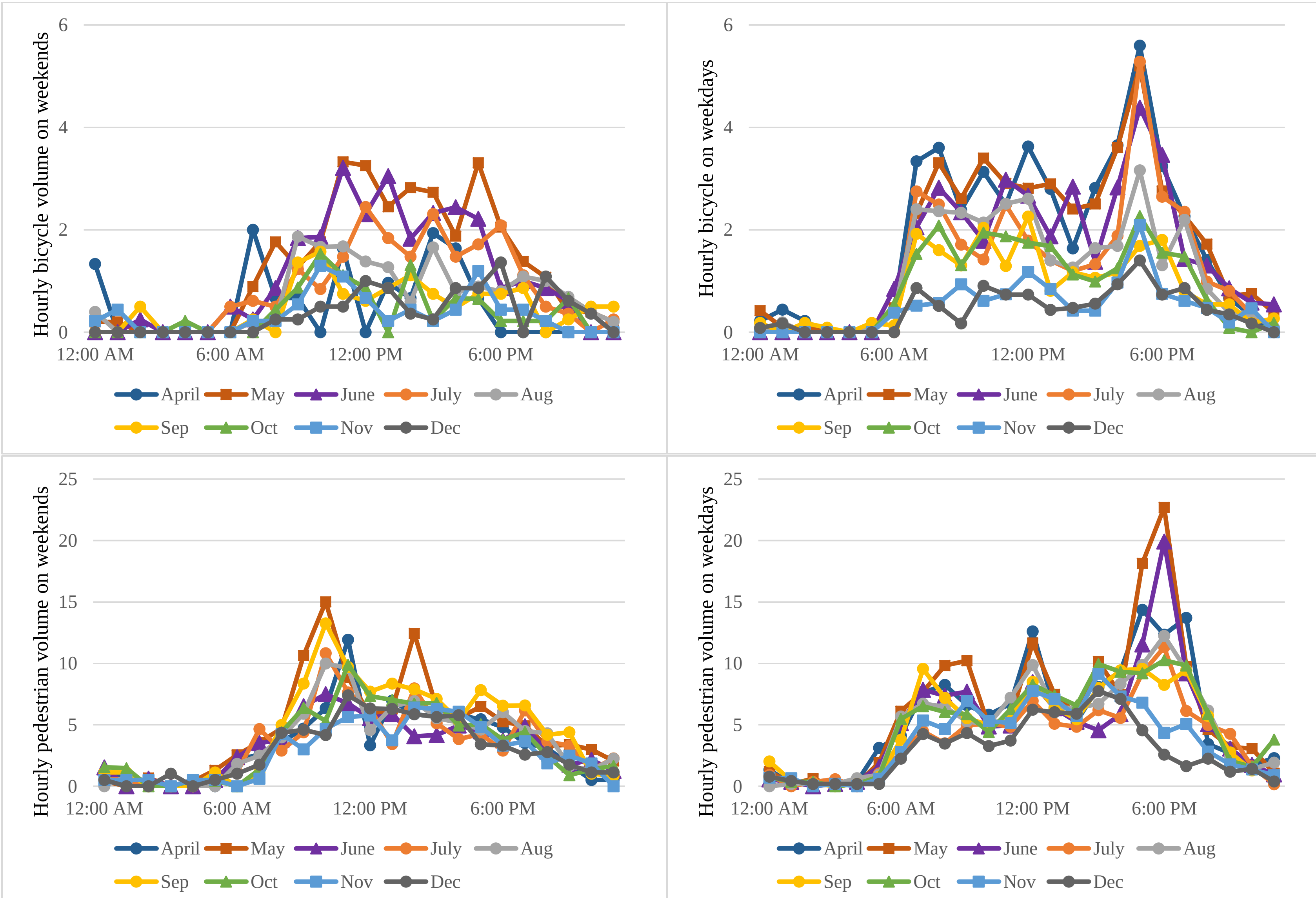

Figure 52. Average weekend and weekday hourly bicycle and pedestrian traffic at Draper Road.

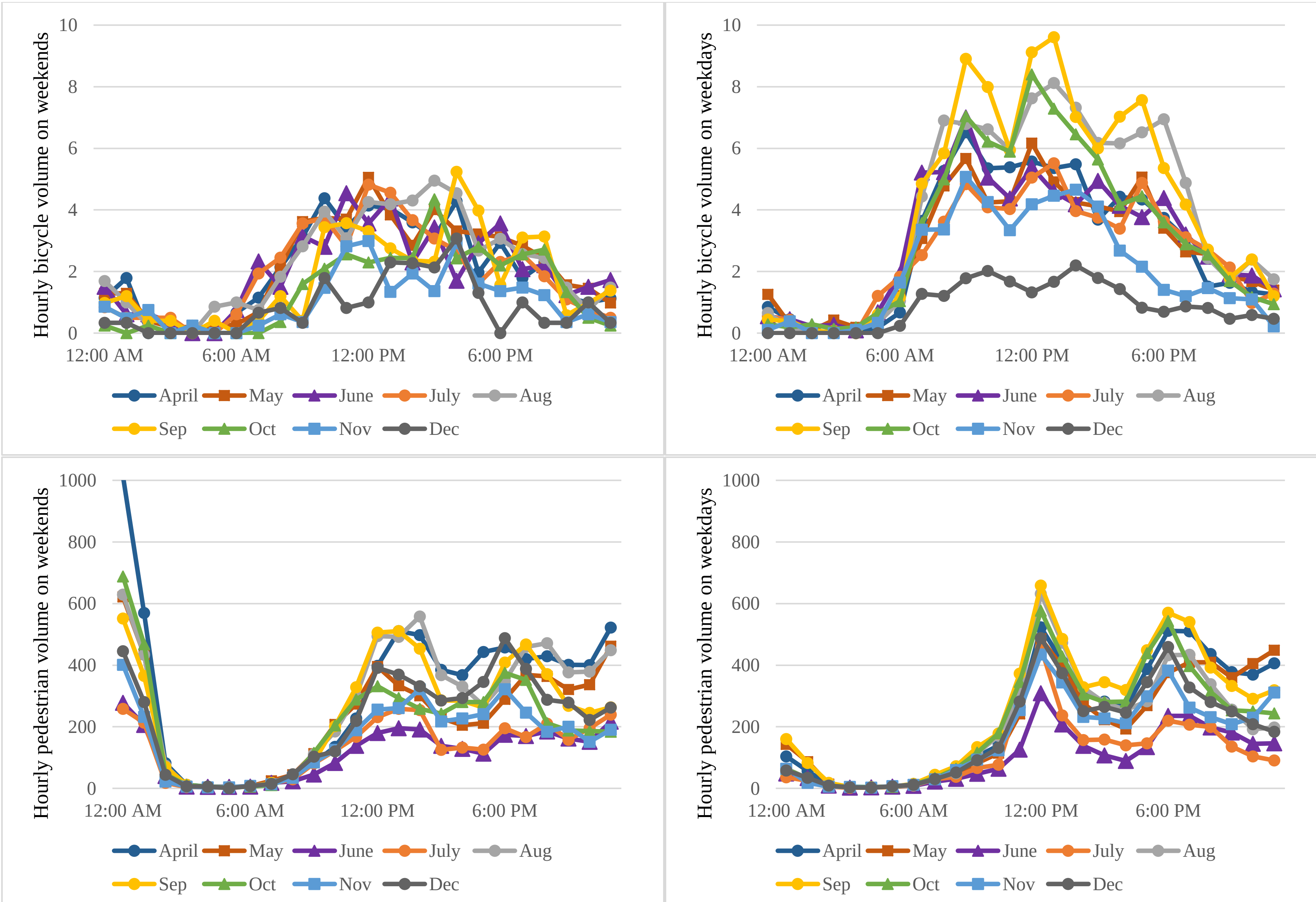

Figure 53. Average weekend and weekday hourly bicycle and pedestrian traffic at College Avenue.

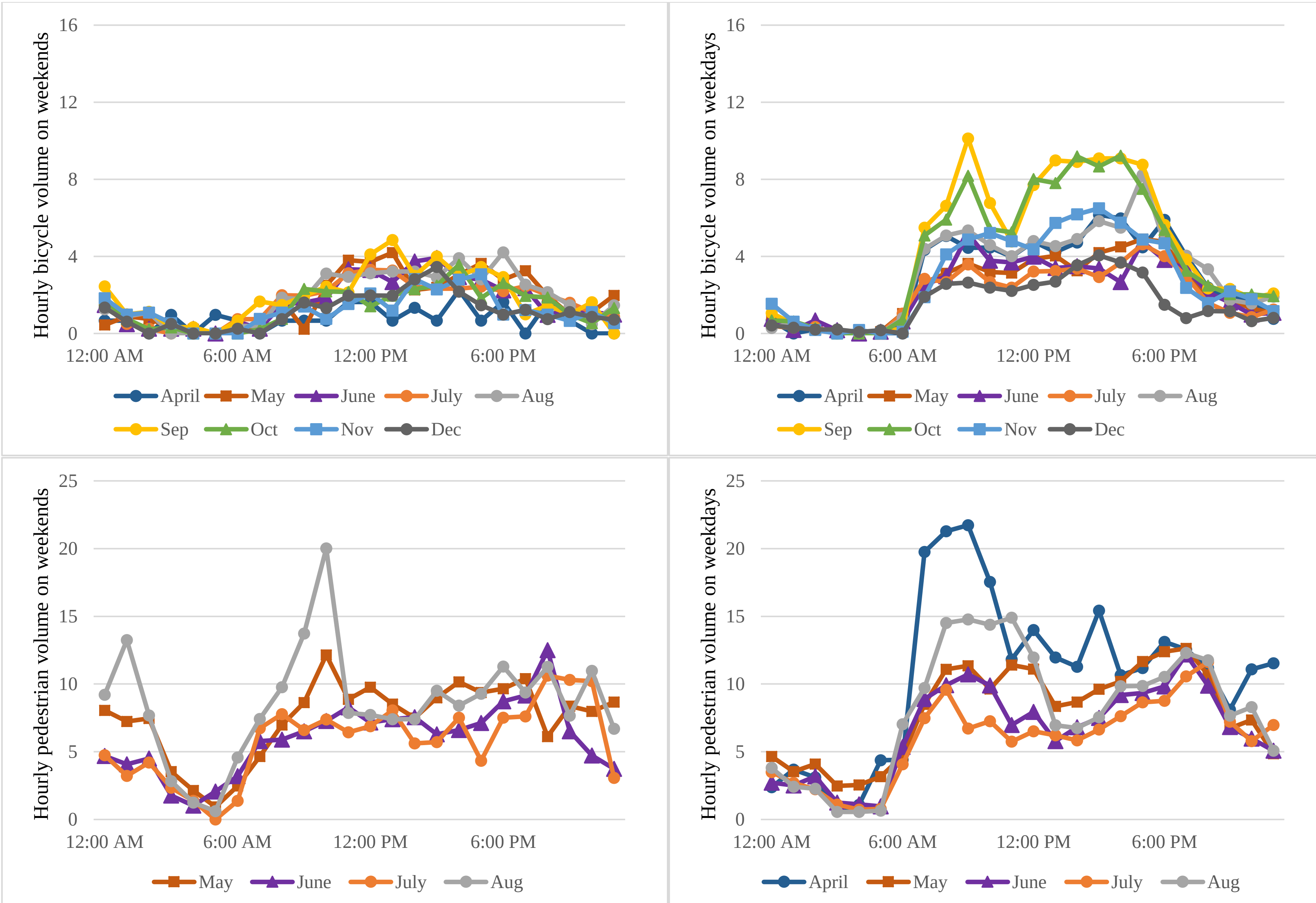

Figure 54. Average weekend and weekday hourly bicycle and pedestrian traffic at Giles Road.

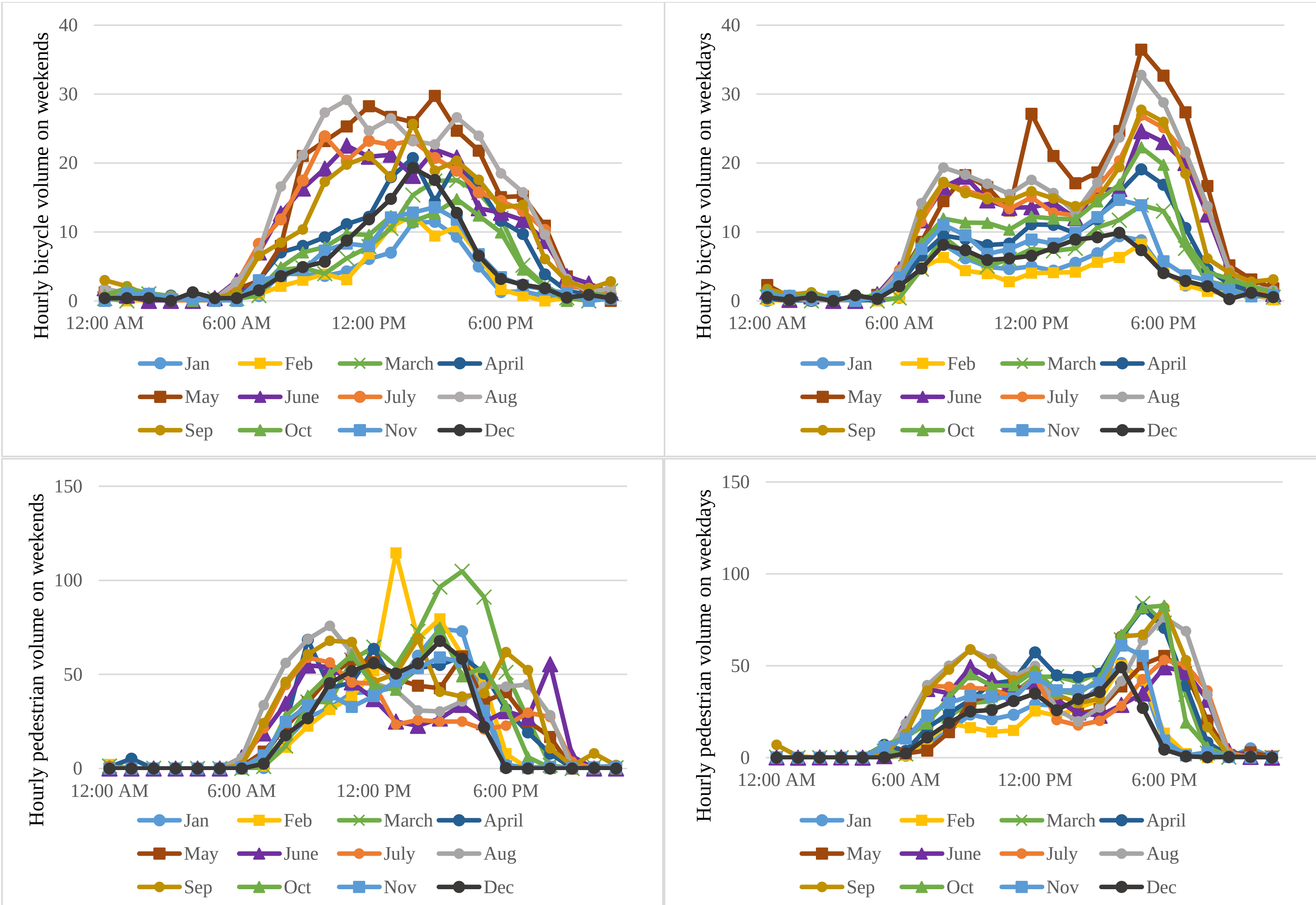

Figure 55. Average weekend and weekday hourly bicycle and pedestrian traffic at Huckleberry Trail.

APPENDIX C DAILY ESTIMATES FOR ALL SAMPLED SITES

Table 26. Weather and temporal variables used for estimating AADT

Date	TMAX Deviation (°C)	TMAX (°C)	Precipitation (mm)	Wind Speed (mph)	Weekday/Weekend	University Opening
Jan 1	-4.011	1.1	0	7	0	0
Jan 2	-0.111	5	0	4.7	0	0
Jan 3	-0.111	5	1.5	3.3	1	0
Jan 4	3.789	8.9	4.6	7.3	1	0
Jan 5	10.989	16.1	0.8	12.2	0	0
Jan 6	-4.011	1.1	0	6.1	0	0
Jan 7	-1.811	3.3	0	15.7	0	0
Jan 8	-9.511	-4.4	0	6	0	0
Jan 9	-9.011	-3.9	0	9.4	0	0
Jan 10	-4.011	1.1	0	5.1	1	0
Jan 11	-5.711	-0.6	0	1.5	1	0
Jan 12	2.689	7.8	4.1	1.4	0	0
Jan 13	0.933	6.1	2.5	6	0	0
Jan 14	-4.067	1.1	0.5	1.8	0	0
Jan 15	-4.067	1.1	0	4.3	0	0
Jan 16	-3.022	2.2	0	8	0	0
Jan 17	-0.822	4.4	0	3	1	0
Jan 18	4.178	9.4	0	6	1	0
Jan 19	3.022	8.3	0	6.1	0	0
Jan 20	7.522	12.8	0	2.9	0	1
Jan 21	9.667	15	0	3.6	0	1
Jan 22	5.267	10.6	0	3.8	0	1
Jan 23	0.711	6.1	0	3	0	1
Jan 24	-4.344	1.1	18	6.3	1	0
Jan 25	-3.244	2.2	0	5.9	1	0

Jan 26	5.100	10.6	0	5	0	1
Jan 27	0.544	6.1	0	11.2	0	1
Jan 28	-3.911	1.7	0	5.4	0	1
Jan 29	-2.367	3.3	0	2.9	0	1
Jan 30	-0.122	5.6	0.3	12.9	0	1
Jan 31	-5.778	0	0.8	7.1	1	0
Feb 1	-0.833	5	0	4.2	1	0
Feb 2	3.011	8.9	3.3	13	0	1
Feb 3	1.856	7.8	4.6	5.2	0	1
Feb 4	-1.600	4.4	0	2.7	0	1
Feb 5	5.589	11.7	0	10.2	0	1
Feb 6	-6.167	0	0	4.8	0	1
Feb 7	-0.678	5.6	0	4.8	1	0
Feb 8	7.567	13.9	0	6.7	1	0
Feb 9	10.756	17.2	0	2.7	0	1
Feb 10	9.044	15.6	1.5	5.1	0	1
Feb 11	-1.667	5	0	2.4	0	1
Feb 12	4.378	11.1	0	12.9	0	1
Feb 13	-5.133	1.7	0.3	7.1	0	1
Feb 14	-9.800	-2.8	0	10.6	1	0
Feb 15	-2.711	4.4	1.3	12.6	1	0
Feb 16	-15.522	-8.3	0	5.3	0	1
Feb 17	-16.233	-8.9	16.8	5.2	0	1
Feb 18	-9.200	-1.7	0	7.6	0	1
Feb 19	-9.811	-2.2	0.8	11.2	0	1
Feb 20	-21.678	-13.9	0	6.9	0	1
Feb 21	-13.989	-6.1	1.3	5.5	1	0
Feb 22	-5.856	2.2	16.3	3.4	1	0
Feb 23	0.733	8.9	0	8.3	0	1
Feb 24	-8.333	0	0	2.3	0	1

Feb 25	-11.300	-2.8	0.5	5.7	0	1
Feb 26	-5.867	2.8	7.4	4.5	0	1
Feb 27	-6.033	2.8	0	7	0	1
Feb 28	-10.100	-1.1	0	3	1	0
March 1	-7.467	1.7	0	2.6	1	0
March 2	-1.533	7.8	0.3	7.9	0	1
March 3	-2.800	6.7	0	3	0	1
March 4	-2.467	7.2	3	1.5	0	1
March 5	0.767	10.6	22.1	5	0	1
March 6	-9.400	0.6	28.4	1.3	0	1
March 7	-10.167	0	0	5.3	1	0
March 8	-0.989	9.4	0	4.9	1	0
March 9	4.444	15	0	2.3	0	0
March 10	4.278	15	0.3	2.3	0	0
March 11	4.111	15	5.3	3.4	0	0
March 12	5.644	16.7	3.3	3.9	0	0
March 13	5.422	16.7	0	4.7	0	0
March 14	-3.144	8.3	9.7	3.4	1	0
March 15	2.789	14.4	5.6	12.3	1	0
March 16	4.867	16.7	0	6.4	0	1
March 17	10.800	22.8	0	10.4	0	1
March 18	6.733	18.9	0	6.9	0	1
March 19	-0.189	12.2	0	3.6	0	1
March 20	-6.456	6.1	11.4	3.3	0	1
March 21	-4.422	8.3	1	7.2	1	0
March 22	5.356	18.3	0	4.8	1	0
March 23	3.589	16.7	0	5.5	0	1
March 24	2.822	16.1	0	5.2	0	1
March 25	3.200	16.7	0	7	0	1
March 26	3.533	17.2	0	5	0	1

March 27	8.967	22.8	23.1	8	0	1
March 28	-6.256	7.8	1.8	13.9	1	0
March 29	-14.222	0	0	5.3	1	0
March 30	-3.789	10.6	0	8.1	0	1
March 31	-1.311	13.3	0.5	9.9	0	1
April 1	5.822	20.6	0	5.5	0	1
April 2	2.800	17.8	0	4.4	0	1
April 3	3.133	18.3	0	5.3	0	1
April 4	3.567	18.9	7.4	11.2	1	0
April 5	-3.356	12.2	0	3.2	1	0
April 6	0.378	16.1	0	3.1	0	1
April 7	6.311	22.2	7.4	2.1	0	1
April 8	2.189	18.3	8.9	2.3	0	1
April 9	8.122	24.4	11.9	6.2	0	1
April 10	4.656	21.1	0	7	0	1
April 11	5.533	22.2	3.8	8.2	1	0
April 12	1.467	18.3	0	4.7	1	0
April 13	4.100	21.1	0	5.1	0	1
April 14	3.933	21.1	2.5	4.3	0	1
April 15	-0.133	17.2	17	4.3	0	1
April 16	-5.856	11.7	0.8	2.1	0	1
April 17	-7.722	10	13.2	2.4	0	1
April 18	6.511	24.4	0	2.9	1	0
April 19	8.044	26.1	0	9.2	1	0
April 20	-2.122	16.1	34.3	4.9	0	1
April 21	4.411	22.8	6.1	9.2	0	1
April 22	-2.456	16.1	0	8.7	0	1
April 23	0.678	19.4	0	11.8	0	1
April 24	-4.489	14.4	0	8.1	0	1
April 25	-2.356	16.7	0	3.8	1	0

April 26	-11.367	7.8	17	3.6	1	0
April 27	-9.333	10	0.5	7.4	0	1
April 28	-6.700	12.8	0	3.5	0	1
April 29	-1.367	18.3	0	1.8	0	1
April 30	0.222	20	0	4.4	0	1
May 1	-1.044	18.9	18.5	4.7	0	1
May 2	-5.656	14.4	8.6	3.7	1	0
May 3	-0.822	19.4	0	1.1	1	0
May 4	2.967	23.3	0	2.7	0	1
May 5	5.100	25.6	0	1.8	0	1
May 6	7.189	27.8	0	1.3	0	1
May 7	5.978	26.7	0.3	3.3	0	1
May 8	6.311	27.2	0	3.3	0	1
May 9	6.200	27.2	0	3.9	1	0
May 10	5.589	26.7	0	5.3	1	0
May 11	4.322	25.6	0	2.5	0	1
May 12	8.011	29.4	0	5.9	0	1
May 13	5.700	27.2	0	8.8	0	1
May 14	0.089	21.7	0	4.3	0	1
May 15	-0.678	21.1	0	2	0	1
May 16	3.711	25.6	0	2.5	1	1
May 17	5.800	27.8	0.5	0.4	1	0
May 18	5.089	27.2	16.5	2.6	0	0
May 19	5.522	27.8	0.3	4.7	0	0
May 20	5.411	27.8	0	5.7	0	0
May 21	3.100	25.6	0	7.3	0	0
May 22	-2.667	20	6.6	5.9	0	0
May 23	-2.778	20	0	2.5	1	0
May 24	1.011	23.9	0	2.5	1	0
May 25	1.944	25	0	3.7	0	0

May 26	2.933	26.1	0	2.8	0	0
May 27	3.867	27.2	2	3.1	0	0
May 28	3.756	27.2	0	1.2	0	0
May 29	4.189	27.8	1.5	1.6	0	0
May 30	3.478	27.2	6.1	2.5	1	0
May 31	3.911	27.8	0	1.7	1	0
June 1	3.200	27.2	0	2.3	0	0
June 2	3.633	27.8	4.3	1.9	0	0
June 3	1.267	25.6	17.5	6.8	0	0
June 4	-7.744	16.7	0	4.9	0	0
June 5	-4.011	20.6	0	1.7	0	0
June 6	-0.878	23.9	17.5	3.2	1	0
June 7	2.856	27.8	0.3	5.5	1	0
June 8	-0.056	25	0	3.2	0	0
June 9	1.978	27.2	8.4	4.2	0	0
June 10	0.711	26.1	0	1.3	0	0
June 11	2.300	27.8	0	2.2	0	0
June 12	4.933	30.6	4.1	2.8	0	0
June 13	3.067	28.9	0.3	3.7	1	0
June 14	4.056	30	0	2.6	1	0
June 15	3.289	29.4	0.8	3.5	0	0
June 16	4.878	31.1	0	4.8	0	0
June 17	4.711	31.1	0	1.8	0	0
June 18	3.500	30	9.9	3.2	0	0
June 19	3.989	30.6	0.3	1.4	0	0
June 20	2.122	28.9	0	5.2	1	0
June 21	2.511	29.4	4.6	6.6	1	0
June 22	4.100	31.1	1.5	1.6	0	0
June 23	2.889	30	0	4.1	0	0
June 24	3.878	31.1	0	2.7	0	0

June 25	2.122	29.4	0	2.2	0	0
June 26	3.211	30.6	1	3.7	0	0
June 27	1.456	28.9	15.2	3.9	1	0
June 28	-1.456	26.1	1.3	9.1	1	0
June 29	-3.211	24.4	0	2.1	0	0
June 30	-2.667	25	1	4.2	0	0
July 1	-0.522	27.2	0.5	2.5	0	0
July 2	-0.578	27.2	0	1.6	0	0
July 3	-5.033	22.8	0.8	4	0	0
July 4	-4.589	23.3	12.2	3.1	1	0
July 5	1.456	29.4	0	4.5	1	0
July 6	-2.344	25.6	38.6	2.9	0	0
July 7	-1.900	26.1	1.3	2.6	0	0
July 8	0.300	28.3	0.3	3.3	0	0
July 9	-3.000	25	2	4	0	0
July 10	2.000	30	0	4.3	0	0
July 11	1.400	29.4	2.5	3.6	1	0
July 12	-0.200	27.8	0	0.9	1	0
July 13	-1.900	26.1	35.8	4.6	0	0
July 14	1.400	29.4	8.4	5.8	0	0
July 15	-0.200	27.8	3.6	5.7	0	0
July 16	-3.000	25	0	2.9	0	0
July 17	0.956	28.9	0	2.4	0	0
July 18	0.956	28.9	0	2.1	1	0
July 19	2.656	30.6	0	2.1	1	0
July 20	2.111	30	0	3.2	0	0
July 21	2.111	30	0	4.6	0	0
July 22	1.011	28.9	0.3	3.5	0	0
July 23	-0.033	27.8	0	2.1	0	0
July 24	-1.133	26.7	0	1.5	0	0

July 25	1.122	28.9	0	2.4	1	0
July 26	2.222	30	0	1.5	1	0
July 27	2.822	30.6	0	1.9	0	0
July 28	0.078	27.8	0.5	2	0	0
July 29	2.878	30.6	2	1.9	0	0
July 30	1.178	28.9	0	3.9	0	0
July 31	3.433	31.1	0	2.5	0	0
Aug 1	0.633	28.3	0	3.9	1	0
Aug 2	0.633	28.3	0	1.5	1	0
Aug 3	-0.467	27.2	0	2.8	0	0
Aug 4	2.333	30	0	3.3	0	0
Aug 5	2.933	30.6	0	3.6	0	0
Aug 6	3.433	31.1	1.3	3.6	0	0
Aug 7	-0.411	27.2	18.3	4.5	0	0
Aug 8	-3.711	23.9	0	1.9	1	0
Aug 9	0.689	28.3	2.5	1.2	1	0
Aug 10	1.289	28.9	0	2.3	0	0
Aug 11	-1.511	26.1	46.5	5.5	0	0
Aug 12	0.189	27.8	2	4.8	0	0
Aug 13	-0.911	26.7	0	1.4	0	0
Aug 14	-0.911	26.7	0	1.5	0	0
Aug 15	1.289	28.9	1.5	1.1	1	0
Aug 16	1.344	28.9	0	1.6	1	0
Aug 17	3.044	30.6	4.3	0.9	0	0
Aug 18	1.344	28.9	3.8	2.3	0	0
Aug 19	-0.800	26.7	19.3	1.8	0	0
Aug 20	2.500	30	3.6	2.3	0	0
Aug 21	-0.244	27.2	0.5	2.3	0	0
Aug 22	-1.789	25.6	0	2.1	1	0
Aug 23	-0.189	27.2	0	1.8	1	0

Aug 24	0.467	27.8	0	3.8	0	1
Aug 25	1.622	28.9	0	3	0	1
Aug 26	-1.567	25.6	0	2.8	0	1
Aug 27	-3.211	23.9	0	1.6	0	1
Aug 28	-0.956	26.1	0	2.3	0	1
Aug 29	0.856	27.8	0	0.9	1	0
Aug 30	-0.133	26.7	0	1	1	0
Aug 31	-0.022	26.7	0.3	2	0	1
Sep 1	2.289	28.9	0	1.6	0	1
Sep 2	3.500	30	0	1.7	0	1
Sep 3	3.611	30	0	2.3	0	1
Sep 4	3.778	30	11.7	1.9	0	1
Sep 5	4.489	30.6	0.3	4	1	0
Sep 6	1.856	27.8	0	3.1	1	0
Sep 7	2.022	27.8	0	1.3	0	1
Sep 8	3.289	28.9	0	1.8	0	1
Sep 9	2.856	28.3	0	1.6	0	1
Sep 10	4.122	29.4	1.3	1.6	0	1
Sep 11	-0.056	25	17.5	1.1	0	1
Sep 12	1.811	26.7	0.3	3.1	1	0
Sep 13	-4.667	20	1	5.4	1	0
Sep 14	-7.300	17.2	0.3	3	0	1
Sep 15	-2.578	21.7	0	1.7	0	1
Sep 16	2.044	26.1	0	1.6	0	1
Sep 17	2.267	26.1	0	1.6	0	1
Sep 18	3.589	27.2	0	0.6	0	1
Sep 19	4.356	27.8	0	1	1	0
Sep 20	5.078	28.3	0	2.9	1	0
Sep 21	0.300	23.3	18.3	4.4	0	1
Sep 22	-7.178	15.6	0.8	3.5	0	1

Sep 23	-3.656	18.9	0.3	3.9	0	1
Sep 24	1.567	23.9	0	7.8	0	1
Sep 25	1.189	23.3	0	11.2	0	1
Sep 26	-5.189	16.7	16.3	12.3	1	0
Sep 27	-4.967	16.7	15	10.1	1	0
Sep 28	-4.300	17.2	22.4	5.8	0	1
Sep 29	-0.678	20.6	24.1	2.2	0	1
Sep 30	1.744	22.8	89.4	3.2	0	1
Oct 1	3.011	23.9	0.5	6.7	0	1
Oct 2	-2.867	17.8	6.6	9.3	0	1
Oct 3	-8.300	12.2	15.2	8.5	1	0
Oct 4	-9.233	11.1	19.3	9.8	1	0
Oct 5	-6.267	13.9	2.8	5.3	0	1
Oct 6	0.656	20.6	0	0.3	0	1
Oct 7	2.422	22.2	0	1	0	1
Oct 8	5.333	25	0	0.9	0	1
Oct 9	6.100	25.6	0	2.2	0	1
Oct 10	5.067	24.4	11.4	3	1	0
Oct 11	-4.767	14.4	2	1.3	1	0
Oct 12	1.544	20.6	0	1.8	0	1
Oct 13	2.811	21.7	1.8	5.7	0	1
Oct 14	2.922	21.7	0	7	0	1
Oct 15	0.789	19.4	0	2.9	0	1
Oct 16	0.400	18.9	0	4.9	0	0
Oct 17	-0.533	17.8	0	7.3	1	0
Oct 18	-6.522	11.7	0	6.4	1	0
Oct 19	-7.011	11.1	0	1.3	0	1
Oct 20	-2.344	15.6	0	1.2	0	1
Oct 21	2.767	20.6	0	0.9	0	1
Oct 22	5.578	23.3	0	1.9	0	1

Oct 23	6.289	23.9	0	2.1	0	1
Oct 24	8.656	26.1	0	4.5	1	0
Oct 25	-0.133	17.2	0	3	1	0
Oct 26	0.033	17.2	0.3	5.5	0	1
Oct 27	-5.956	11.1	3.6	8.2	0	1
Oct 28	-5.189	11.7	29.5	7	0	1
Oct 29	4.322	21.1	5.3	2.7	0	1
Oct 30	0.589	17.2	0	4.6	0	1
Oct 31	-4.244	12.2	0	3.1	1	0
Nov 1	-2.978	13.3	0.5	1.5	1	0
Nov 2	2.789	18.9	1.5	3.5	0	1
Nov 3	-2.044	13.9	1	2.3	0	1
Nov 4	3.178	18.9	0	2.3	0	1
Nov 5	5.544	21.1	0	0.9	0	1
Nov 6	8.511	23.9	0	3.5	0	1
Nov 7	9.833	25	1	3.6	1	0
Nov 8	1.156	16.1	5.1	3.7	1	0
Nov 9	-3.622	11.1	1	4.9	0	1
Nov 10	-4.500	10	25.1	7.2	0	1
Nov 11	2.422	16.7	0	5.2	0	1
Nov 12	3.144	17.2	0	6.5	0	1
Nov 13	5.067	18.9	0	12.4	0	1
Nov 14	-1.856	11.7	0	10.6	1	0
Nov 15	-2.233	11.1	0	1.2	1	0
Nov 16	3.044	16.1	0	0.1	0	1
Nov 17	0.467	13.3	0	4.1	0	1
Nov 18	0.744	13.3	0	8.4	0	1
Nov 19	1.622	13.9	47.2	3.8	0	1
Nov 20	8.600	20.6	0	7.4	0	1
Nov 21	-0.678	11.1	0	2.7	1	0

Nov 22	-0.400	11.1	0	9.7	1	0
Nov 23	-6.222	5	0	7.2	0	0
Nov 24	-5.344	5.6	0	1.8	0	0
Nov 25	1.033	11.7	0	3.5	0	0
Nov 26	1.311	11.7	0	1.8	0	0
Nov 27	5.433	15.6	0	0.7	0	0
Nov 28	7.911	17.8	0	0.5	1	0
Nov 29	8.189	17.8	0.3	1.2	1	0
Nov 30	6.211	15.6	9.9	6.8	0	1
Dec 1	-3.511	5.6	23.6	1.2	0	1
Dec 2	3.311	12.2	27.7	4.2	0	1
Dec 3	5.289	13.9	3.8	9.6	0	1
Dec 4	-1.689	6.7	0	1.1	0	1
Dec 5	1.833	10	0	0.5	1	0
Dec 6	4.256	12.2	0	0.8	1	0
Dec 7	4.478	12.2	0	1	0	1
Dec 8	2.444	10	1.5	0.4	0	1
Dec 9	5.967	13.3	0	1.8	0	1
Dec 10	5.633	12.8	0.3	2.2	0	1
Dec 11	8.600	15.6	0	2.8	0	1
Dec 12	12.567	19.4	0	1.7	1	0
Dec 13	15.033	21.7	0	0.8	1	0
Dec 14	12.400	18.9	0	5.6	0	1
Dec 15	11.967	18.3	0.5	7.7	0	1
Dec 16	10.478	16.7	0	3.5	0	1
Dec 17	8.889	15	4.8	2.4	0	1
Dec 18	5.100	11.1	16.3	9.5	0	1
Dec 19	-1.989	3.9	0	9.5	1	0
Dec 20	-1.378	4.4	0	3	1	0
Dec 21	4.333	10	0	1.2	0	0

Dec 22	6.089	11.7	4.6	2.3	0	0
Dec 23	11.200	16.7	7.4	4.4	0	0
Dec 24	11.256	16.7	19.3	2.9	0	0
Dec 25	12.411	17.8	11.2	1.3	0	0
Dec 26	11.367	16.7	7.6	3.6	1	0
Dec 27	9.722	15	0	2.8	1	0
Dec 28	17.578	22.8	0	9.9	0	0
Dec 29	8.078	13.3	6.9	2.7	0	0
Dec 30	13.133	18.3	0	1.3	0	0
Dec 31	6.533	11.7	4.6	6.4	0	0

Table 27. AADT Estimates for all sampled sites

FID	Longitude	Latitude	NAME	AADB	Days	Avg_SF	Avg_RefSites	AADP	Days	Avg_SF	Avg_RefSites
0	-80.401951	37.265803	COTTONWOOD	4	7	1.4700988	4.00				
1	-80.416886	37.249123	JANIE	13	8	1.3209047	4.00				
2	-80.429356	37.244819	SUNRIDGE	24	7	1.6783153	3.86	90	7	1.2387703	3.43
3	-80.437157	37.245463	VILLAGE WAY NORTH	2	7	1.1159495	3.00				
4	-80.441984	37.243617	VILLAGE WAY SOUTH	1	7	1.3209601	4.00				
5	-80.447016	37.240043	SHADOW LAKE	16	7	1.4356848	3.71				
6	-80.446722	37.233606	HARDWOOD	3	9	1.4855044	3.78				
7	-80.433553	37.219257	SMITHFIELD	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
8	-80.427129	37.223558	GROVE	6	12	1.4934564	3.75				
9	-80.412859	37.222176	WARREN	11	7	1.2873669	4.00				
10	-80.388618	37.223770	CUPP	0	7	1.1384105	4.00				
11	-80.438826	37.213112	INVENTIVE	4	8	1.3209047	4.00				
12	-80.427827	37.235699	KELSEY	4	7	1.4356848	3.71				
13	-80.414497	37.258965	PRIMROSE	4	7	1.365643	4.00	60	7	1.0073926	3.57
14	-80.453438	37.204849	TALL OAKS	3	7	1.3543097	4.00				
15	-80.403328	37.267647	BISHOP	2	8	1.3209047	4.00				
16	-80.422990	37.249795	PROGRESS	12	7	1.1490927	3.57	95	7	0.8479221	3.14
17	-80.412609	37.261467	MAIN	8	7	1.8625244	3.86				
18	-80.434585	37.232622	OLD GLADE	39	7	0.9994375	4.00				
19	-80.441551	37.221041	PLANTATION	24	7	1.6783153	3.86				
20	-80.431308	37.220560	SMITHFIELD	114	13	1.5352988	4.00				
21	-80.454420	37.208572	TALL OAKS	11	9	1.4400117	4.00				
22	-80.446774	37.216937	TALL OAKS	14	7	1.6783153	3.86	115	7	1.2387703	3.43
23	-80.453153	37.217030	HETHWOOD	32	7	1.4356848	3.71				
24	-80.418281	37.227687	KENT	290	7	0.703408	4.00	1346	7	1.1958667	3.00
25	-80.421352	37.226847	DRILLFIELD	43	7	0.8663867	4.00	4350	7	1.433936	2.43

26	-80.422677	37.232017	STANGER	376	10	0.9148648	4.00	486	7	1.201408	3.00
27	-80.419731	37.232420	TURNER	53	24	1.011222	1.50	1223	24	1.355085	1.96
28	-80.422808	37.235301	WEBB	33	7	1.1773625	4.00	173	10	0.7747926	3.70
29	-80.410680	37.231570	ROANOKE	32	7	1.3007746	4.00	359	7	0.7643876	3.71
30	-80.409645	37.228676	CLAY	28	8	1.0933845	3.75	83	8	0.8208131	3.50
31	-80.401458	37.225486	WILLARD	5	12	1.2044638	3.92	72	12	1.1526643	3.42
32	-80.403064	37.224127	PALMER	21	7	1.1818523	3.86	91	9	1.2109165	3.67
33	-80.407478	37.227612	EHEART	13	13	1.5159627	3.77	132	12	1.0850756	3.17
34	-80.399571	37.219461	COUNTRY CLUB	11	7	1.1773625	4.00	114	7	0.8580799	3.00
35	-80.397957	37.220347	PALMER	20	7	1.1773625	4.00	105	7	0.8580799	3.00
36	-80.394215	37.213958	GRISSOM	26	7	1.4700988	4.00	200	7	0.827325	4.00
37	-80.397806	37.211967	MARLINGTON	6	7	1.4700988	4.00	137	7	0.827325	4.00
38	-80.404123	37.209408	HUBBARD	29	7	1.491517	4.00	46	7	0.9727887	3.71
39	-80.417427	37.211387	RESEARCH CENTER	25	9	1.4400117	4.00				
40	-80.405304	37.217141	DRAPER	21	257	1.1666599	Continuous	98	263	1.0549456	Continuous
41	-80.409500	37.223637	DRAPER	24	7	1.2937429	4.00	223	7	0.7407703	3.57
42	-80.398655	37.193784	INDUSTRIAL PARK	10	7	1.3230618	4.00				
43	-80.405690	37.204300	RESEARCH CENTER	19	7	1.0396142	4.00				
44	-80.464685	37.243244	MEADOWBRO OK	13	7	1.1384105	4.00				
45	-80.448869	37.250990	MEADOWBRO OK	13	7	1.2887237	4.00				
46	-80.436855	37.251967	TOMS CREEK	22	9	1.4855044	3.78				
47	-80.415873	37.233021	PROGRESS	36	13	1.5352988	4.00	286	8	1.0934202	3.63
48	-80.416402	37.240683	GILES	38	11	1.2505081	3.91	142	10	1.1697559	3.40
49	-80.411608	37.245853	GILES	55	246	1.0762022	Continuous	289	102	0.582152	Continuous
50	-80.412255	37.232884	HARDING	36	7	1.491517	4.00	304	7	0.7629644	3.71

51	-80.417614	37.230706	ALUMNI MALL	104	7	0.703408	4.00	856	7	0.9152746	3.00
52	-80.419079	37.223424	WASHINGTON	108	7	0.8663867	4.00	2379	7	0.9866538	3.00
53	-80.413643	37.227790	DRAPER	105	7	1.4700988	4.00	720	7	0.827325	4.00
54	-80.426389	37.227600	WEST CAMPUS	164	7	0.8663867	4.00	455	7	1.1107331	3.00
55	-80.433421	37.219577	Smithfield Rd	182	7	1.2100241	3.29	36	7	0.8394983	2.86
56	-80.410450	37.257067	North Main St	32	7	1.6143288	2.86	37	6	1.3546645	2.50
57	-80.415282	37.198600	Huckleberry Trail	167	7	1.370183	4.00	97	7	1.2950321	3.00
58	-80.427478	37.228747	Near W Campus Dr	76	7	1.4755926	3.57	148	7	1.5045509	2.71
59	-80.403834	37.213499	Kennedy Ave	20	7	1.0733561	4.00	25	7	0.9961404	3.43
60	-80.412991	37.223710	Harrell St_Huckleberry	285	6	1.1218191	4.00	484	5	0.8682923	2.80
61	-80.446537	37.240146	Shadow Lake Rd	13	7	0.9801974	4.00	15	7	0.7504312	4.00
62	-80.419457	37.218031	CRC Trail	79	7	1.0512355	4.00	255	7	1.0685933	3.00
63	-80.415366	37.205642	CRC Trail End	74	7	1.3023467	4.00	69	7	0.8137918	3.86
64	-80.417447	37.189041	Near Hightop Rd	117	7	1.3226227	4.00	102	7	1.3429091	2.43
65	-80.406178	37.201093	Ramble Rd	18	7	1.7959717	4.00	93	7	1.3592973	3.71
66	-80.448070	37.218733	Heather Dr	23	7	1.3972943	3.00	72	7	0.9992264	2.14
67	-80.444414	37.212022	Stroubles Creek	170	7	1.1972175	4.00	215	7	0.7405552	3.86
68	-80.440530	37.232041	Oriole Dr	0	7	1.3209601	4.00	4	7	0.7704642	3.86
69	-80.428425	37.247879	Givens Ln, Chickahominy	9	7	1.3230618	4.00	7	7	0.7530865	3.57
70	-80.415656	37.221253	Behind Lane Stadium	44	7	1.7952179	3.43	96	6	1.3109445	2.83
71	-80.404070	37.230518	Devon Ln	2	7	1.4013196	3.86	1	7	1.448692	2.71
72	-80.414241	37.234801	303 Wilson Ave	5	7	1.1424925	3.57	26	7	0.7919225	3.86
73	-80.410721	37.261936	Reagan Rd	5	7	0.8663867	4.00	19	6	1.0662789	3.00
74	-80.409282	37.267201	Birch Leaf Ln	12	7	1.2289995	4.00	13	7	1.0915692	2.86
75	-80.399804	37.211910	MAIN	28	7	1.3111418	4.00	238	7	0.8109807	3.86
76	-80.404040	37.232089	CLAY	14	7	1.1490927	3.57	94	7	0.8479221	3.14
77	-80.402541	37.239474	HARDING	23	7	1.3007746	4.00				

78	-80.408895	37.235110	HARDING	41	7	1.4700988	4.00	239	7	0.7955468	3.57
79	-80.409485	37.242224	PATRICK	35	7	1.1490927	3.57	162	7	0.8479221	3.14
80	-80.427322	37.232273	PRICES FORK	37	6	1.731254	4.00	256	7	1.0384688	3.43
81	-80.426688	37.236265	TOMS CREEK	74	7	1.269244	3.00	412	7	1.0178334	3.43
82	-80.434496	37.236594	UNIVERSITY	41	18	0.9921892	1.50	105	18	1.3328484	2.00
83	-80.441478	37.235837	GLADE	67	7	1.1773625	4.00	133	7	0.8580799	3.00
84	-80.447922	37.224203	PRICES FORK	22	7	0.9810931	4.00	127	10	0.751507	3.90
85	-80.422423	37.239389	PROGRESS	42	7	1.1490927	3.57	224	7	0.8479221	3.14
86	-80.457212	37.236771	GLADE	28	9	1.1217569	3.67				
87	-80.456807	37.217214	PRICES FORK	18	10	1.0070612	4.00	54	10	0.751507	3.90
88	-80.421311	37.216873	SOUTHGATE	8	7	1.2232604	3.71				
89	-80.408308	37.219765	AIRPORT	23	7	1.2937429	4.00	164	7	0.7407703	3.57
90	-80.416820	37.254350	GIVENS	13	7	0.9801974	4.00	91	7	0.9727887	3.71
91	-80.412781	37.228224	MAIN	64	10	1.0070612	4.00	877	9	0.7448846	3.89
92	-80.413646	37.248094	MAIN	44	7	1.269244	3.00	229	10	0.9372344	2.40
93	-80.396961	37.207204	ELLETT	30	7	1.1773625	4.00	132	7	0.8580799	3.00
94	-80.403997	37.262997	MOUNT TABOR	25	7	1.2323216	3.29				
95	-80.426524	37.244454	PATRICK	53	24	1.011222	1.50	307	24	1.355085	1.96
96	-80.404812	37.216542	COUNTRY	20	24	1.011222	1.50	88	24	1.355085	1.96
97	-80.408565	37.224372	MAIN	42	7	1.3111418	4.00	302	7	0.8109807	3.86
98	-80.419061	37.233975	MAIN	53	7	1.269244	3.00	670	8	0.9208621	2.50
99	-80.417186	37.243149	MAIN	35	7	1.269244	3.00	219	7	0.9610154	2.43
100	-80.416081	37.230214	College Ave	54	247	1.1584805	Continuous	4232	229	1.0452496	Continuous
101	-80.412249	37.217790	Huckleberry Trail	179	350	0.9916225	Continuous	518	336	0.9916313	Continuous