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FINAL REPORT

Designing a Bicycle and Pedestrian Traffic Count Program to Estimate Performance Measures on Streets and Sidewalks in Blacksburg, VA

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16. Abstract

We developed and implemented a traffic count program in Blacksburg, VA to estimate performance measures of bicycle and pedestrian traffic. We deployed and validated automated counters at 101 count sites; the count sites consisted of 4 permanent reference sites and 97 short-duration count sites (~1 week of counts per site). In total we collected ~40,000 hours of bicycle and pedestrian counts during the year 2015. We used the counts to explore seasonal, daily, and hourly patterns of bicycle and pedestrian traffic. We also developed a set of day-of-year scaling factors based on the reference sites to annualize all short-duration counts to Annual-Average Daily Traffic (AADT) estimates. We explore how AADT varies by spatial location, street functional class, and level of supporting infrastructure. Our traffic count campaign covers ~10% of the transportation network in Blacksburg. We developed a set of spatial models (i.e., direct-demand models) to allow for estimation of traffic volumes at locations without traffic counts. We close by discussing how future research could help develop best practices and a consistent set of protocols across regions, sates, and the country.

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DISCLAIMER

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PROBLEM

Non-motorized traffic includes cyclists, pedestrians and other non-motorized road and trail users (e.g., skateboard, inline skates, wheelchair, etc.). To better understand all uses of a 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).

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 between motorized and non-motorized traffic patterns: (1) non-motorized traffic varies more than motorized traffic by time of day and season, and is more sensitive to changes in weather (Ryus et al., 2014), (2) non-motorized trips are comparatively shorter and more correlated with adjacent land uses (Ryus et al., 2014), (3) non-motorized traffic is more difficult to detect and monitor with existing technologies (FHWA, 2013).

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 "the best way to improve transportation networks for any mode is to collect and analyze trip data to optimize investments." More information is needed on best practices for implementing non-motorized traffic monitoring campaigns.

APPROACH

To address the problem statement defined above, we developed a systematic non-motorized traffic (i.e., bicycle and pedestrian) monitoring campaign in a small, rural college town (Blacksburg, VA). We use data from the bicycle and pedestrian count campaign 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 et al., 2014; Nordback et al., 2013; Nosal & Miranda-Moreno, 2014). In this report we summarize four research tasks (Figure 1) to assess seasonal, daily, and hourly patterns of non-motorized traffic. We then 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. Finally, we develop a set of facility-demand models to estimate non-motorized traffic volumes at locations without counts.

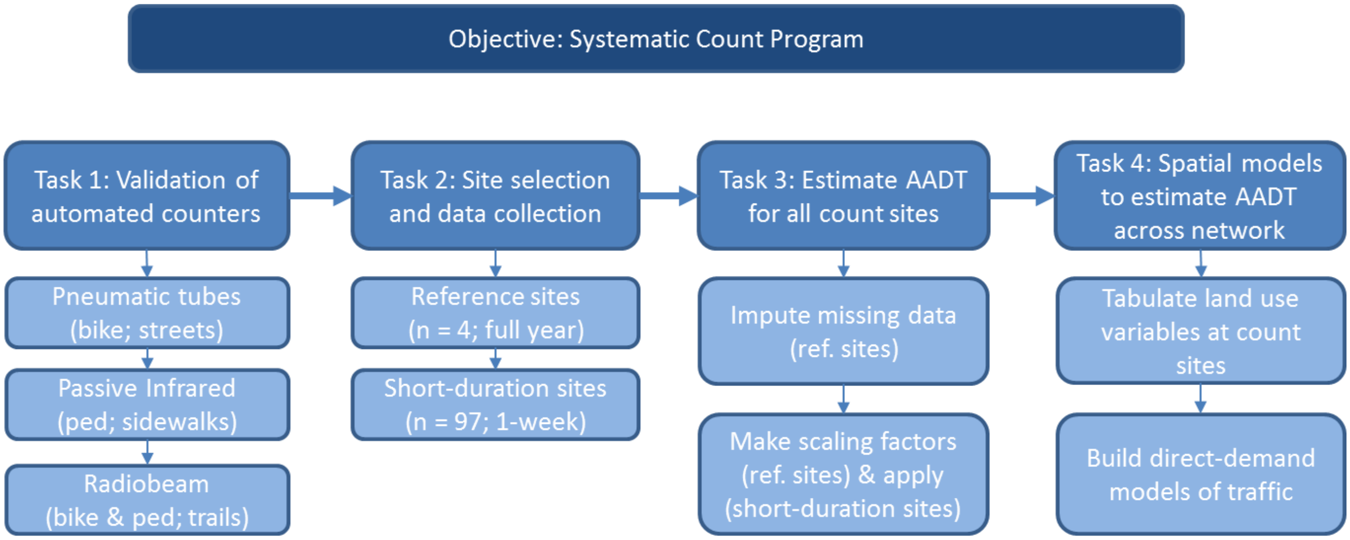

Figure 1. Workflow and research objectives.

METHODOLOGY

To systematically monitor the bicycle and pedestrian traffic in Blacksburg, VA we developed 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). In this section we summarize the methods used to accomplish the four tasks listed in Figure 1. We then describe and discuss our findings in the subsequent sections.

Task 1: Automated counter description and validation

We used 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 for choosing these counters were previous reported performance, location type, portability, and cost. MetroCount counts bicycles on roads with mixed traffic and includes easy installation and low cost (~$1,000 per unit). Eco-counter counts pedestrians only on sidewalks with a cost of ~$3,000 per unit. RadioBeam separately counts bicycles and pedestrians on off-street trails with limited monitoring distance (~10 feet; ~$4,500 per unit).

Manual validation counts

Manual field-based counts are the most common and labor intensive method to collect non-motorized traffic counts. We collected manual field counts (for the purpose of validating automated counters) 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., developing correction equations). We designed a standard screenline field-based manual count form, and attached a reference map to inform volunteers of traffic direction and screenline location. We documented 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.

Automated counters

MetroCount pneumatic tubes: We used the MetroCount MC 5600 Vehicle Classifier System (pneumatic tube counters) to monitor bicycles on 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).

We 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. Major roads were installed with two MetroCount counters on each half of the road (considering the width of the major roads); local roads were installed with only one counter (Figure 3).

Figure 2. MetroCount counter and related equipment.

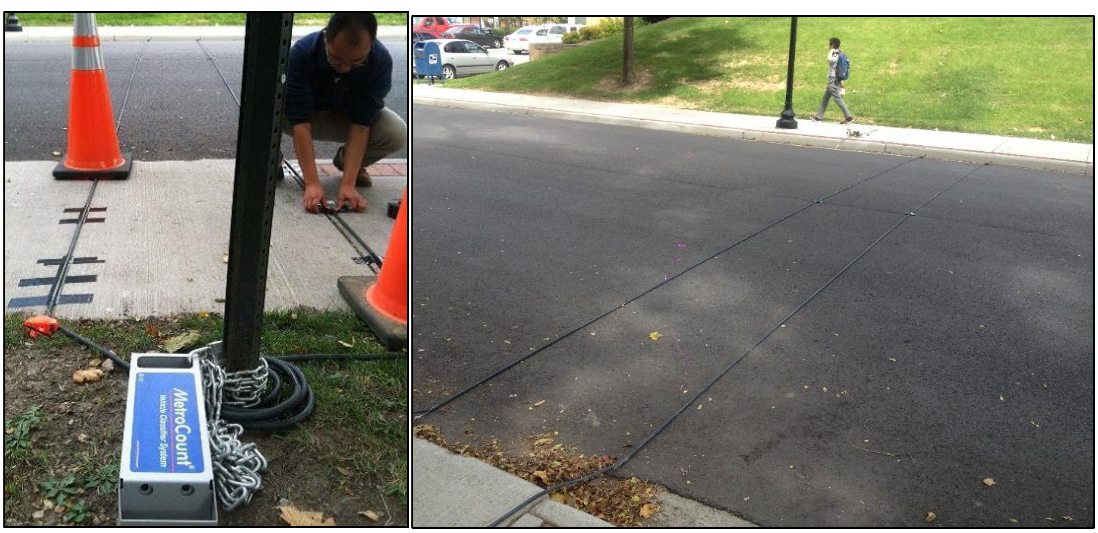

Figure 3. MetroCount counter installation.

Eco-Counter "Pyro" passive infrared: We 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 meant to be attached onto an existing pole; however, due to the lack of suitable permanent poles on the sidewalks, home-made poles fixed in concrete stanchions were used (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. 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.

Figure 4. Eco-counter "Pyro" counter and portable stanchion.

RadioBeam Bicycle-People Counter (Chambers Electronics RBBP8): We used the RadioBeam Bicycle-People Counter (RBBP8) to monitor bicycle and pedestrian volumes on off-street trails (Figure 5). The RBBP8 has two protective housings that are installed on both sides of the trail at 65 cm above ground level. When a bicycle or pedestrian passes, a count is registered; specifically, the counter uses two beams (at two different frequencies) to detect the passing pedestrian and passing metal (i.e., bicycles). The two units can be 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. Home-made poles (same as the Eco-counter) were used to allow portability of the two units for most of the trails where permanent poles are not available.

Figure 5. RadioBeam counter for a short-duration count site.

Counter validation and developing correction equations

We developed correction equations to apply to output from the automated counters due to potential systematic undercounts due to occlusion. 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 occur for the RadioBeam counter when a cluster of pedestrians pass at the same time; however, bicycles sometimes are over-counted with the RadioBeam due to repeated detection of metal. We developed and applied correction equations for MetroCount, Eco-counter and RadioBeam counters to adjust all raw data from the counters for further analysis.

MetroCount correction equations

Due to the fact that the pneumatic tubes are deployed in mixed traffic they represent the most complicated device to develop 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). We compared three bicycle-based classification schemes provided by MetroCount (i.e., ARX Cycle, BOCO and Bicycle 15; Table 1). 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 1. Criteria for scheme classification

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

We used manual counts from selected locations to develop correction equations. To test the MetroCount data with different schemes, we 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 automated counters is as follows:

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

Where e_i is the percent error for the count interval i, A_i is the automated pneumatic counts for count interval i, and M_i is the 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:

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

Where E_i is the absolute error for the count interval i, Ai is the automated pneumatic counts for count interval i, and M_i is the manual counts for count interval i. All the validation counts for bicycles were conducted at 8 locations in Blacksburg (Figure 6) and 181 valid hours of manual counts were used in this analysis.

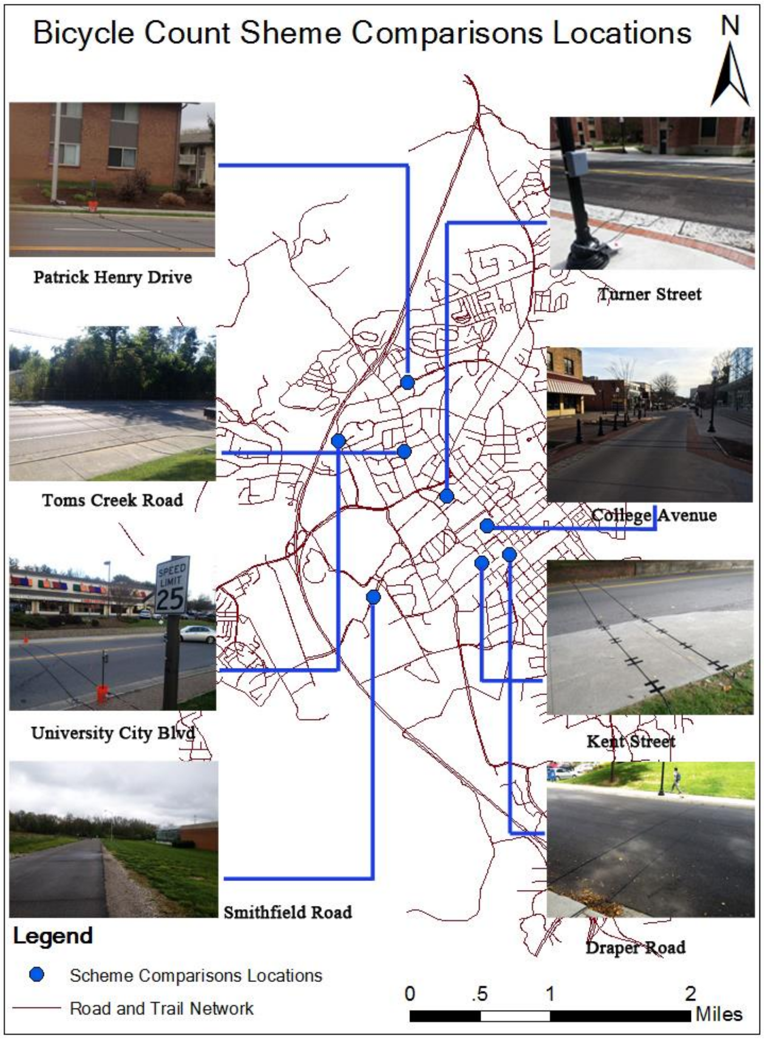

Figure 6. MetroCount bicycle count scheme validation locations.

To compare each scheme, we 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. Table 2 and 3 give summary statistics of error and goodness-of-fit for each classification scheme and time interval. Figures 7-9 show scatter plots of automated vs. manual counts for each case.

For average percent error, the 60-minute time interval has the least error using all three schemes compared with the 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 2). In this case, a 60-minute time interval is recommended for adjusting counts using correction equations.

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 3). 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 et al., 2014; Nordback et al., 2015). Therefore, according to the percent error, absolute error and R^2 comparisons, we used BOCO scheme to validate bicycle traffic for hourly counts with polynomial correction equation.

Table 2. 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%

Table 3. 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

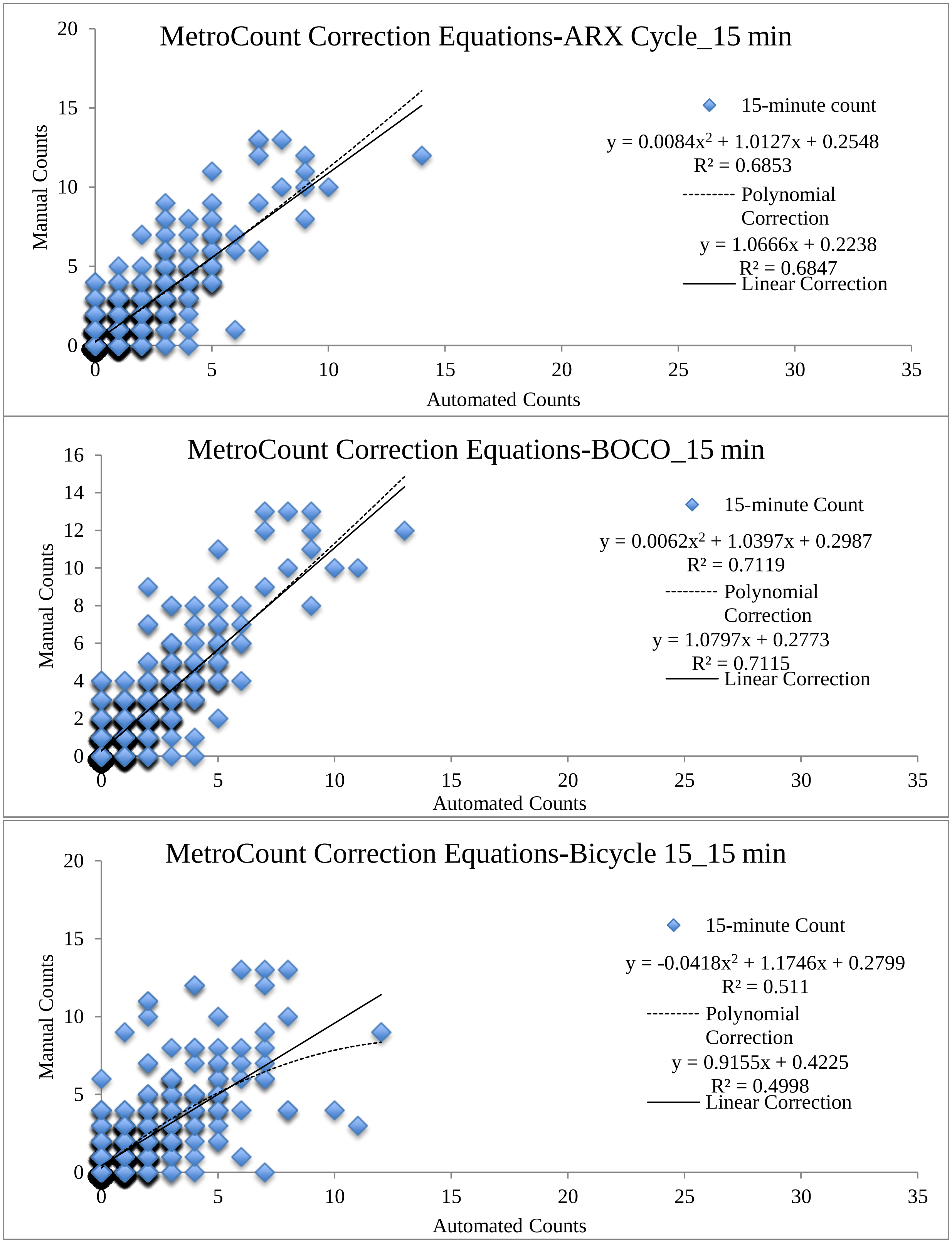

Figure 7. MetroCount correction equation scheme comparisons 15 minute interval.

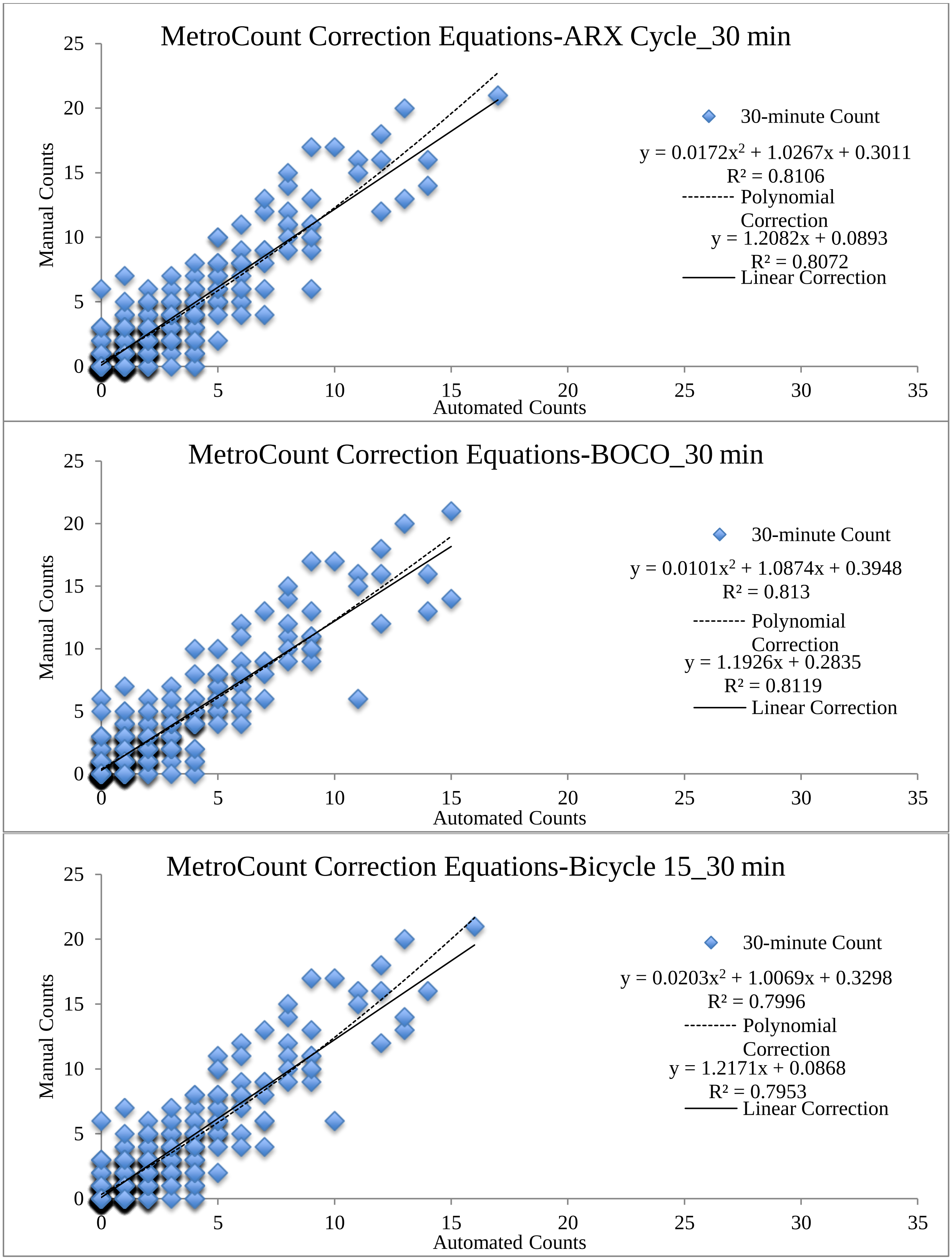

Figure 8. MetroCount correction equation scheme comparisons 30 minute interval.

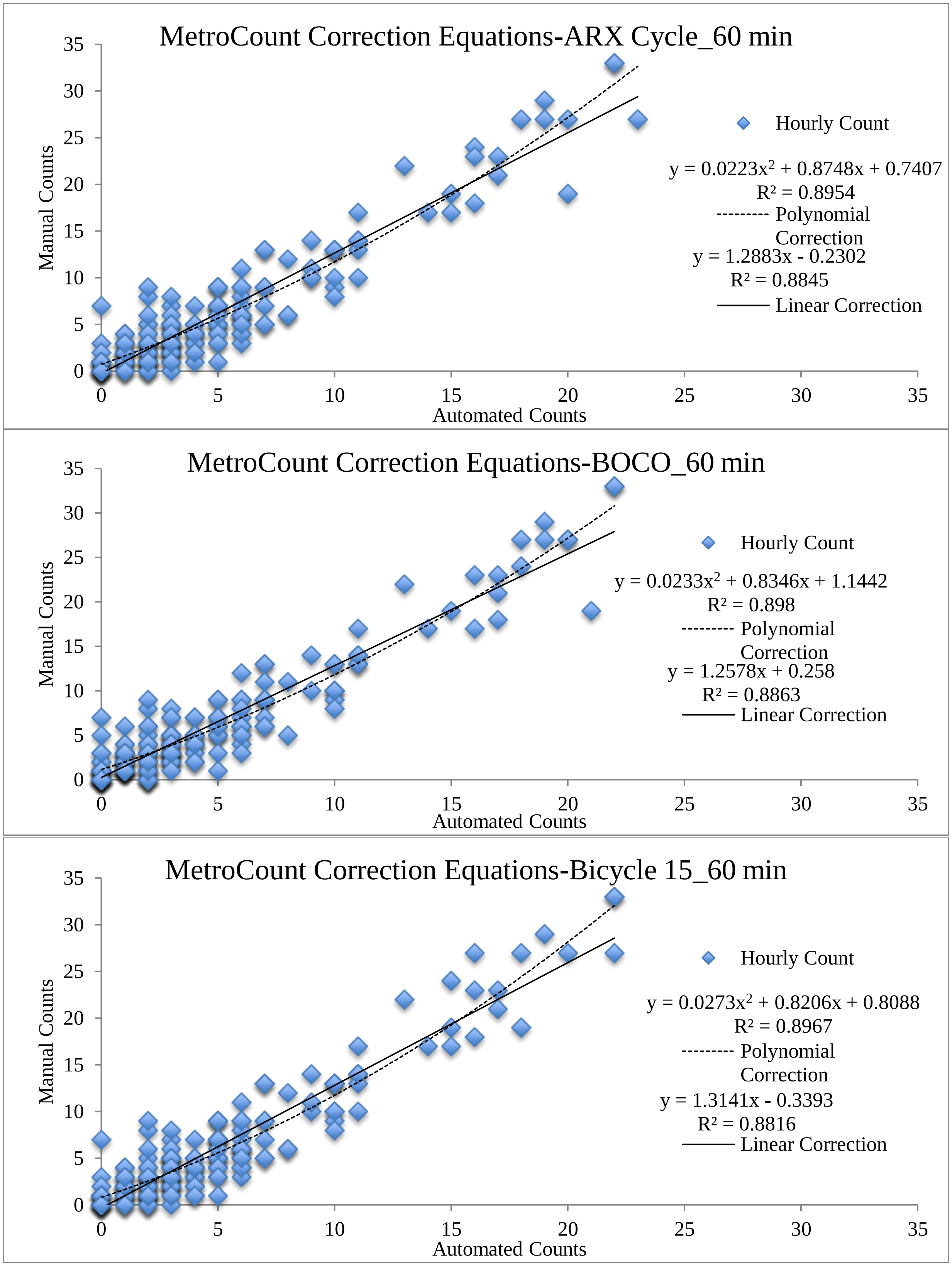

Figure 9. MetroCount correction equation scheme comparisons 60 minute interval.

Eco-counter correction equations

Similar to the MetroCount data we used field-based manual counts to develop correction equations for the Eco-counter. 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 the 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.

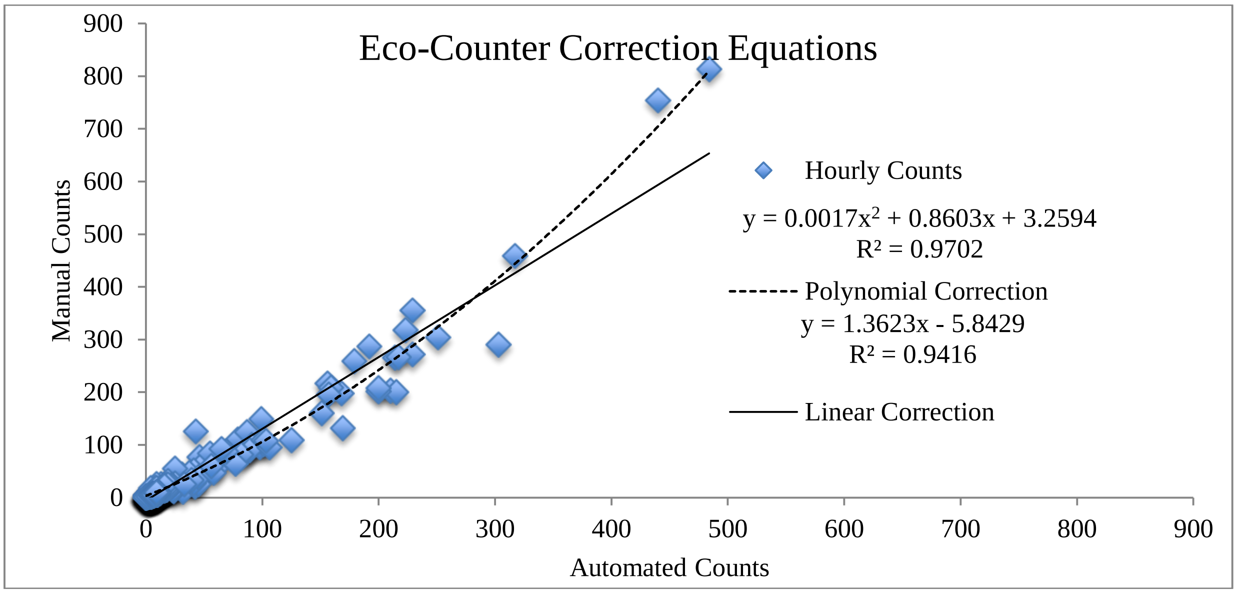

Figure 10. Eco-counter correction equations.

RadioBeam correction equations

We collected 29 hours of field-based manual counts at the Huckleberry Trail to validate both bicycle and pedestrian counts (Figure 11). Since the count data reveals a linear pattern, we used linear equations to adjust the count data. The calculated average absolute errors for bicycles and pedestrians are 19.2% and 22.4%. An important aspect to note is that the RadioBeam was the only counter to overcount (i.e., for cyclists). This is due to the fact that the sensitivity on these units was increased to detect cyclists at sufficient distance across the trail resulting in double counting of some cyclists. As demonstrated in Figure 11 this overcount was systematic and correctable.

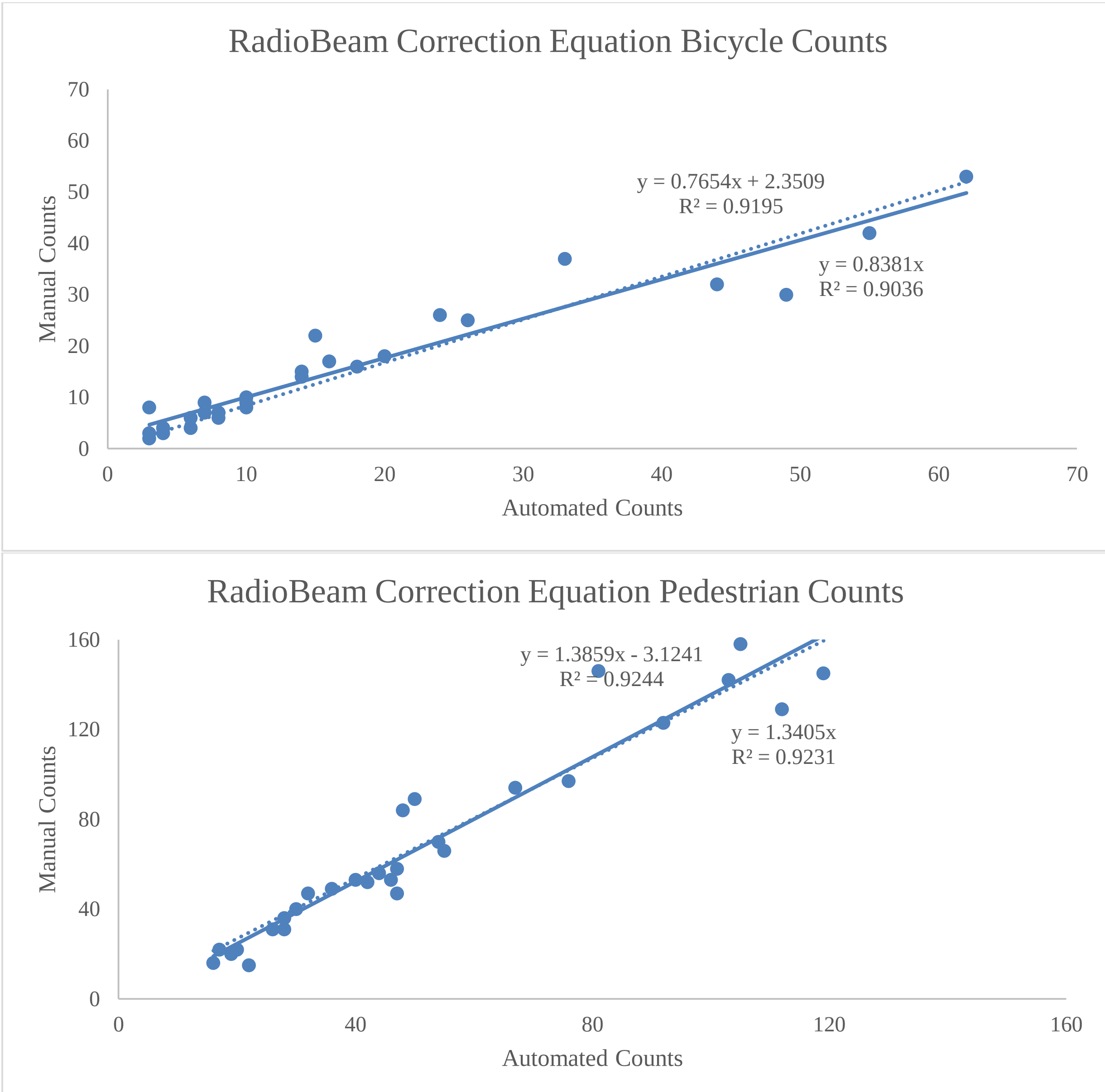

Figure 11. RadioBeam correction equations for bicycles (top-panel) and pedestrians (bottom-panel).

Table 4 summarizes comparisons of adjusted and raw counts of all counters to show the difference between corrected and raw counts. For example, MetroCount undercounts bicycles. Eco-counter undercounts pedestrians, especially when the raw count approaches large volumes which indicates a polynomial correction when the pedestrian volume is very high. RadioBeam overcounts bicycles to some extent; however, it undercounts pedestrians. These findings are mostly consistent with previous studies.

Table 4. Comparisons of adjusted and raw counts of all counters

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

Task 2: Site selection and data collection

Based on the number of available counters we selected 4 reference sites and 97 short-duration count sites from existing major roads, local roads, and off-street trails using a combination of systematic and random selection. In total, the major roads included 14 count sites with a bike lane and 15 sites without a bike lane. 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. The off-street trails include 10 transport trails (long distances or transport function) and 10 neighborhood trails. The process for selecting count sites is described below.

<u>Site selection process and description</u>

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), and (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 road near campus and downtown (College Avenue), one neighborhood local road without bike lanes (Giles Road), and one neighborhood local road with a bike lane (Draper Road) (Table 5; Figure 12). 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 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 5. Continuous reference site locations

Location	Location Type	Counter	Install Date
Draper Road	Neighborhood road; bike lane	1 MetroCount; 1 Eco-counter	April 18, 2015
College Avenue	Near campus and retail	1 MetroCount; 2 Eco-counter	March 19, 2015
Giles Road	Neighborhood road; no bike lane	1 MetroCount; 1 Eco-counter	April 18, 2015
Huckleberry Trail	Off-street trail	1 RadioBeam	December 18, 2014

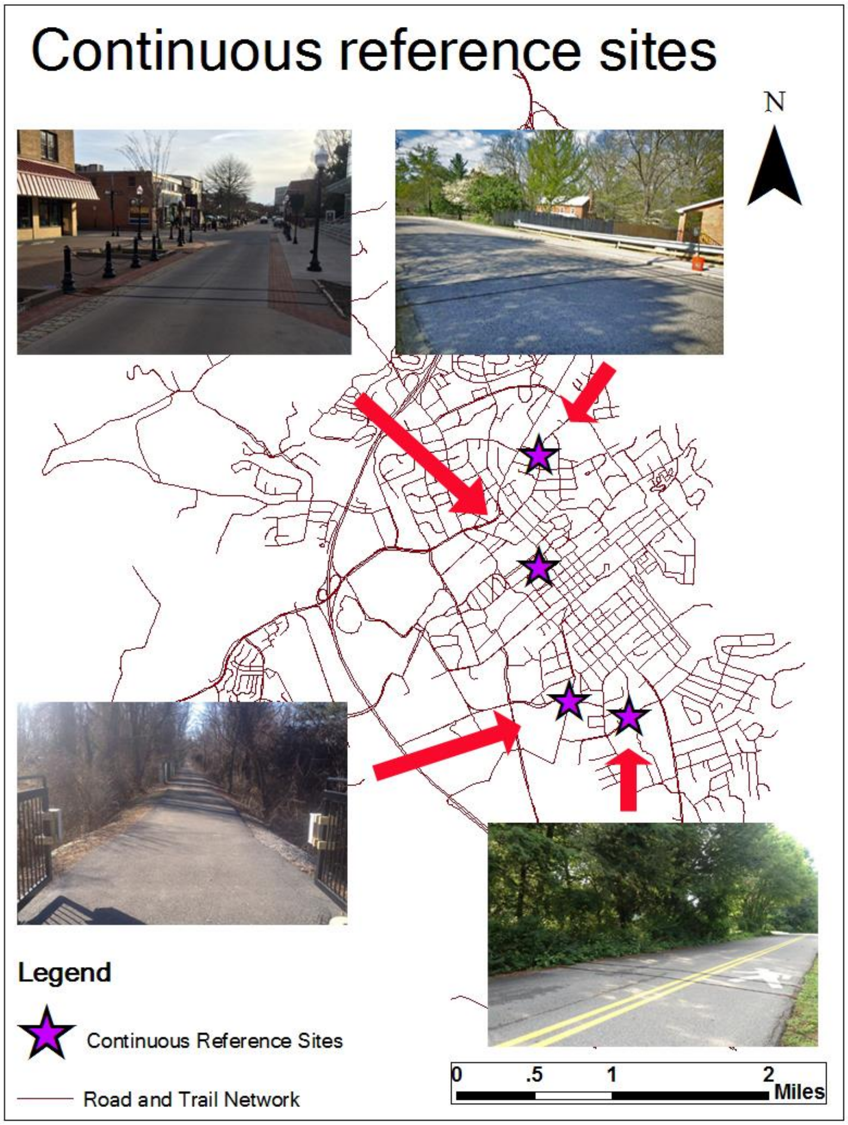

Figure 12. Continuous reference sites for bicycle and pedestrian monitoring.

Short-duration count sites: The core goal of choosing the short-duration count sites is to span the variable space for both (1) bicycle and pedestrian traffic volumes and (2) potential predictor variables to allow for spatial modeling (see Task 4). This section provides a summary of how we chose the count sites. Variables that we considered during this process were (Figure 1 shows each variable mapped in Blacksburg):

1) *Street functional class*: Transportation networks are designed in a hierarchal fashion. Both motorized and non-motorized traffic are associated with functional class.
2) *Bicycle and pedestrian infrastructure*: Trails, bike lanes, bike markings, sidewalks, etc. are correlated with bike and pedestrian traffic.
3) *Centrality*: Spatial patterns of origins, destinations, and the road network may impact traffic patterns. We use a measure called Centrality to estimate bicycle trip potential in the absence of actual counts.

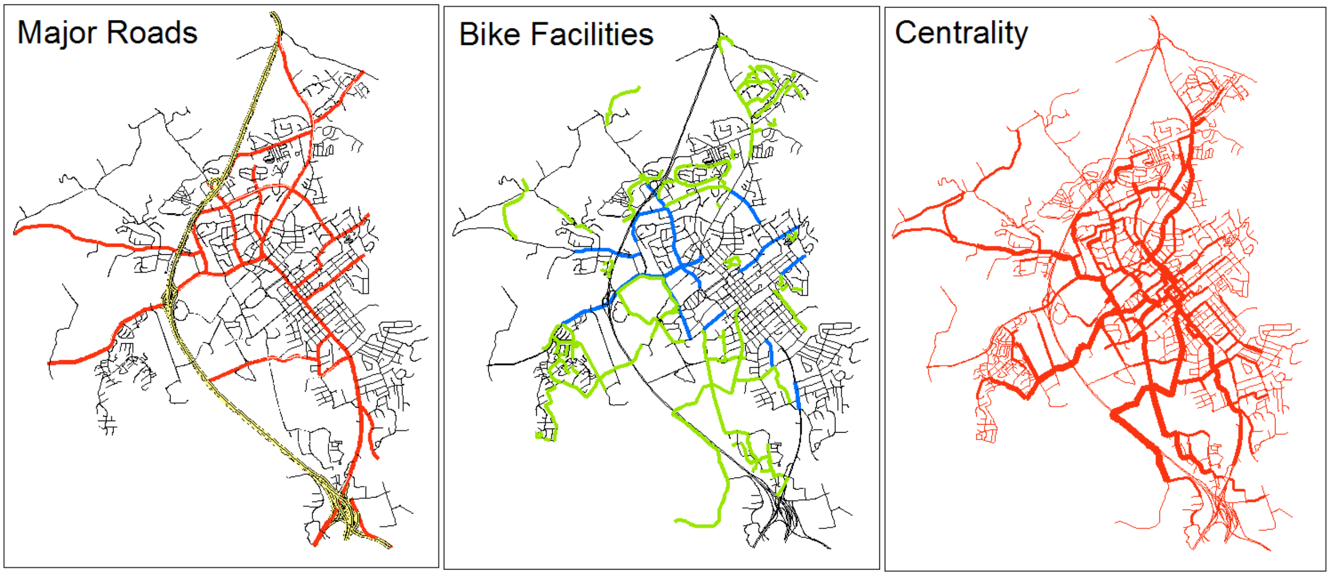

Figure 13. Major roads (left), bicycle network (middle), and centrality (right) for Blacksburg.

We chose count sites primarily based on the goal of ensuring each street functional class was sampled sufficiently. We oversampled both existing and planned cycling infrastructure and ensured there was variability for the segment attribute of centrality within each road type.

1) *Major roads (n = 29 locations)*: All roads classified as minor arterials and collectors.
2) *Off-street trails (n = 20 locations)*: All multi-purpose trails that are separate from streets.
3) *Local roads (n = 51 locations)*: All other roads in Blacksburg. This category represents nearly ¾ of segments in Blacksburg.

Sites were chosen using a combination of systematic (professional judgement) and random selection. Sites were chosen sequentially by category in this order: (1) major roads, (2) off-street trails, (3) local roads – first for future planned bicycle facilities and then for places with low centrality to adjust for oversampling places likely to have high volumes. Table 1 summarizes counts by method of selection. We trimmed the dataset for selection by removing all segments that were <250 feet in length from the selection process.

We first selected count sites on major roads. Since there are relatively few major roads in Blacksburg we were able to monitor all major road segments in the Town. Next, we selected count sites on off-street trails. We separated trails into two categories: Transport trails (trails that were long distance and connected to the network) and neighborhood trails (trails that were part of subdivision development and disconnected from the network). We then randomly selected 10 locations within each trail type. Finally, we selected ~50 locations on local roads. We first systematically selected locations where there is a planned infrastructure buildout according to the bicycle master plan. Since this resulted in oversampling locations with high Centrality (i.e., high trip potential) we also randomly selected 15 locations on local roads with low Centrality (it is important to capture low and high volumes for spatial modeling. This process resulted in 100 short-duration count locations. Upon inspection of the count locations 3 were removed from the dataset due to difficulty in sampling at those locations (e.g., dirt roads). Table 6 gives a summary of the count locations and Table 7 compares our count locations to the entire network. Figure 14 maps the short-duration count locations; Figure 15 shows examples of counters deployed at these locations.

Table 6. Summary of counts by location type

Location Type	Count locations	% of count locations	Potential segments	% sampled	Sample type
Major Roads					
Bike lanes	10	10%	45	22%	Systematic
No facility	19	19%	121	16%	Systematic
Off-street trails					
Transport	10	10%	15	67%	Systematic
Neighborhood	10	10%	26	38%	Random
Local roads					
Bike buildout	36	36%	976	4%	Systematic
Low centrality	15	15%	976	2%	Random

Table 7. Summary of share and centrality of count locations vs. Town of Blacksburg

	Share of locations		Mean (IQR) O-D centrality	
	Count Locations	Town of Blacksburg	Count Locations	Town of Blacksburg
Total Locations	100	1,848	-	-
Road Type				
Major Road	29%	14%	48,000 (14,900-64,000)	43,000 (6,700-55,000)
Local Road	51%	72%	87,500 (1,100-121,000)	33,500 (1,300-26,400)
Trail	20%	14%	252,400 (8,500-369,000)	68,800 (1,000-66,400)
Bike facility type				
On-street	15%	6%	103,000 (27,562-136,000)	76,300 (12,600-121,000)
Trail	20%	14%	252,400 (8,500-369,000)	68,800 (1,000-66,400)
None	65%	81%	110,000 (2,400-98,000)	32,200 (1,400-26,700)
Streets with sidewalks				
<100m away	80%	76%	86,800 (18,100-125,800)	49,500 (2,800-52,400)
>100m away	20%	24%	46,500 (1,000-39,000)	15,900 (700-11,000)

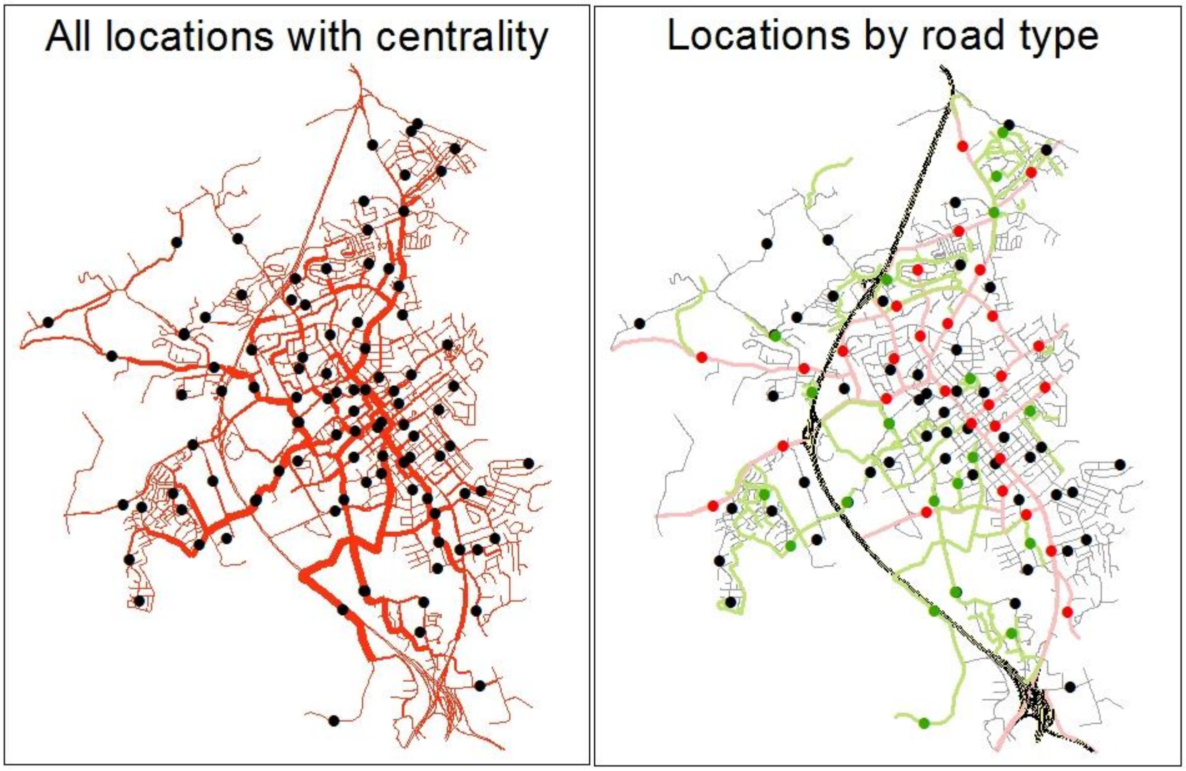

Figure 14. All count locations with centrality (left) and by road type (right).

Figure 15. Example short-duration count sites: Major road (top-panel); local road (middle-panel); off-street trail (bottom-panel).

Data collection process

To accomplish the count campaign we deployed 12 MetroCounters, 10 Eco-counters, and 3 RadioBeam counters. Three MetroCounters, 4 Eco-counters, 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. We installed the counters in a randomized order during March-September of 2015 based on weather condition (e.g., snow plowing) and counter availability. Generally, each site was monitored for at least one week and we 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. We kept an event log for each site to validate traffic counts.

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 inform the QA/QC process, we 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 8).

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) a statistical check based on the variability of the overall dataset. First, we 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, we 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, we summarized the valid monitoring days to show temporal coverage of the dataset (Table 8) and reasons for censoring data (Table 9). Since some reference sites were not deployed for a full calendar year, the summary of valid percent 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 10).

Table 8. Valid monitoring days for the continuous reference sites

	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%
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 9. Total flagged days for continuous reference sites

Reason	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	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 10. Valid monitoring days for 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%

Task 3: Estimating AADT for all count sites

AADT estimation procedure

We used a combination of information from the reference sites and short-duration sites to estimate AADT at all sites (Figure 16). Specifically, we (1) use the count data from the continuous reference sites to impute missing days using negative binomial regression models, (2) combine observed and estimated data from the reference sites to estimate AADT for each site, (3) develop day-of-year scaling factors from the continuous reference sites, and (4) apply the day-of-year factors to the short-duration counts to estimate AADT at all sites.

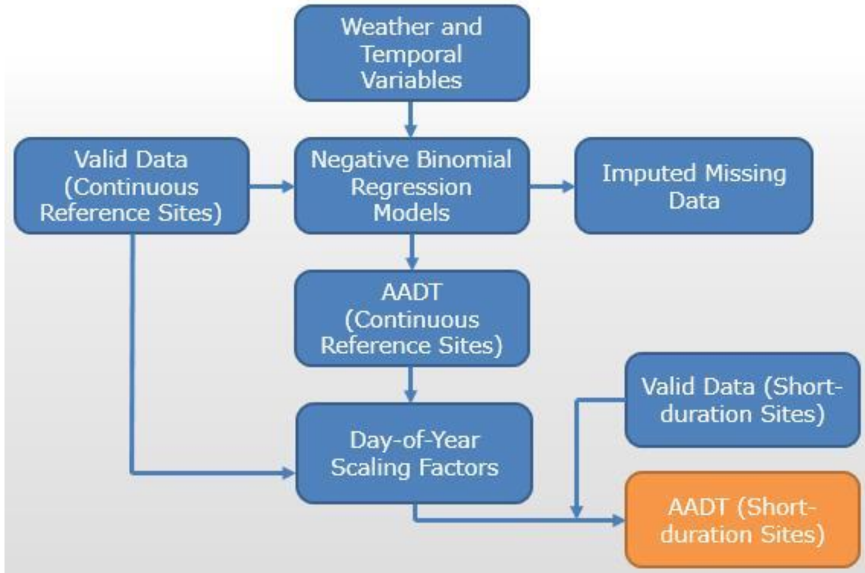

Figure 16. Flow chart of estimating AADT.

Negative binomial regression models

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, we 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. We compared the model estimates with observed (automated) counts and estimated AADT for reference site. 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:

$$P(y = m|\lambda, x_1, x_2 \cdots) = \frac{e^{-\lambda}\lambda^m}{m!} \qquad \text{Equation 3}$$

We used a type 2 negative binomial regression (Cameron et al., 2016), which assumes: mean is λ and variance is $\lambda + \alpha\,\lambda^2$. Maximum likelihood estimation (MLE) is used in the STATA package to estimate the parameters as follows:

$$ln\,\lambda = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \qquad \text{Equation 4}$$

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

$$\mathrm{E}\,(\mathrm{y}\,|\,x_1, x_2, \cdots) = \hat{\lambda} = \exp\,(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots) \qquad \text{Equation 5}$$

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:

$$R^2_{McFadden} = 1 - \frac{ln(L_{Full})}{ln(L_{Intercept})} \qquad \text{Equation 6}$$

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).

We 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 year average (1980-2010) with either positive or negative expected sign. *Precipitation* is treated as a barrier for outdoor activities with a negative expected sign. Each temperature and precipitation variable was 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 the student population at Virginia Tech is expected to influence the traffic volumes, we 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).

Table 11. Variables used in regression models of bicycle and pedestrian traffic

Variables	**Definition**	**Mean**	**Expected signs**
tmaxdev	High temperature deviation from the 30-year average (1980-2010)	0.91	+/-
tmax	Daily maximum 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 12. 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.

The overall results of the site-specific negative binomial regression models are as expected (Table 12). Almost all sites show correlations with the included variables; however, there are some differences by site and mode. 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 utilitarian nature of the site (e.g., eating, attending class, meeting friends). The results show that cyclists are more sensitive to weather conditions than pedestrians, which is consistent with previous research, e.g., 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). 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 Rd and Huckleberry Trail, while it is not significant at Draper Rd. or College Ave. 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.

<u>Model validation and imputing missing counts at the continuous reference sites</u>

We applied the negative binomial regression models to estimate missing counts days at the reference sites. We compared the model-generated counts to the existing observed (automated) counts (Figures 17-20). The left-panel of the figures show a comparison between a full year of estimated counts and observed (automated) counts; the right-panel shows correlation between the estimated counts and observed counts. The goal is to combine the observed data with the imputed data to estimate a full year of counts at each reference site.

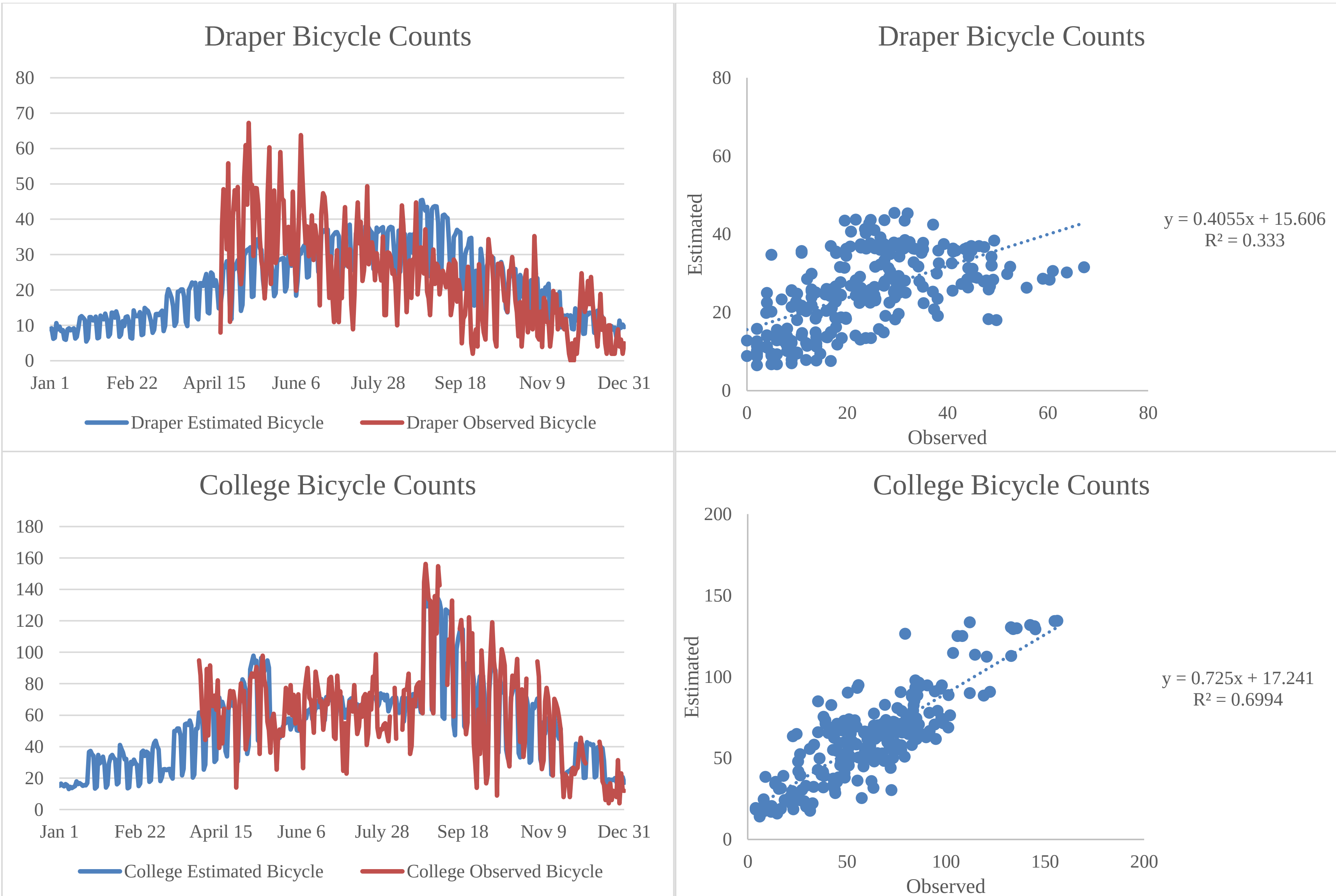

Figure 17. Observed and model-estimated daily bicycle traffic at Draper Road and College Avenue.

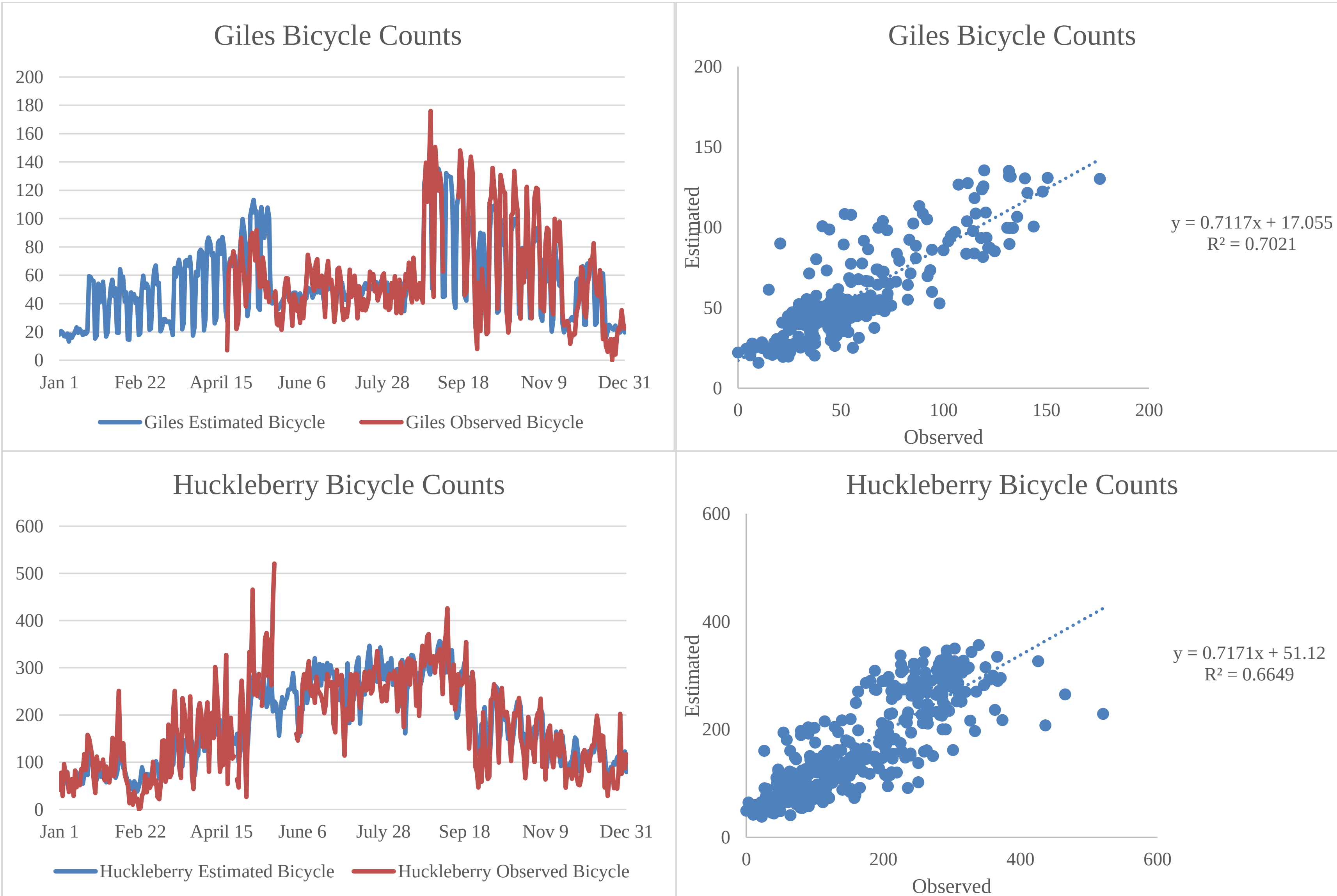

Figure 18. Observed and model-estimated daily bicycle traffic at Giles Road and Huckleberry Trail.

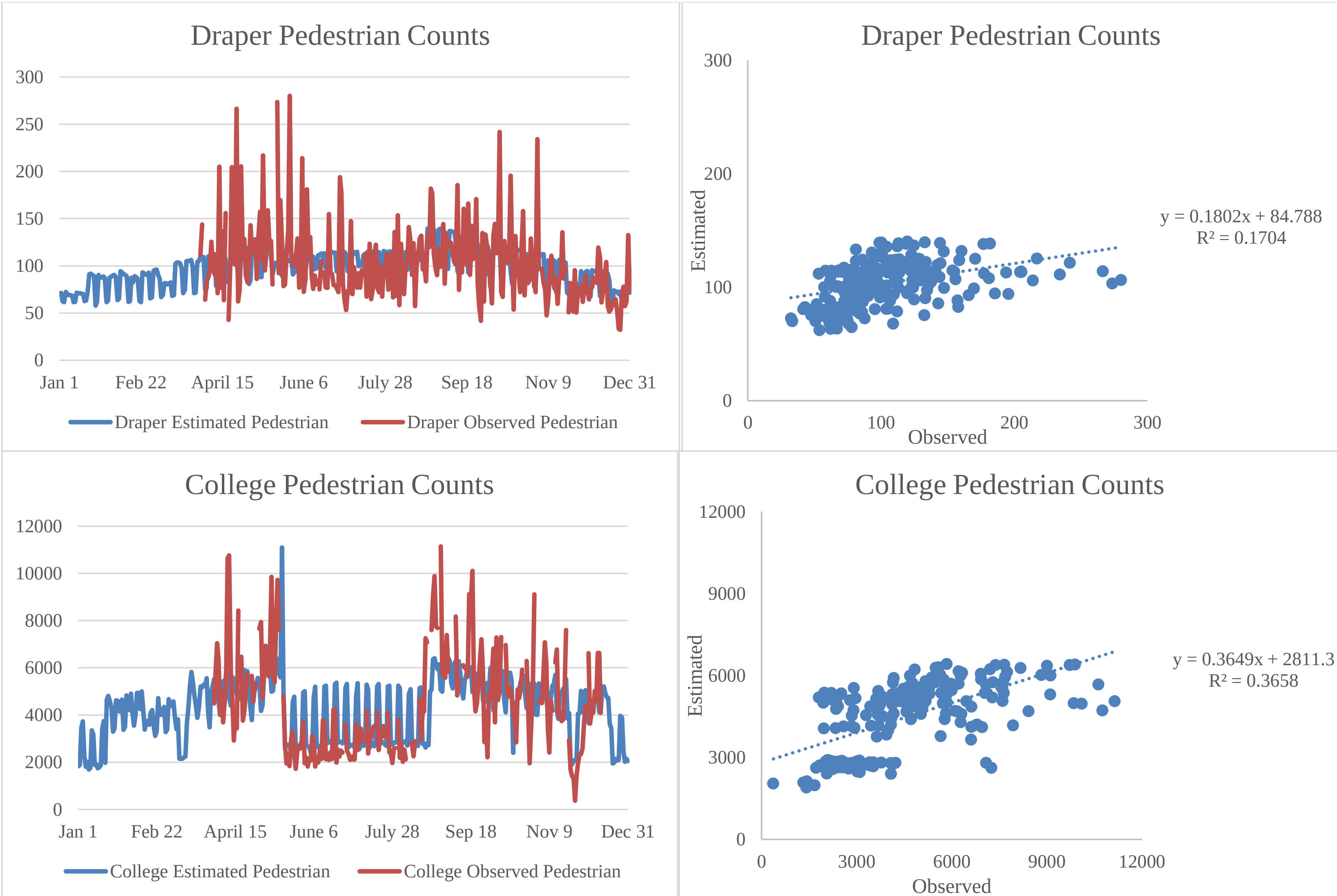

Figure 19. Observed and model-estimated daily pedestrian traffic at Draper Road and College Avenue.

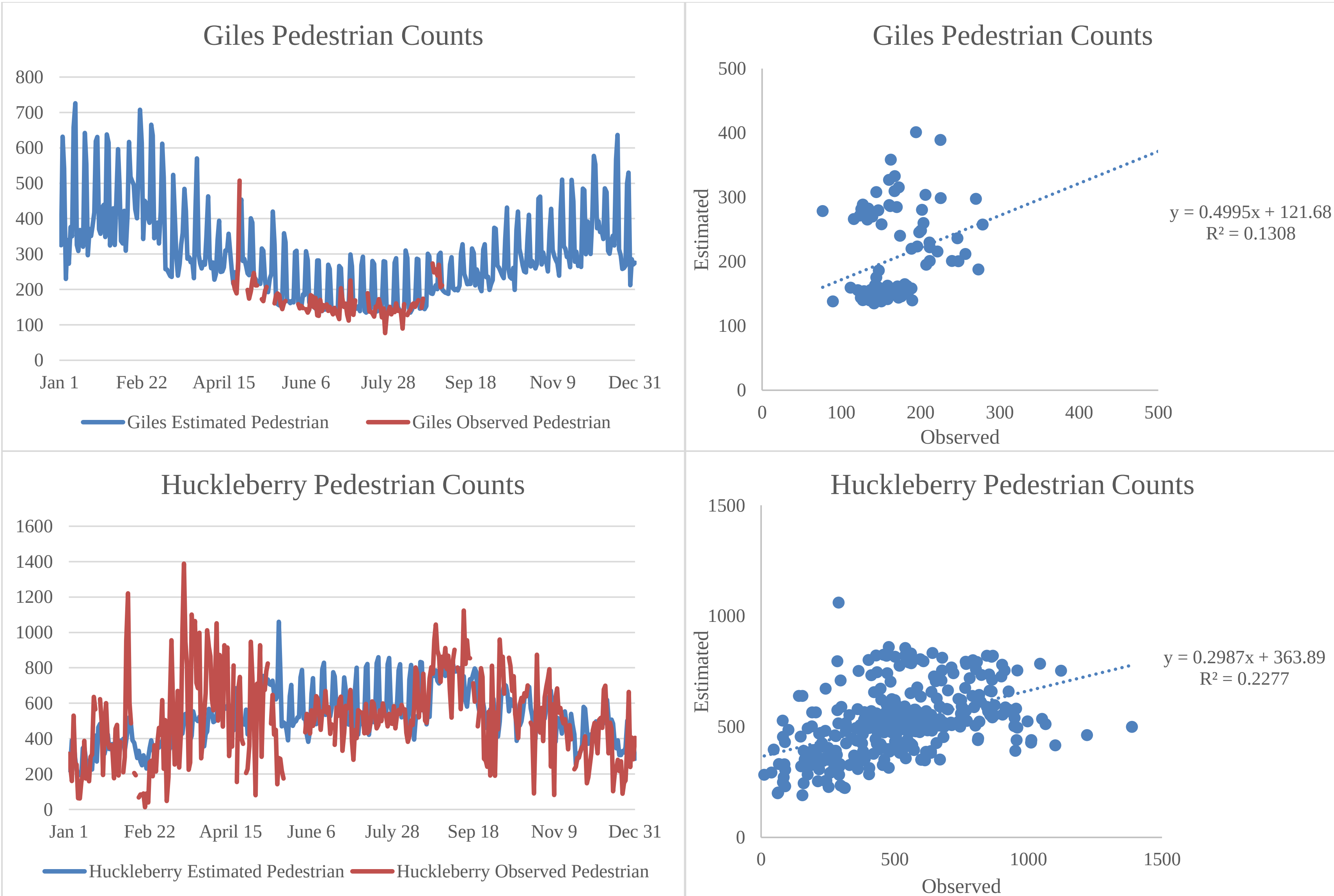

Figure 20. Observed and model-estimated pedestrian traffic at Giles Road and Huckleberry Trail.

Overall, the negative binomial models performed more reliably for bicycle traffic (validation R^2 = ~0.70) than for pedestrian traffic (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.

For the bicycle models, College Avenue, Giles Road and the 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. However, the eight site-specific models work reasonably well to estimate the bicycle and pedestrian traffic for the minority of days (~10%) that are missing data.

We combined the observed values with the model-generated estimates for missing days to develop a full year-2015 dataset for each reference site. The end goal is to use the full year of bicycle and pedestrian data to calculate the AADT (Table 13) for each reference site. This AADT can then be used during the development of the day-of-year scaling factors used to extrapolate the short-duration counts to long-term averages. The combined datasets (i.e., observed counts + model-generated estimates of missing days) are shown in Figures 21 and 22.

Table 13. AADT for continuous reference sites

		Draper	**College**	**Giles**	**Huckleberry**
AADT using observed values + model-generate estimates of missing days	Bicycle	21	54	55	179
	Pedestrian	98	4,232	289	518
AADT using observed values only	Bicycle	24	62	59	177
	Pedestrian	103	4,424	168	514

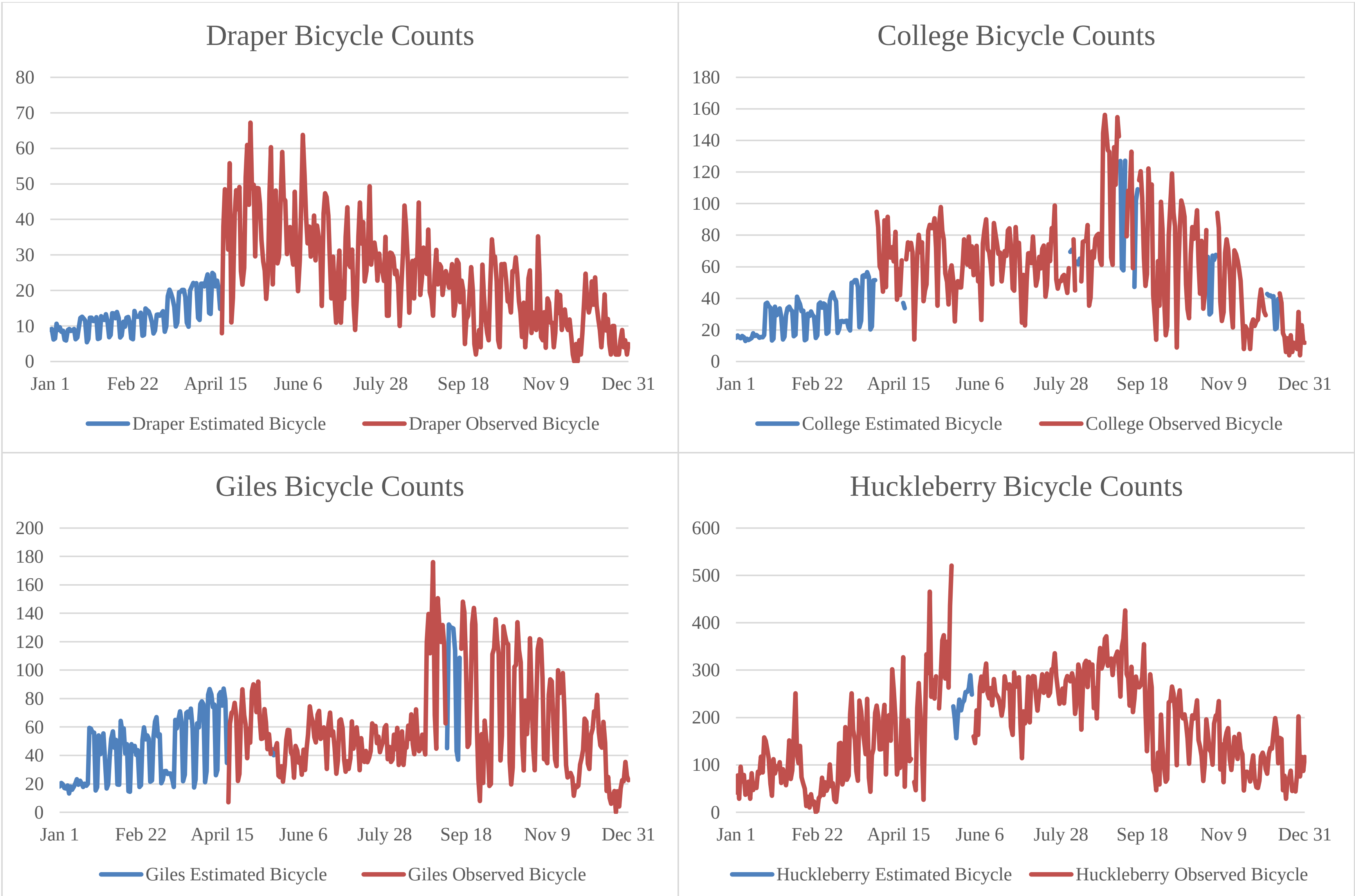

Figure 21. Full year-2015 bicycle traffic at the four continuous reference sites.

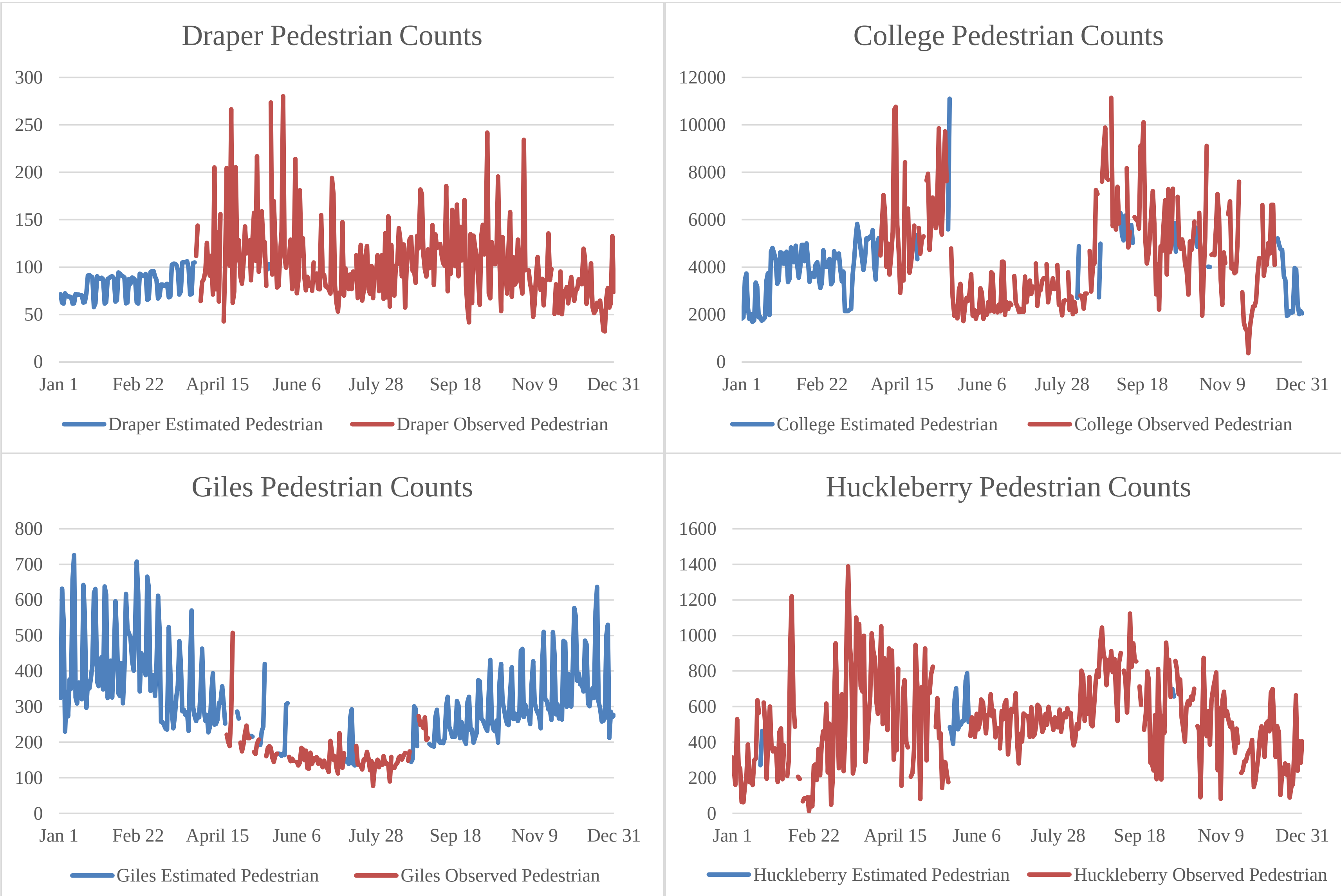

Figure 22. Full year-2015 pedestrian traffic at the four continuous reference sites.

Developing scaling factors

Hankey et al. (2014) and Nosal et al. (2014) introduced a day-of-year scaling factor approach to produce AADT estimates with smaller error (for non-motorized traffic) 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. We generated 365 day-of-year scaling factors from the 4 continuous reference sites for both bicycle and pedestrian traffic. Equation 7 shows the scaling factor calculation used for each site; Figure 23 shows the averaged (across the four reference sites) day-of-year scaling factors developed for Blacksburg, VA during year-2015. The overall pattern of the bicycle and pedestrian scaling factors demonstrates an "M" shape likely owing to weather patterns and when the University is in session. In other words, there is less traffic in the winter because of cold weather and relatively less in the summer because students leave. This indicates that peak traffic occurs in the spring and fall seasons for Blacksburg.

$$\text{Day-of-year scaling factor} = \frac{Traffic\ volume\ on\ a\ specific\ day}{AADT} \qquad \text{Equation 7}$$

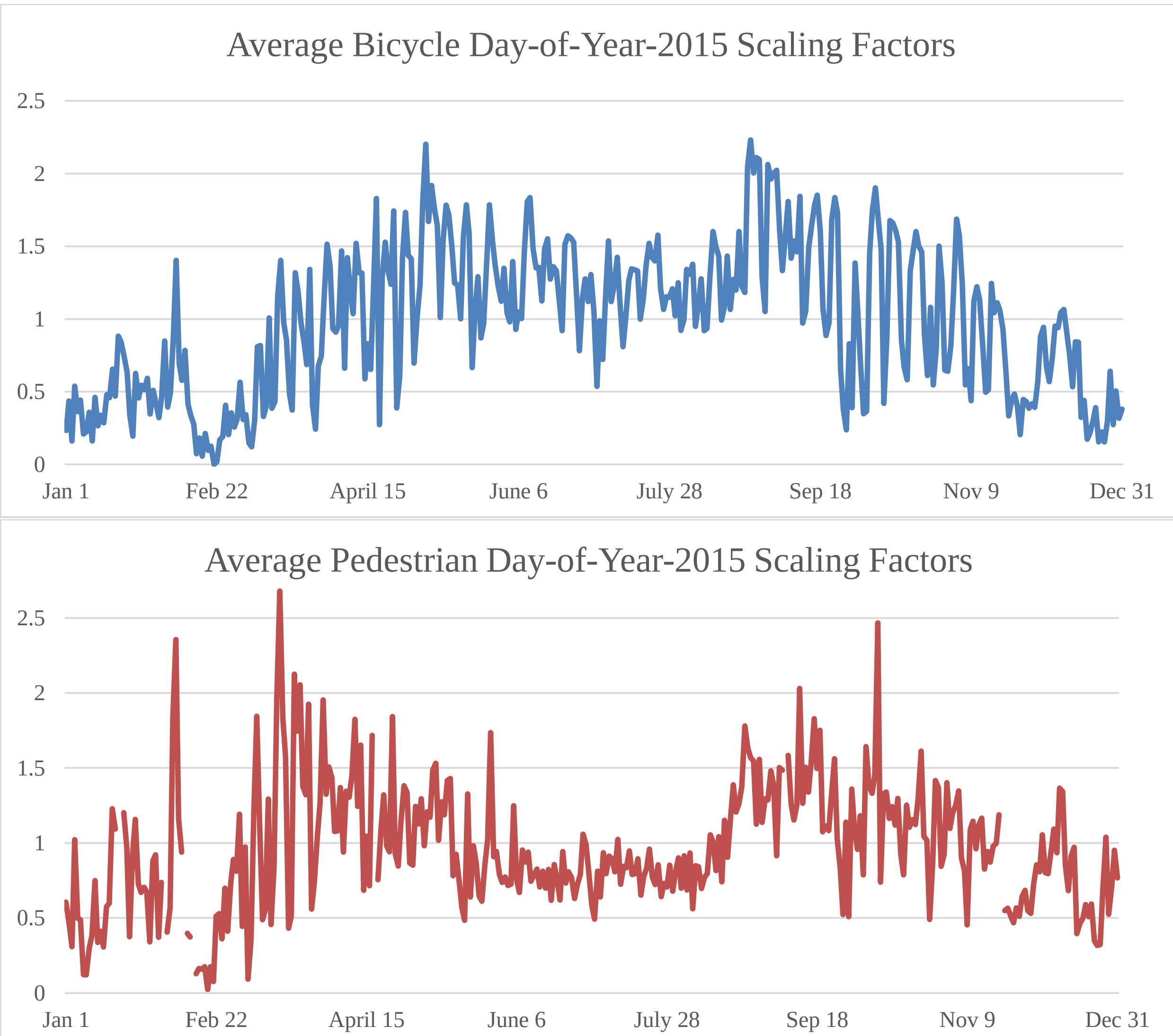

Figure 23. Average Day-of-Year scaling factors for bicycle (top-panel) and pedestrian (bottom-panel) traffic.

<u>AADT estimation at short-duration count sites</u>

We used the 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); we then averaged the AADT estimates to calculate a final AADT for each short-duration site. For example, at Sunridge Drive (a short-duration count site), the monitoring period was from May 5 to May 11 (May 9 and May 10 are weekends; Table 14). The scaling factors were retrieved for each count day. The number of reference sites provides additional information on the number of sites that are used to calculate the average day-of-year factor for each day. The final AADT estimate for each short-duration count site is as follows:

$$\text{AADT Estimate} = \frac{1}{n}\sum_{i=1}^{n}\frac{AdjC_i}{SF_i} \qquad \text{Equation 8}$$

Where, $AdjC_i$ is the adjusted count on day i, n equals the number of days for short-duration counts, and SF_i denotes scaling factors retrieved from observed data on day i. Table 14 shows the example for Sunridge Drive.

Table 14. Example of the estimation process for AADT of bicycle traffic at a short-duration count site (Sunridge Drive)

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**

Task 4: Spatial models to estimate AADT at sites without counts

Tasks 1-3 primarily focus on collecting and analyzing non-motorized traffic counts at ~100 count sites. We also developed a tool to estimate traffic volumes at locations without counts based on land use and road characteristics. Our approach is generally known as direct-demand or facility-demand modeling. The approach generally includes: (1) assembling land use and road characteristic variables at each count site, (2) using the traffic counts and land use variables to develop a regression model, and (3) use the regression model to estimate traffic volumes at locations without counts. Here, we present work towards steps #1 and #2. The resulting model can then be used to estimate counts at locations of interest in Blacksburg (#3). A key outcome of this work is the ability to explore spatial patterns of cycling and walking.

<u>Assembling independent variables</u>

We assembled independent variables related to land use and road characteristics for model building (Table 15). In general, our independent variables are measures of factors shown to affect an individual’s likelihood to walk or bike (e.g., population density, type of land use, etc). The variables generally fall in four categories: (1) land cover, (2) land use, (3) population characteristics, and (4) transportation network attributes. We assembled all variables from publicly available sources. All variables were used for model-building except on-street facilities in the pedestrian model and sidewalks in the bicycle model.

Table 15. Variables included in the model-building process

Variable	Variable Type	Unit	Bicycle Model	Pedestrian Model
Impervious surface	Land cover	Square meters	X	X
Non-tree vegetation	Land cover	Square meters	X	X
Paved parking	Land cover	Square meters	X	X
Tree vegetation	Land cover	Square meters	X	X
Industrial area	Land use	Square meters	X	X
Non-residential addresses	Land use	Count in buffer	X	X
Residential addresses	Land use	Count in buffer	X	X
Retail area	Land use	Square meters	X	X
HH Income	Population	Area-weighted average	X	X
Population density	Population	Area-weighted average	X	X
Bus stops	Transportation	Count in buffer	X	X
Centrality	Transportation	Trip potential	X	X
Intersections	Transportation	Count in buffer	X	X
Local roads	Transportation	Length in buffer	X	X
Major roads	Transportation	Length in buffer	X	X
Off-street trail	Transportation	Length in buffer	X	X
On-street bike facility	Transportation	Length in buffer	X	
Sidewalks	Transportation	Length in buffer		X

We calculated all independent variables at varying spatial scales to allow for selection in the regression models at different spatial scales. Specifically, we calculated network buffers around each count location (using Network Analyst in ArcGIS 10.1) at the following buffer sizes (in meters): 100, 250, 500, 750, 1000, 1250, 1500, 1750, 2000, 2500, 3000. Then, variables were offered for selection into the regression models using the stepwise linear regression process described below. We generated 17 buffer variables (17 variables x 11 buffer sizes = 187 variables) and 1 discrete variables resulting in a total of 188 variables available for selection in the regression models. Our buffers were calculated using a network buffer (to reflect access to destinations) rather than circular buffers. This process creates unique buffers for each count location based on the configuration of the road network. Figure 24 shows an example of network buffers generated to tabulate land use variables for a facility-demand model in Minneapolis, MN. A similar approach was used in this work.

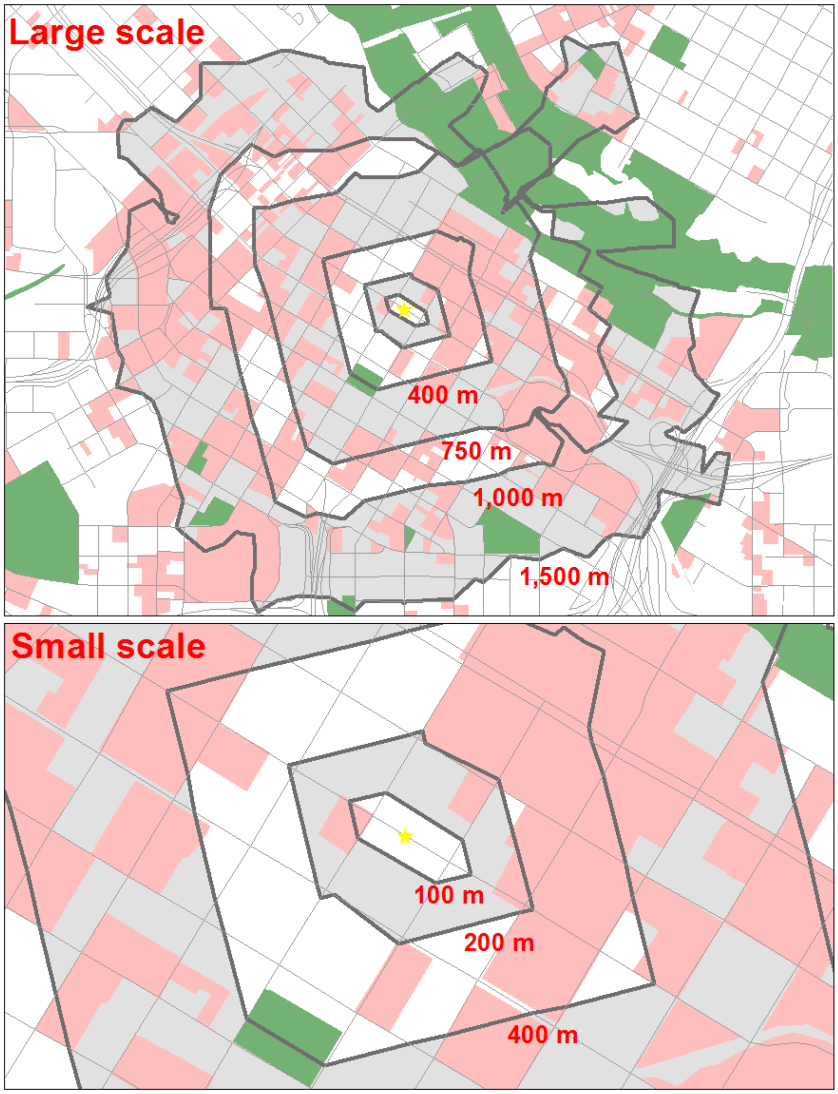

Figure 24. Example of network buffers used to tabulate land use variables at varying spatial scales for model-building. This map shows an example in Minneapolis, MN; the same method was used in Blacksburg, VA.

Model-building approach

We used a stepwise linear regression approach originally developed for urban air quality modeling. In this approach, independent variables are assembled at various buffer sizes and offered to the model for selection. Each variable is tested against the dependent variable (i.e., bicycle or pedestrian count) for strength of correlation. The independent variable most correlated with the dependent variable is selected and the regression is run. Then, the independent variable most correlated with the model residuals is entered into the regression. This process repeats until either (1) the last entered variable is not significant in the model ($p > 0.05$) or (2) the Variance Inflation Factor (VIF) is greater than 5 (VIF is a check for multi-collinearity).

A key advantage of the stepwise regression approach is that independent variables can be selected at different spatial scales; thus, we can assess whether certain aspects of the built environment have impacts at large or small spatial scales. Additionally, by including only variables that are statistically significant (and do not have issues with multi-collinearity), we develop more parsimonious models while maintaining predictive power.

FINDINGS

In this section we summarize our core findings in three sections: (1) traffic patterns observed at the reference sites, (2) traffic patterns at the short-duration count sites, and (3) model results from the spatial models used for estimating traffic at locations without counts. We then summarize our conclusions and recommendations in the final section. In general we discuss temporal patterns using the data from the reference sites, spatial patterns using data from the short-duration sites, and infer impacts of land use from the spatial models.

Continuous reference sites

We analyzed the average daily traffic, mode share, weekend to weekday traffic ratio, and hourly traffic patterns for all continuous reference sites. Our goal is to illustrate seasonal, daily, and hourly traffic patterns for bicycles and pedestrians in Blacksburg. Table 16 gives descriptive statistics of the counts at the reference sites.

Table 16. Descriptive statistics of daily bicycle and pedestrian traffic volumes for the continuous reference sites

Mode	Site	Observations (days)	Mean	Median	IQR	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

IQR = Interquartile Range.

<u>Average daily traffic and mode share</u>

We present the average daily traffic (adjusted using the correction equations) and mode share to demonstrate the traffic patterns by month at the reference sites. From February to August, the average daily bicycle volume increases gradually at the Huckleberry Trail and peaks approximately at 300 cyclists per day (Figure 25). The Huckleberry demonstrated a slight depression in traffic during the summer months (presumably attributable to the student population leaving town) and the peaked again in August before decreasing as the weather became colder. College and Giles followed similar patterns although at much lower overall volumes (~50 cyclists per day). Draper Road seemed to demonstrate a constantly decreasing traffic volume as the year progressed.

The average daily pedestrian is highest on College Avenue (peaking at ~6,000 people per day) with a noticeable reduction in traffic volume when student leave campus during June and July. The Huckleberry Trail peaks at ~600-700 people per day in the spring and fall season; again, there is a noticeable reduction during the summer months likely due to the student population. Draper Road demonstrates a similar pattern but a much lower overall volumes (~100 people per day). Giles Road seems to show a similar pattern to the other sites (i.e., peak traffic in the spring a fall; reduced traffic in summer due to the student population and in the winter due to weather); however, data from this site is incomplete due to vandalism to the Eco-counter located at this count site. Figure 25 shows the seasonal patterns.

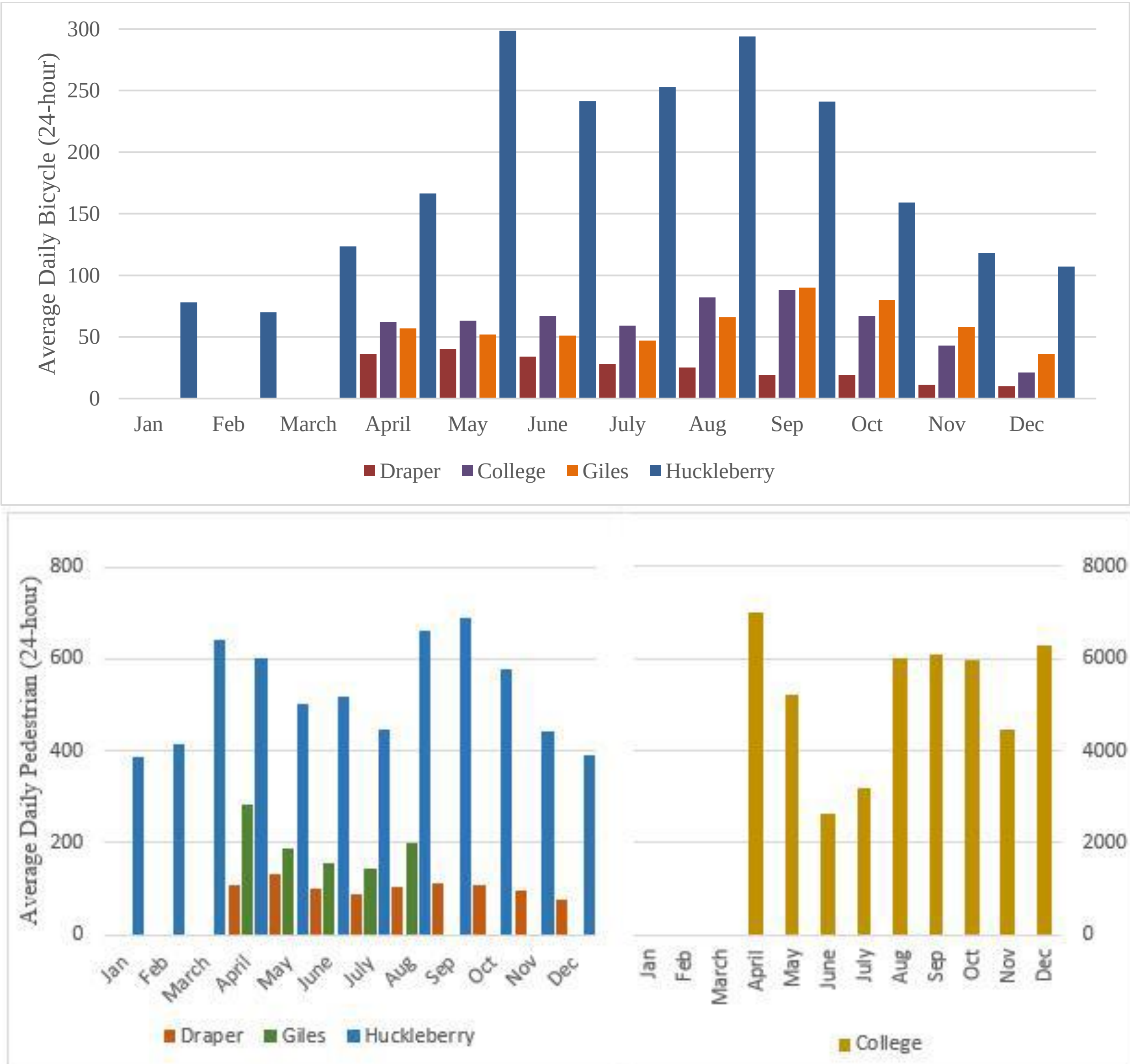

Figure 25. Average daily bicycle (top-panel) and pedestrian (bottom-panel) volume (24-hour) by month for the continuous reference sites.

We also calculated mode share at each reference location to assess if sites were dominated by either cycling or pedestrian traffic. Overall, pedestrian mode share was high at all 4 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. Figure 26 gives mode share by month.

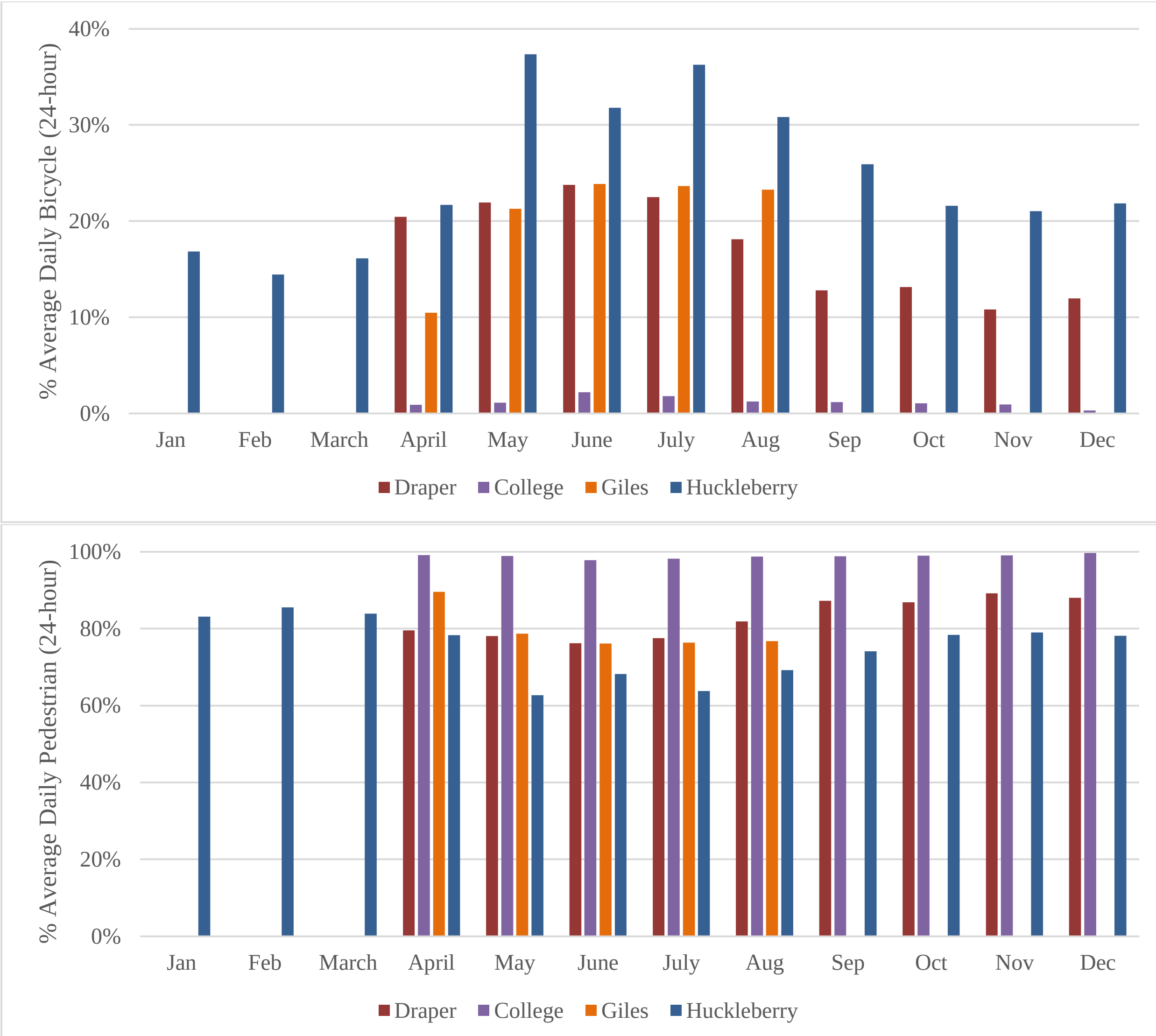

Figure 26. Mode share by month. Bicycle mode share (top-panel) and pedestrian mode share (bottom-panel).

Weekend to weekday ratio

We summarized the 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 may still be some commute users on weekends at sites with recreational pattern, and recreational users on weekdays at sites with commute pattern. Figure 27 shows the ratios for each site by month.

For bicycles on Giles Road, College Avenue, and Draper Road, the ratios are below 1, which suggests a commute pattern. The Huckleberry Trail has a ratio that remains close to 1 throughout the year indicating that this site has a mix of commute and recreational users. All sites seemed to have a reduced ration during the late fall and early winter indicating a shift to more commute uses during that season.

For pedestrians, all sites remain relatively close to a ratio of 1 throughout the year indicating mixed traffic. There are a few noticeable exceptions. For example, the Huckleberry Trail seems to shift towards more recreational uses in the winter. The Draper Road location seems to demonstrate a more commute based pattern than the other sites. There is also slight evidence of the shift towards more commute uses in the late fall as observed by the bicycle patterns.

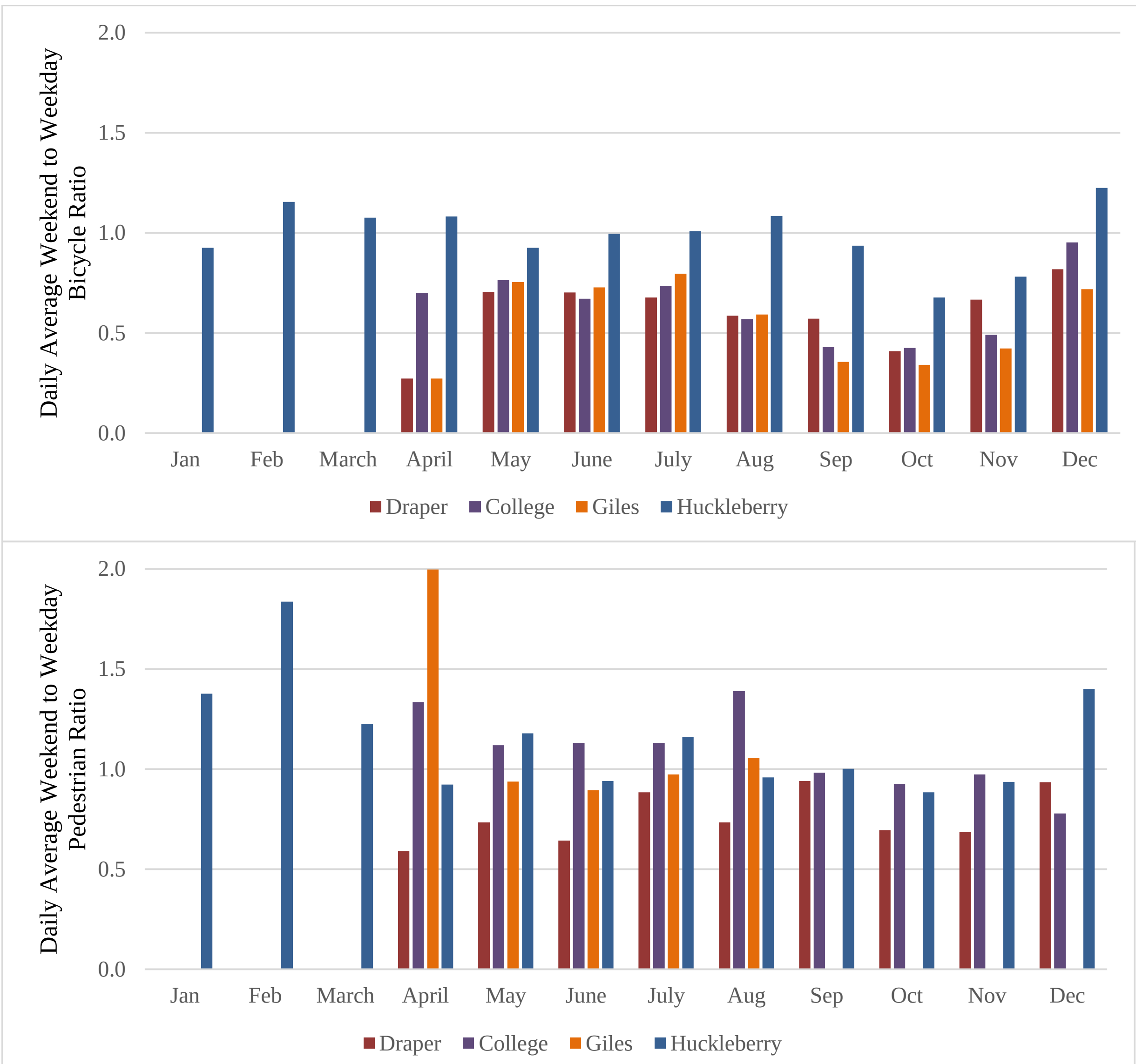

Figure 27. Continuous reference sites daily average weekend to weekday pedestrian ratio.

<u>Hourly traffic patterns</u>

Figure 28 shows the hourly traffic patterns at the continuous reference sites. For bicycle traffic all sites show a recreational pattern on weekends; each site has peak traffic from 11am – 6pm. Some sites demonstrate a slight peak at 1-2am. For weekdays, bicycle traffic is highest from 6am – 8pm. Draper Road and the Huckleberry show noticeable afternoon peak-hours; College Ave has a slight morning peak-hour.

For pedestrian traffic, results are mixed. In general, weekends demonstrated a mostly recreational pattern. At two locations (College Ave and Giles Rd) there was a significant peak in traffic during the 1-2am period. For weekdays, there was a noticeable 12pm peak (presumably for lunch) that did not occur for bicycles. There was also a noticeable afternoon peak-hour for each count site.

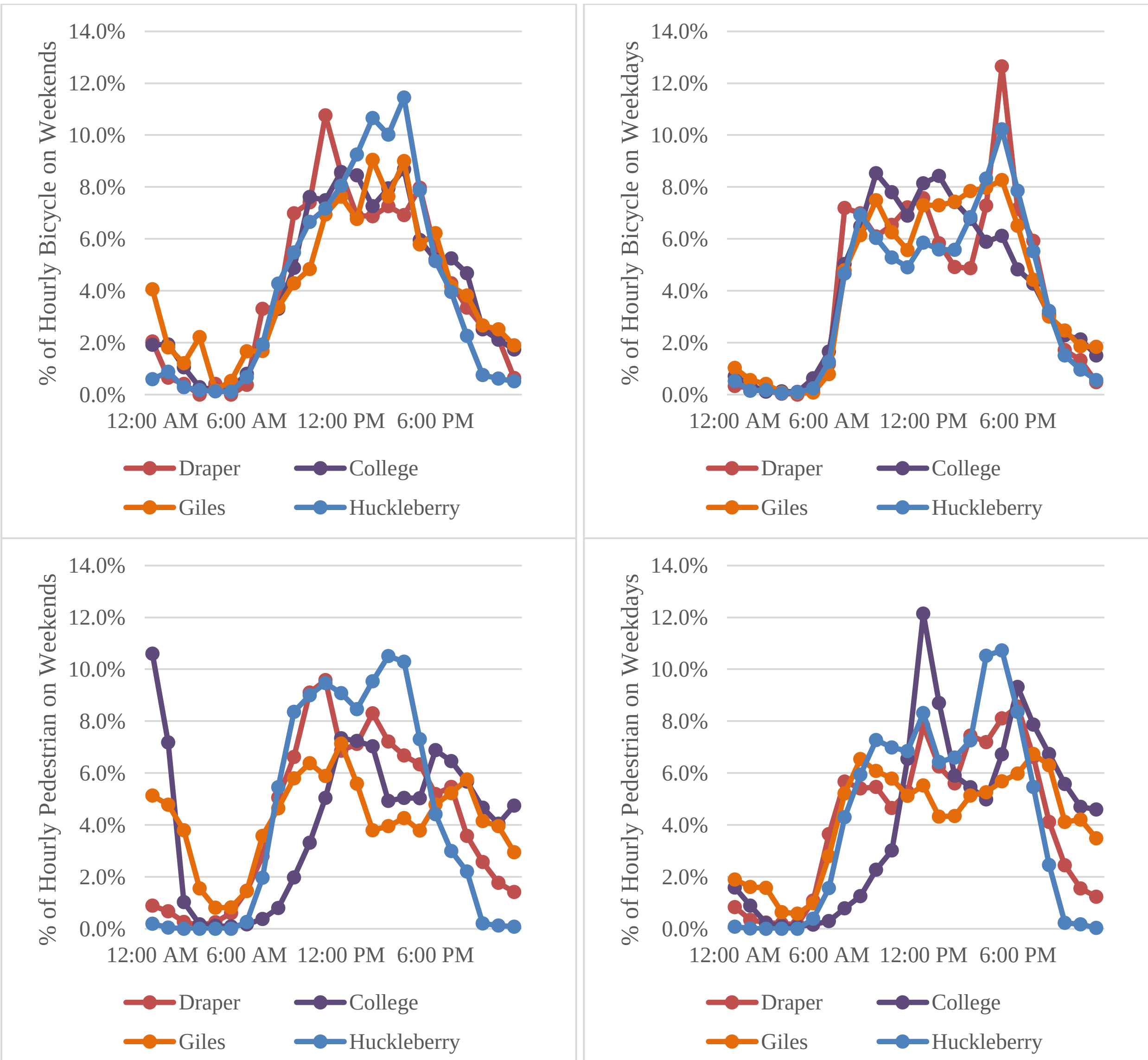

Figure 28. Hourly traffic patterns at the reference sites. Bicycle traffic (top-panels) and pedestrian traffic (bottom-panels).

Short-duration sites

In this section we summarize results from the short-duration count sites by: (1) assessing potential factor groups, (2) describing traffic patterns by day of week and (3) mapping our estimates of AADT.

Determining potential factor groups

Based on the metrics used by Miranda-Moreno et al. (2013) and Hankey et al. (2014), we classified all short-duration sites into potential factor groups. The purpose of this exercise is to explore what factor groups may exist for non-motorized traffic. In motorized traffic application, factor groups are used to match continuous reference sites with short-duration sites for the purpose of scaling. For example, continuous reference sites labeled as commute pattern are used to scale short-duration sites with a commute pattern. However, due to limitations of the number (n=4) of continuous reference sites, we did 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, we define only three factor groups: Commute, Recreation, and Mixed (Table 17). Our goal is to calculate WWI and AMI for each site and classify them into factor groups.

$$WWI = \frac{Average\ Weekend\ Traffic}{Average\ Weekday\ Traffic} \qquad \text{Equation 9}$$

$$AMI = \frac{Average\ Weekday\ Traffic\ from\ 7\ a.m.\ to\ 9\ a.m.}{Average\ Weekday\ Traffic\ from\ 11\ a.m. to\ 1\ p.m.} \qquad \text{Equation 10}$$

Table 17. Factor group definitions

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

We generated box plots to display the distribution of bicycle and pedestrian WWI and AMI among the short-duration sites. 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). To explain the spatial distribution of the travel patterns across Blacksburg, VA, we mapped the factor groups for bicycles and pedestrians (Figure 30). 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).

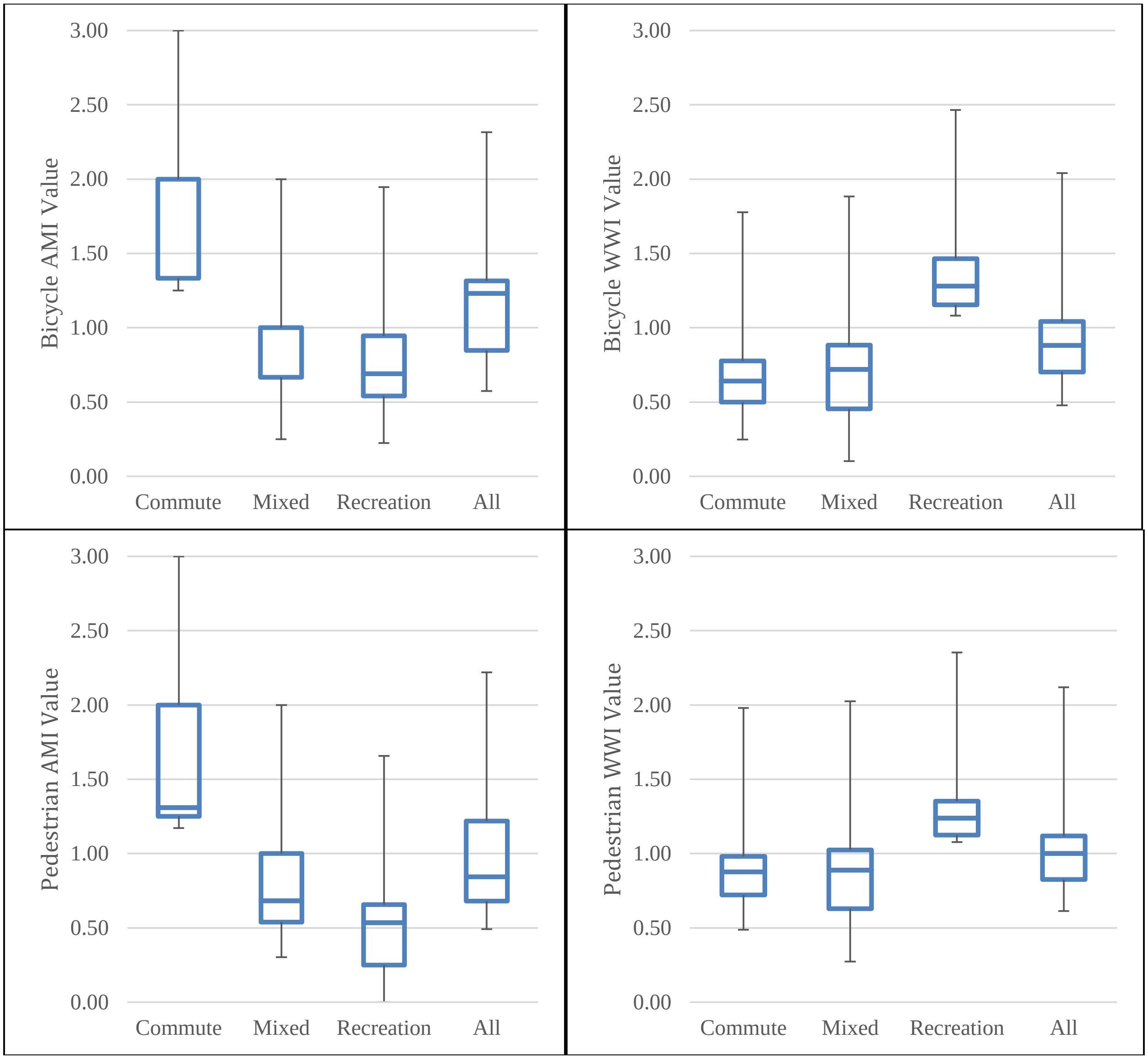

Figure 29. WWI and AMI among short-duration count sites for bicycles (top-panels) and pedestrians (bottom-panels).

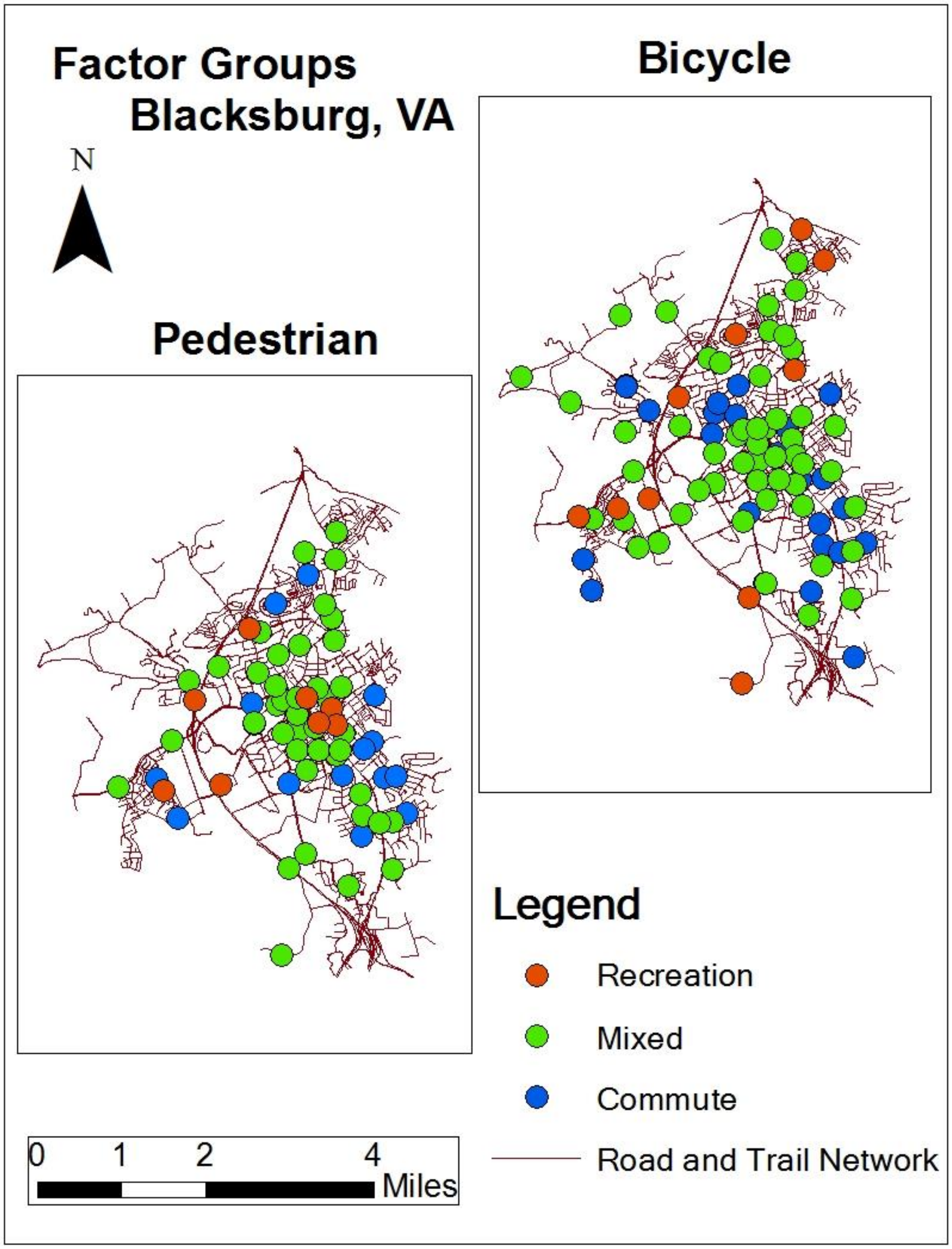

Figure 30. Factor groups (i.e., commute, recreational, and mixed) of traffic count sites in Blacksburg, VA.

<u>Weekend and weekday traffic patterns</u>

Similar to the approach for the reference sites we assessed hourly traffic patterns at the short-duration sites by stratifying by the three potential factor groups (i.e., commute, mixed, recreation). As expected the hourly followed either more recreational or more commute patterns depending on how the sites were classified in the factor groups. This was especially true for weekdays for both modes (as well as weekends for pedestrians). Figure 31 shows the hourly patterns by factor group.

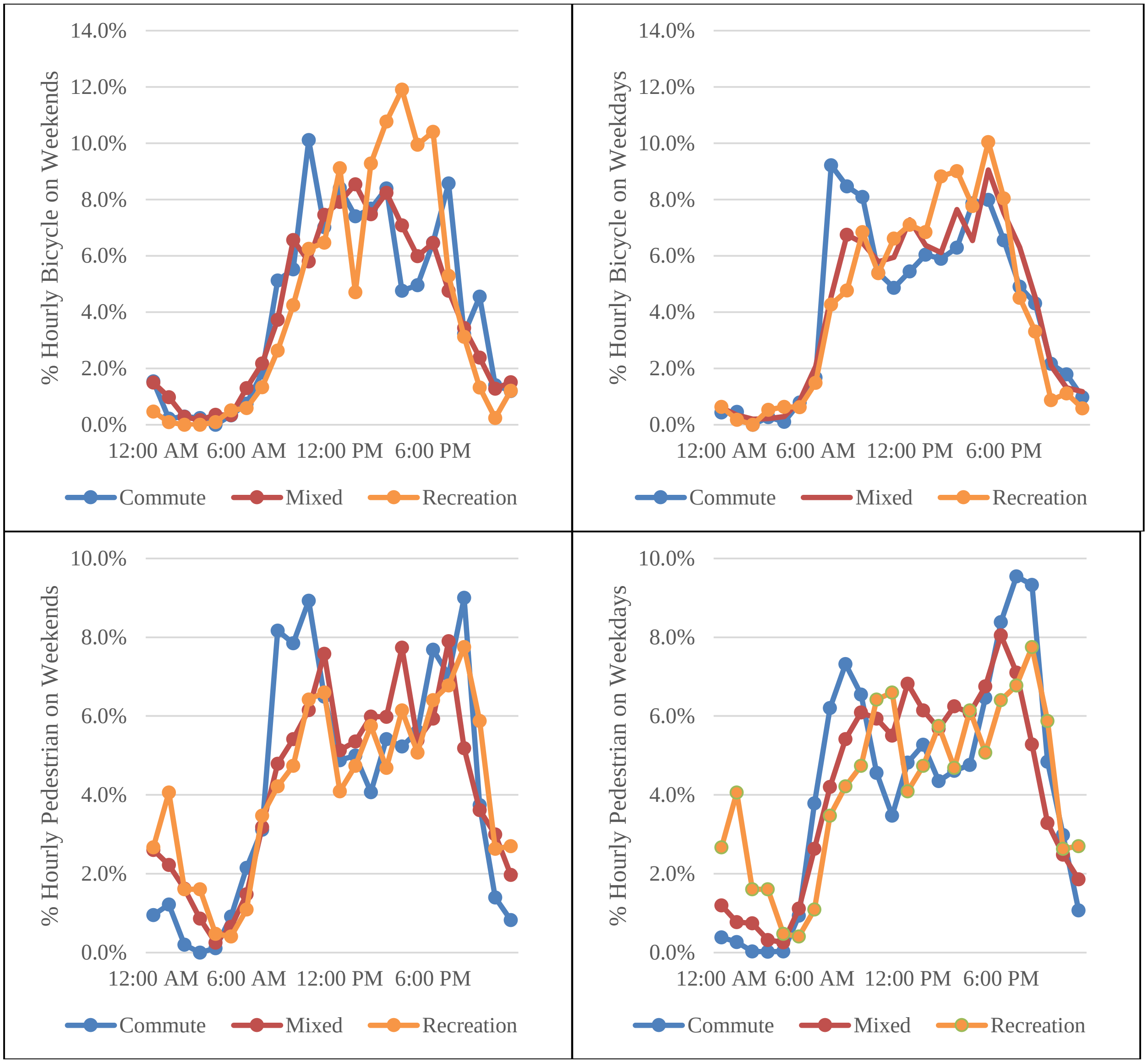

Figure 31. Hourly traffic patterns at short-duration count sites by factor group.

<u>Traffic patterns by road and street type</u>

Descriptive statistics of daily bicycle and pedestrian traffic for the short-duration sites is shown in Table 18. In general, traffic volumes were correlated with street functional class.

Table 18. 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	1,066
	Off-street Trail	20	92	50	136	108

We also generated bar charts to analyze number of sites showing the relevant factor groups by road type (Figure 32). 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, i.e., pedestrians on local roads demonstrate the largest proportion of commute pattern.

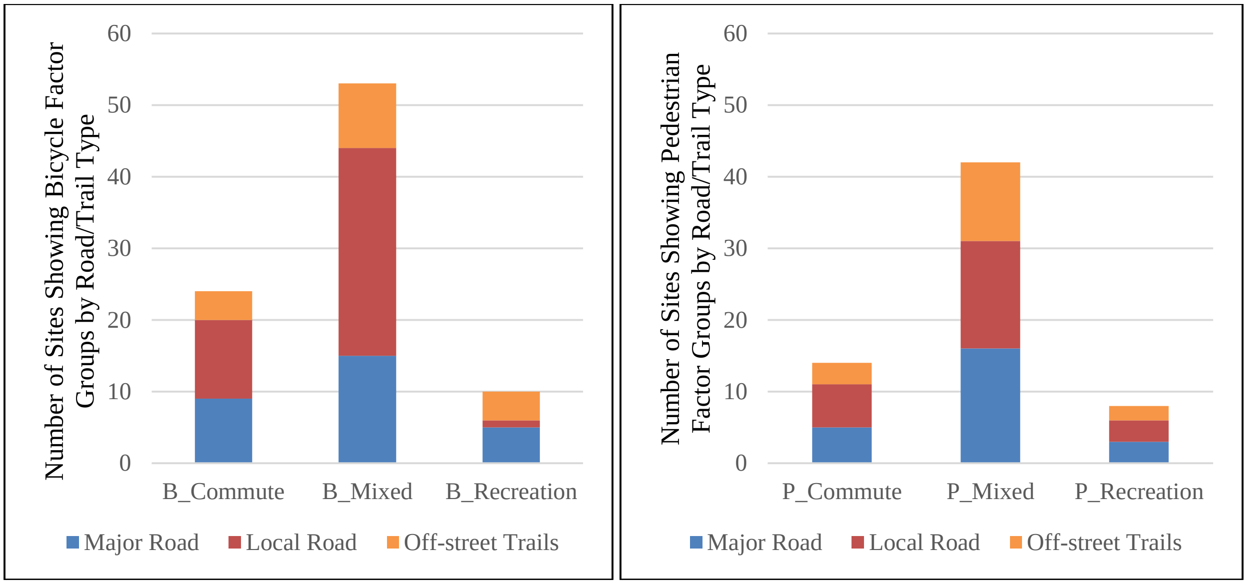

Figure 32. Bicycle and pedestrian factor groups by road type.

Figure 33 shows the distribution of bicycle and pedestrian AADT by street functional class and bike facility. For bicycle AADT, we performed an independent sample t-test 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). 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.

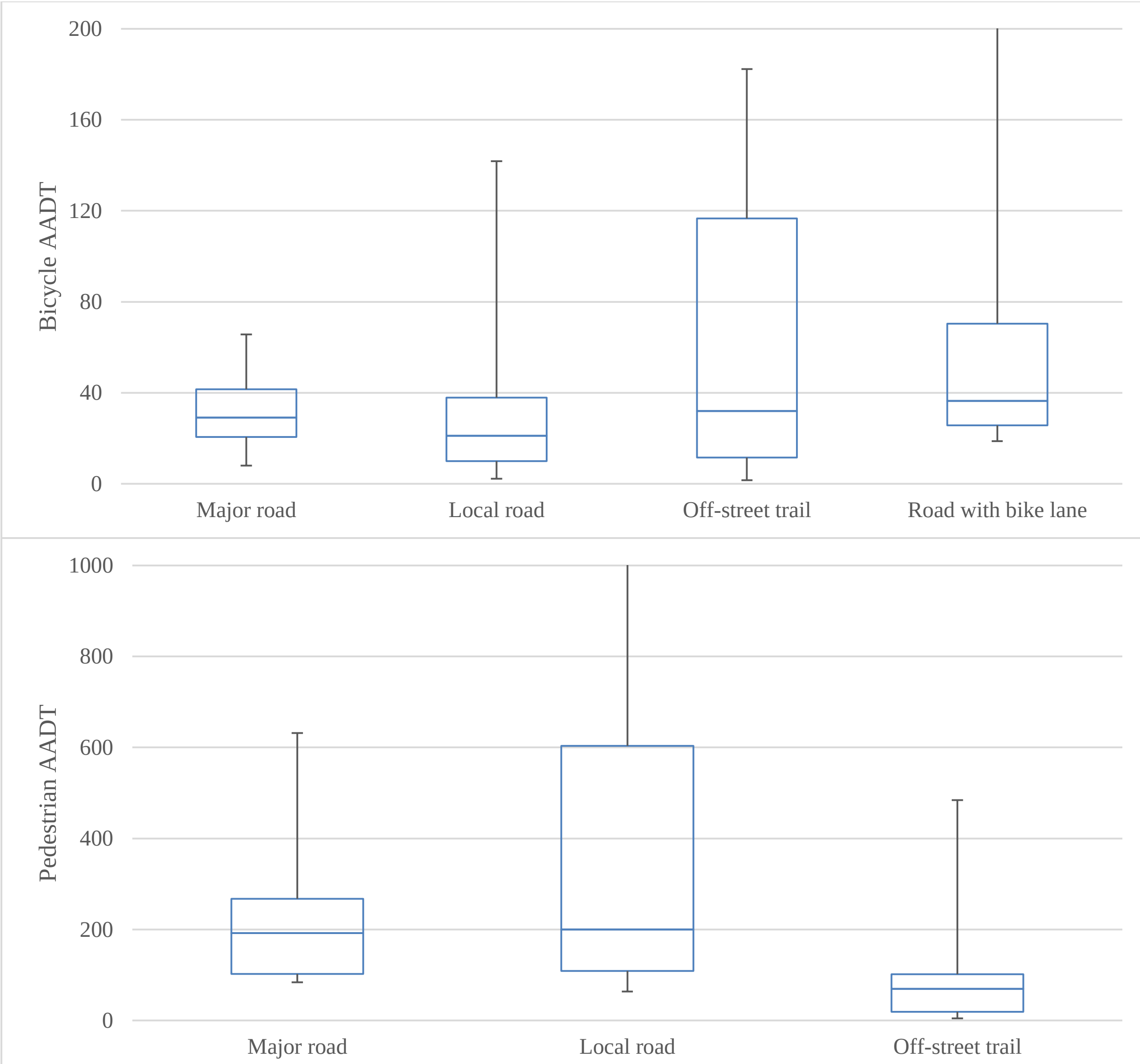

Figure 33. Bicycle (top-panel) and pedestrian (bottom-panel) AADT by road/trail type.

<u>Mapping AADT estimates</u>

We mapped all AADT estimates (including continuous reference sites; Figure 34). The maps show that more bicycles are found along the transport trails (e.g., Huckleberry Trail, Smithfield Trail) and near the university campus. 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. The maps give a visual representation of the spatial variability of the traffic counts. We also further explore impacts of land use via the spatial models described in the next section.

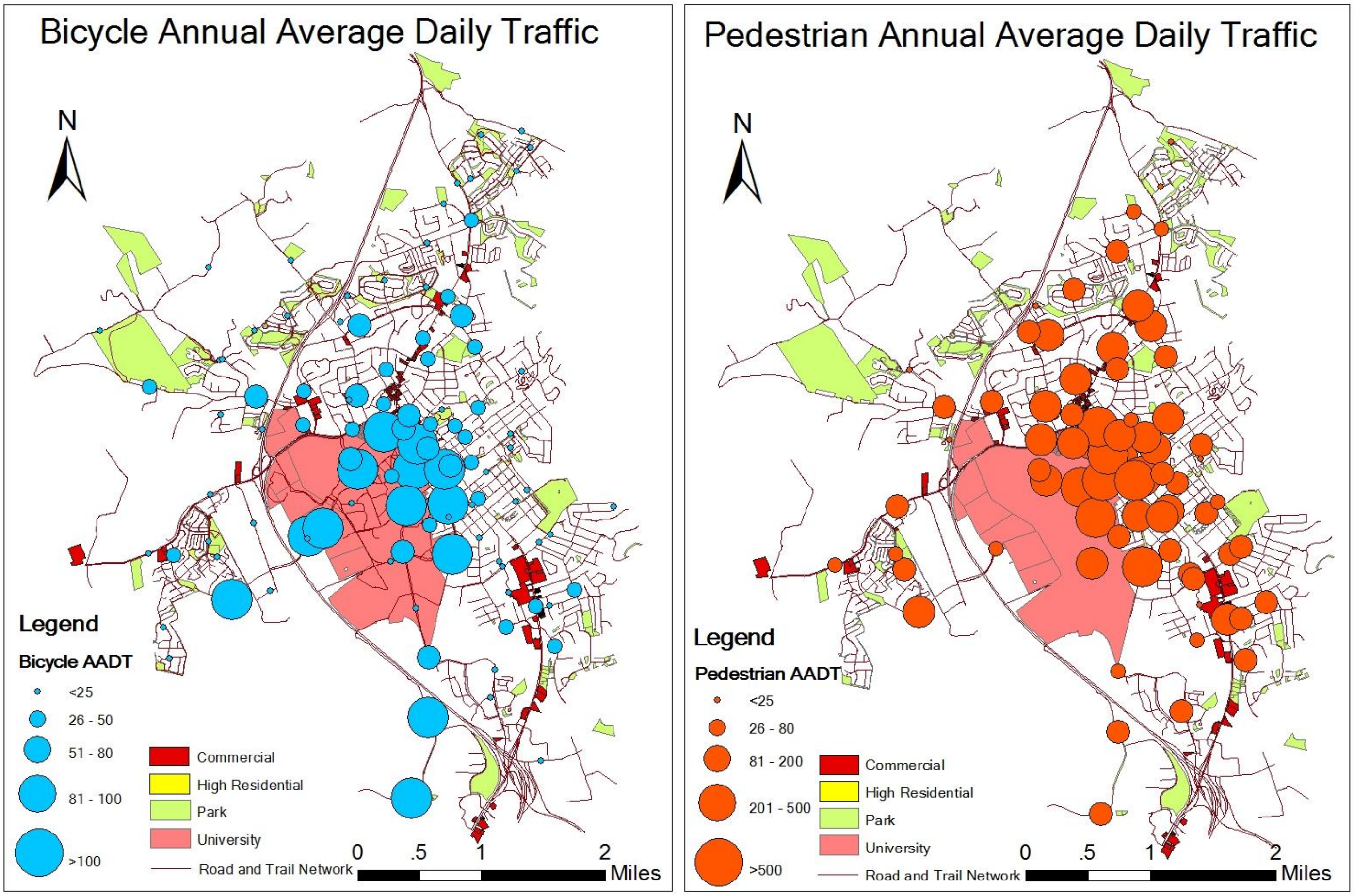

Figure 34. Maps of AADT estimates for bicycle (left-panel) and pedestrian (right-panel) at the traffic count sites.

Spatial models of bicycle and pedestrian traffic

The information provided above describes patterns of bicycle and pedestrian traffic at specific count locations in Blacksburg. However, a useful tool for planners is a method to estimate traffic volumes at locations without counts. Here, we present one such method (e.g., direct-demand modeling) to combine information about land use at the count sites to develop regression models. These models can then be used to estimate traffic volumes at locations without counts.

Bicycle model results

A total of five variables were selected in the final model for bicycle traffic volumes with overall satisfactory goodness-of-fit (i.e., adj-R^2: 0.52). Centrality (the variable for which we designed our sampling campaign) was significant with a positive coefficient as expected. The centrality metric incorporates features of the road network (e.g., off-street trails) and origins and destinations in the metric. Household income was negatively correlated with bicycle traffic indicating that volumes are smaller in these neighborhoods. Major roads, on-street facilities, and population density were all positively correlated with bicycle traffic volumes. Notably, many of the variables were selected at the 100 and 250 meter buffer size. This indicates that small-scale variability in land use may have an impact on bicycle traffic volumes. Population density was selected at a relatively larger buffer size (1,250 meters) and thus is correlated at a regional or neighborhood scale. Table 19 gives model results for the final bicycle model; Figure 35 shows a scatterplot of observed vs. predicted bicycle counts.

Table 19. Final bicycle regression model results

Parameter	**Buffer**	**Beta**	**p-value**	**VIF**
HH Income	250	-8.8E-06	0.01	1.87
Centrality	-	2.8E-06	<0.01	1.22
Major Roads	100	2.7E-03	0.01	1.09
Population density	1,250	3.1E-04	<0.01	1.67
On-street facility	100	3.6E-03	0.04	1.06
Intercept	-	2.5	<0.01	-
R^2	**Adj-R^2**	**N**		
0.54	0.52	101		

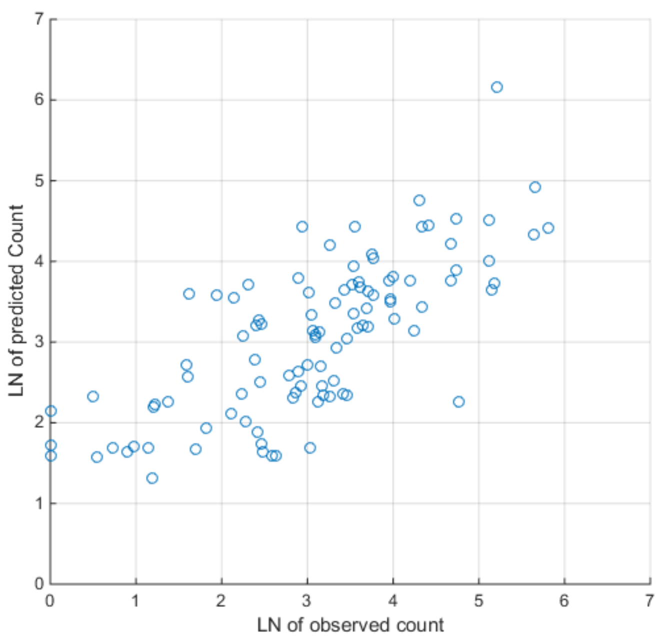

Figure 35. Scatterplot of observed vs. predicted bicycle counts.

<u>Pedestrian model results</u>

Six total variables were selected in the final pedestrian model with good model fit (adj-R^2: 0.71). Similar to the bicycle models there was a mix of transportation and land use variables included in the model. Sidewalks (an important piece of infrastructure for pedestrians) was the first variable selected in the model. Similar to the bicycle model, pedestrian traffic decreased in high income neighborhoods; pedestrian volumes were also negatively correlated with concentrations of residential uses. Off-street trails also were negatively correlated with traffic potentially suggesting that utilitarian uses (i.e., along retail corridors and on campus) dominate recreational uses (presumed to be predominantly on trails). Both concentration of bus stops and population density were positively correlated with pedestrian volumes. Overall, there were a mix of variables selected at small and large spatial scales. Table 20 gives model results for the final bicycle model; Figure 36 shows a scatterplot of observed vs. predicted bicycle counts.

Table 20. Final pedestrian regression model results

Parameter	Buffer	Beta	p-value	VIF
Sidewalk	750	7.8E-05	<0.01	2.14
Off-street Trail	100	-4.0E-03	<0.01	1.27
HH Income	1,750	-1.6E-05	<0.01	1.34
Residential Address	1,000	-6.2E-04	<0.01	1.49
Population density	750	1.7E-04	0.01	1.51
Bus stops	250	0.13	0.03	1.46
Intercept	-	5.14	<0.01	-
R^2	**Adj-R^2**	**N**		
0.73	0.71	72		

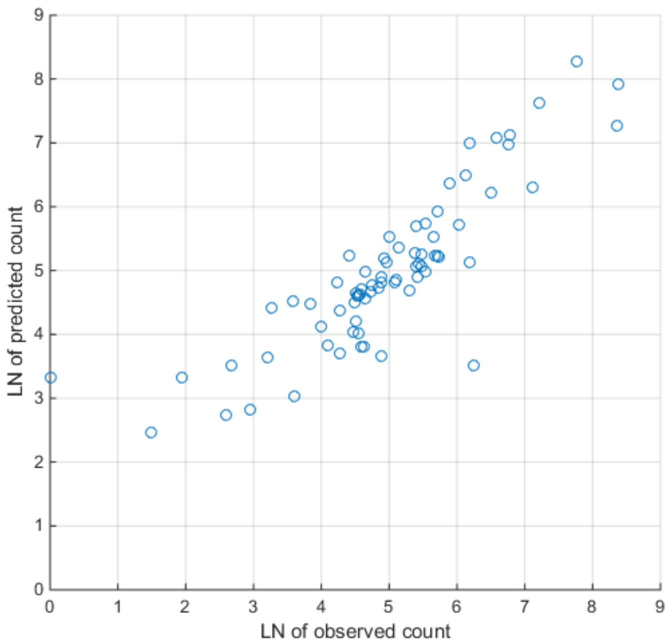

Figure 36. Scatterplot of observed vs. predicted pedestrian counts.

<u>Potential uses of spatial models</u>

We explored building spatial models of bicycle and pedestrian traffic to allow for generating traffic volume estimates at locations without counts. The models could be used for various purposes. For example, we plan to generate estimates of bicycle and pedestrian traffic on all street segments in Blacksburg, VA to give a comprehensive picture of travel patterns in the Town. This information could be used to plan for bicycle and pedestrian transportation during the buildout of the Town Bicycle Master Plan. Similarly, estimates of traffic volumes could be used in sketch planning exercises to give an estimate of what type and level of traffic can be expected in given corridors. While our models will not give accurate estimates in all cases, we can provide more information than is currently available to planners in Blacksburg.

CONCLUSIONS & RECOMMENDATIONS

This report describes a bicycle and pedestrian count campaign to assess and model patterns of traffic in Blacksburg, VA. Here, we summarize our main conclusions and recommendations in three areas: (1) considerations for implementing a non-motorized traffic count campaign, (2) considerations for processing data and estimating performance measures, and (3) considerations for future work.

Considerations for implementing a non-motorized traffic count campaign

We collected ~40,000 hours of bicycle and pedestrian counts consisting of 4 continuous reference sites (1 year of counts) and 97 short-duration sites (~1-week counts) in Blacksburg, VA. Here, we briefly summarize key considerations for implementing a non-motorized count campaign:

- Choosing appropriate count technology: A variety of automated counters exist; each are appropriate for different situations. Depending on the type of infrastructure (i.e., street vs. sidewalk vs. trail) and mode (bicycle vs. pedestrian vs. mixed-mode) multiple counters are likely needed to characterize the network. In our case, three types of counters were sufficient.
- Counter validation: We performed validation counts at multiple sites for each counter-type. We found strong correlation between validation counts and automated counts. However, correction equations varied by counter-type. This finding is consistent with previous studies and highlights the need to perform counter-specific validation studies prior to deploying each counter in a count campaign.
- Count site selection: A key aspect of choosing sites is the purpose of the count campaign. The counts can be used to track traffic volumes over time, compare spatial locations, assess corridors of interest (i.e., pre- and post-counts), develop spatial models, etc. Choice of sites should match the purpose of the campaign. A key barrier to site selection is that typically practitioners do not have existing information on patterns of biking and walking. To address this issue we used a metric called "centrality" to estimate bicycle trip potential on the network. Since our goal was to develop spatial models and collect baseline information for future infrastructure installation, we selected sites with both high and low centrality as well as locations of future infrastructure investment.
- Labor requirements: We staffed one graduate student at 20 hours per week for 1.5 years to complete this project. That labor input included physical installation of the counters, download of counter data, and processing and analyzing the data. Similar efforts should account for a similar labor input to complete a count campaign of this scale. Additional labor was provided by the Town of Blacksburg at high volume sites to divert traffic during installations.

Considerations for data processing and estimating performance measures

Data quality and processing is important to ensure accurate calculation of performance measures and to better understand bicycle and pedestrian traffic patterns. Here, we summarize key aspects of our analysis that may be useful in future efforts:

- Scaling short-duration counts: We used previously published methods for estimating AADT at short-duration sites. Namely, we collected counts for 1 week at short-duration sites and day-of-year scaling factors derived from permanent reference sites. This approach necessitates installation of permanent reference sites to develop scaling factors and capture long-term temporal trends; a full year of data from the reference sites is needed to generate the day-of-year scaling factors.
- Choice of reference sites: Choosing appropriate reference sites is difficult in the absence of information on current cycling and walking levels in a study area. We chose reference sites at a variety of road and neighborhood types in an attempt to capture overall temporal trends in Blacksburg; future work on this topic (see below) is likely needed.
- QA/QC: We used a two-step process to identify and flag suspect data: (1) direct cleaning based on an event log and (2) a statistical check based on the variability of the overall dataset. We recommend – at a minimum – keeping a detailed event log that includes events (e.g., marathons, concerts, etc.) that might skew the data at particular count sites. Statistical methods can be used to further refine QA/QC if needed. More work to identify appropriate statistical methods for non-motorized counts would be helpful.
- Imputing missing data: We used negative binomial regression models to impute missing data at the reference sites. This approach was used to generate AADT estimates at the reference sites. However, we do not recommend using the imputed data to develop scaling factors (i.e., we did not use the imputed data in the numerator of the scaling factor calculation); we only used the estimates to generate a more reliable AADT at those sites (i.e., as the denominator in the scaling factor calculation).
- Spatial models to estimate traffic volumes at locations without counts: A potentially useful tool is to develop spatial models to estimate traffic volumes at locations without counts. We used a modeling technique called direct-demand modeling. Our models had reasonable goodness-of-fit and would be simple to apply in the field. However, questions remain about transferability of these models to other study areas (see below).

Considerations for future work

Our work is 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 traffic volumes at locations without counts. It offers evidence that non-motorized traffic can be monitored on a routine basis and that performance measures analogous to those for motorized traffic (i.e., AADT) can be used to track progress. Here, we highlight areas for future research:

- Number and location of reference sites: A key outstanding question is how best to locate reference sites and how many reference sites are sufficient in a given study area. Since initial details on bicycle and pedestrian traffic are not available in most jurisdictions, selecting appropriate reference sites can be difficult. More work is needed to give guidance on best practices for siting reference locations.

- Factor groups for count sites: Related to the first bullet point is how many and what type of factor groups exist for bicycle and pedestrian traffic. We followed previous work to identify three preliminary groups (utilitarian, recreational, and mixed); however, more work is needed to finalize group types and give guidance for locating reference sites within these groups.
- Predictor variables in spatial models: We assembled a database of potential predictor variables to be used in the spatial models. More work is needed to compile data that may be better predictors of bicycle and pedestrian traffic.
- Transferability of spatial models: A key issue with direct-demand modeling is that results may not transfer between jurisdictions. While these models may not be transferable, they do seem to provide reliable estimates within a given study area. More work is needed to develop reduced-form models that may better transfer between locations.
- Integrating state and national efforts: Lastly, more work is needed to better integrate non-motorized counting efforts across state and federal agencies. Although counting occurs in many locations, data is often collected in different (sometimes incomparable) ways. Work to give guidance to communities on best practices and accepted protocols at the state and federal level would be helpful in efforts to pool count data across regions, states, and the country.

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