Transportation Research Part D 53 (2017) 193–204

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Designing a bicycle and pedestrian traffic monitoring program to estimate annual average daily traffic in a small rural college town

Tianjun Lu [a], Ralph Buehler [b], Andrew Mondschein [c], Steve Hankey [a,*]

[a] Virginia Tech, 140 Otey Street, Blacksburg, VA 24061, USA
[b] Virginia Tech, 1021 Prince Street, Alexandria, VA 22314, USA
[c] University of Virginia, Campbell Hall, PO Box 400122, Charlottesville, VA 22904, USA

A R T I C L E I N F O

Article history:

Keywords:
Non-motorized transportation
Active travel
Performance measure
Traffic patterns

A B S T R A C T

Cycling and walking are commonly recognized as energy-efficient alternatives to motorized transport. Research and practice lack a comprehensive set of methods to assess spatiotemporal patterns of traffic volumes across an entire transportation network. Current non-motorized traffic monitoring programs are primarily implemented in urban areas and for singular components of the network (e.g., off-street trails, specific corridors). Our approach synthesizes ongoing efforts in non-motorized traffic monitoring to estimate Annual Average Daily Traffic (AADT), across an entire network in Blacksburg, VA – a small, rural college town. We selected count sites across the network, stratified by street functional class (e.g., major roads, local roads), centrality of the link relative to origins and destinations, and planned bicycle facilities. We collected 45,456 h of pedestrian and cyclist counts using three types of automated counters: pneumatic tube (n = 12), passive infrared (n = 10), and radio beam (n = 3) at both reference locations (n = 4; 1-year) and short-duration locations (n = 97; 1-week) during 2015. We found a strong correlation between manual validation counts and automated counts. We used day-of-year scaling factors to estimate AADT for bicycles and pedestrians and found that temporal and spatial patterns differed between modes. Pedestrian volumes were higher and more variable than bicycle volumes (median [interquartile range] AADT for pedestrians: 135 [89–292]; bicycles: 23 [11–43]); both modes were positively correlated with street functional class, presence of facilities, and proximity to campus. Our approach provides insight for planners or policy-makers interested in comprehensive monitoring programs to track performance measures or for use in environmental and health impact studies.

1. Introduction

Non-motorized transportation (i.e., biking and walking) is an energy-efficient alternative to motorized travel and a commonly cited partial solution to the environmental impacts of transportation (PBIC, 2016; Pucher and Buehler, 2010). However, transportation planners and engineers require information on the spatial and temporal patterns of non-motorized traffic to inform decisions aimed at promoting cycling and walking. Implementing robust non-motorized

* Corresponding author.
E-mail address: hankey@vt.edu (S. Hankey).

http://dx.doi.org/10.1016/j.trd.2017.04.017
1361-9209/

traffic monitoring programs could aid engineers and planners in multiple domains, for example, tracking performance measures, prioritizing investment in infrastructure, health and environmental impact assessments, and safety analyses (Ryus et al., 2014). Recognition of these benefits has resulted in targeted funding and pilot demonstration projects at the federal, state, and local levels to assess best practices for bicycle and pedestrian data collection (PBIC, 2016).

Deploying a comprehensive traffic monitoring program often involves large input requirements (e.g., purchase and validation of automated counters, labor to process count data). As a result, most non-motorized monitoring programs and research efforts focus on a single component of the transportation network (e.g., off-street trails or specific transportation corridors; Hankey et al., 2014; Nordback et al., 2013a, 2013b; Nosal et al., 2014). Key questions remain on how to implement comprehensive programs to collect bicycle and pedestrian data effectively and efficiently for an entire transportation network. Guidance from the National Bicycle & Pedestrian Documentation Project and the Federal Highway Administration's Traffic Monitoring Guide have offered standardized methods to collect counts (APD and ITE 2016; FHWA, 2013). Additionally, a national count archive currently under development aims to help aggregate non-motorized count data collection among different locations (Nordback et al., 2015b). Ongoing efforts are providing further guidance on counter performance (Ryus et al., 2014; Brosnan et al., 2015; Nordback et al., 2015a; Schneider et al., 2013), developing scaling factors (Hankey et al., 2014; Nosal et al., 2014; El Esawey et al., 2013), identifying factor groups (Hankey et al., 2014; Miranda-Moreno et al., 2013; Nordback et al., 2013a, 2013b), and count site selection (FHWA, 2013; Ryan, 2013; Ryan et al., 2014).

Motorized traffic monitoring programs are well-established and performed regularly in both small and large jurisdictions across the US. Performance measures such as Annual Average Daily Traffic (AADT) are derived from these counts and used to conduct safety studies, report facility use, and secure transportation funding. However, performance measures are usually not collected for cyclists and pedestrians; efforts to develop standardized methods for estimating performance measures for non-motorized traffic are ongoing (Hankey et al., 2014; Nordback et al., 2013a, 2013b; Nosal et al., 2014). Most non-motorized count programs are conducted in large urban areas (e.g., Minneapolis, Portland, San Francisco, and Vancouver; Ryus et al., 2014; FHWA, 2013). Relatively few studies have focused on designing count campaigns in small, rural areas. Small communities offer a unique opportunity to explore the design of comprehensive monitoring programs as the network is small compared to larger urban areas, making it possible to collect a representative sample of counts across the network and pilot a comprehensive method before scaling up to larger jurisdictions.

In this study, we introduce a systematic non-motorized traffic monitoring campaign in a small college town in a rural setting (Blacksburg, VA; ~50,000 people, 19.7 square miles) with the goal of characterizing bicycle and pedestrian traffic on an entire transportation network, rather than focusing on singular components of the network (e.g., off-street trails, specific corridors). Our goal is to synthesize findings from the literature on aspects related to designing a count program (e.g., counter performance, development of scaling factors, and length of short-duration count) into a single traffic monitoring effort. Our work includes deploying automated counters at 101 locations (including both reference and short-duration count locations) selected to be representative of the transportation network in Blacksburg. We estimate bicycle and pedestrian AADT at all count sites to generate performance measures analogous to those used in motorized transport. Our approach may be helpful to communities that are interested in comprehensive monitoring of cyclists and pedestrians. We expect that this approach could be scaled (up) for use in larger, more complex urban areas.

2. Data collection and methods

Our approach to implement a non-motorized traffic monitoring campaign includes four steps: (1) selection and validation of automated counters, (2) count site selection, (3) estimation of performance measures (i.e., AADT) at the count sites, and (4) mapping and summarization of AADT across the network (Fig. 1). First, we describe our approach to complete each step. Then, we summarize results from the count campaign and discuss implications for implementing traffic monitoring programs for bicycle and pedestrian traffic.

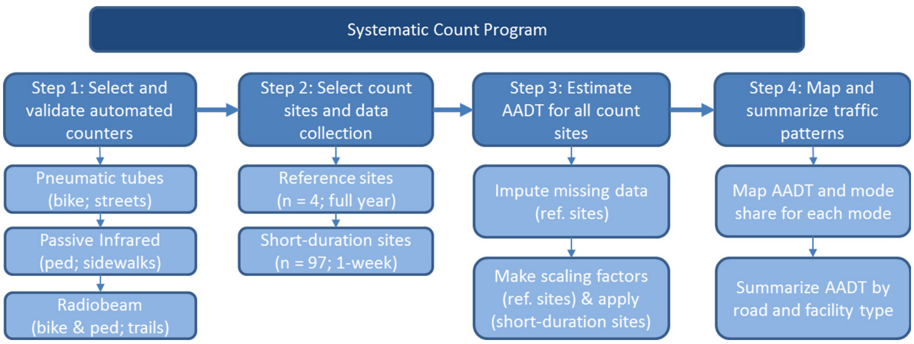

Fig. 1. Summary of approach to develop a pedestrian and bicycle traffic monitoring campaign in Blacksburg, VA.

2.1. Automated counters and validation counts

We used a combination of automated counters to monitor bicycle and pedestrian traffic patterns on various road types and off-street trails. We chose three automated count devices to collect separate counts of bicycles and pedestrians: (1) pneumatic tube counters (MetroCount MC 5600 Vehicle Classifier System), (2) passive infrared counters (Eco-Counter Pyro), and (3) radio beam counters (Chambers RadioBeam Bicycle-People Counter). See Appendix A (Fig. A.1) for a further description of the count devices. We chose automated counters based on previously reported performance (Ryus et al., 2014; Brosnan et al., 2015; Nordback et al., 2015a; Schneider et al., 2013), characteristics of our count locations, portability, and cost. We used pneumatic tubes to count bicycles on roads with mixed traffic, passive infrared counters to count pedestrians on sidewalks, and radio beam counters to separately count bicycles and pedestrians on off-street trails.

Each of the automated counters are known to systematically over- or under-count due to factors such as occlusion (i.e., people walking or biking side-by-side) or double-counting (e.g., the radio beam sometimes counts cyclists twice due to the sensitivity of the sensor). Researchers have commonly used manual field-based validation counts to correct hourly counts obtained from automated counters (Schneider et al., 2013; Hyde-Wright et al., 2014). We collected 210 total hours of validation counts at 8 locations to develop correction equations for each type of counter. We collected the validation counts at various times of day and days of the week to cover a wide range of traffic volumes. We assessed both linear and polynomial fits for each correction equation and applied the corrections to all hourly automated counts for statistical analysis.

2.2. Count site selection and data collection

Based on the number of available counters (n = 25) and our research design (1-week of short-duration counts at each location over ~6 months) we were able to sample ~100 sites across the network. We selected two types of count sites: (1) 4 continuous reference sites and (2) 97 short-duration count sites. The reference sites provide continuous monitoring of bicycle and pedestrian traffic across the duration of the count campaign. We had 12 pneumatic tube, 10 passive infrared, and 3 radio beam counters available for use in this study. Three pneumatic tube, 4 passive infrared, and 1 radio beam counters were installed at the continuous reference sites (counter configuration was site-specific due to the different characteristics of each count site; see Appendix A, Table A.1); the remaining counters (9 pneumatic tube, 6 passive infrared and 2 radio beam) were rotated randomly on a weekly basis from April to October at the short-duration sites. Due to a delay in counter delivery, not all of the reference site counters were deployed by January 1st of 2015 at the reference sites. However, all reference sites were deployed multiple weeks prior to any counts being collected at the short-duration sites. All sites were visually inspected prior to deploying counters and for most sites 1 day was needed before and after each count for relocation. We addressed missing counts due to various incidents (e.g., vandalism, counter malfunction) by either fixing or replacing the counter to ensure monitoring for at least 7 days at each count site.

Prior to our study, little information was available on patterns of bicycle and pedestrian traffic in Blacksburg. Therefore, we chose reference sites based on (1) street functional class (e.g., major roads vs. local roads) and presence of a bicycle facility, (2) surrounding land uses (i.e., proximity to the University, downtown, and residential areas), and (3) professional judgment (perceived use of the locations). In the absence of previous pedestrian and cyclist traffic counts (as is the case for many jurisdictions) we based our decisions on the above existing criteria. We ultimately chose 4 sites: (1) a neighborhood local road (off campus) with a bike lane, (2) a neighborhood local road (off campus) without a bike lane, (3) a retail corridor near campus and downtown (with perceived high pedestrian volume), and (4) an off-street trail (the longest trail in Blacksburg). Once the first iteration of traffic monitoring was complete it would then be possible to reconfigure the reference network to better capture long-term trends.

Prior studies found that short-duration counts of one week between April and October were the point of diminishing return for AADT estimation error (Hankey et al., 2014; Nordback et al., 2013a, 2013b; Nosal et al., 2014). Following these studies, we collected one week of counts during April to October (year-2015) to minimize AADT estimation error. Street functional class (Hankey et al., 2012) and bicycle facilities (Krizek et al., 2009; Dill and Carr, 2003; Buehler and Pucher, 2012) are associated with bicycle and pedestrian traffic. We used a transportation network characteristic called centrality which aims to capture the effects of presence of a facility, road type, and the spatial locations of origins and destinations (McDaniel et al., 2014) to aid in site selection. Briefly, centrality is computed by simulating the least-cost trip across the network for every origin-destination pair including impedance factors for presence of a bike facility, street functional class, and slope. Centrality has been shown to be correlated with bicycle traffic volume (McDaniel et al., 2014).

We selected short-duration count sites using a combination of street functional class and centrality to capture variability for bicycle and pedestrian traffic volumes. Specifically, our site selection approach stratified selection by street functional class (major road, local road, off-street trail) while attempting to incorporate sites with high and low trip potential based on centrality (see Appendix A, Tables A.2 and A.3). Since there are only a few major roads in Blacksburg, we were able to sample all major roads (average interval: 0.8 miles). We chose 29 count sites on major roads (10 with bicycle facilities; 19 without facilities). Next, we selected 20 sites on two types of off-street trails: (1) connected trails (highly connected trails co-located along roads or "rails-to-trails" corridors; average segment length: 0.88 miles) and (2) fragmented neighborhood trails (subdivision trails; average segment length: 0.63 miles). We randomly selected 10 sites from the small number (n = 16) of connected trail segments to ensure good spatial coverage. We then randomly selected 10 sites of the fragmented neighborhood trails (n = 26 segments). These trails were clustered into ~0.5-mile length groups to avoid choosing many small segments within the same subdivision. Since there was a small number of major roads and off-street trails to choose from we saturated sampling in those strata after selecting a total of 49 sites.

After saturating sampling for major roads and off-street trails, we used the remaining sites (n = 48) to choose sites on local roads. We first selected sites on all local roads with a future planned bicycle facility (based on the Blacksburg Bicycle Master Plan; n = 34) to (1) obtain baseline data for future infrastructure installation and (2) sample where people are likely to cycle in the absence of facilities (the master plan largely follows frequently cycled corridors). This procedure resulted in oversampling of sites with high centrality (i.e., high bicycle trip potential). To balance our sample we randomly selected 14 local road sites in the lowest quartile of centrality. Table 1 shows a summary of the count sites by road type and level of centrality as compared to Blacksburg as a whole; Fig. 2 shows the spatial location of the count sites with street functional class, bicycle facilities, and centrality.

2.3. Counter validation and quality control

To adjust for systematic under- or over-counts, we conducted field-based manual counts at 8 count sites for each type of automated counter (MetroCount: 181 h; Eco-counter: 274 h; RadioBeam: 29 h) and developed correction equations to adjust all raw hourly counts from these counters (see Appendix A, Fig. A.2). We tested both polynomial and linear correction equations for each counter.

We compared three bicycle classification schemes provided in the MetroCount software (ARX Cycle, BOCO, and Bicycle 15) to assess the impact of choice of classification scheme on the correction equation for the pneumatic tube counters. The ARX Cycle scheme uses the Australian vehicle classification with an added bicycle class. 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 using the FHWA vehicle classification scheme.

Based on limited research on quality assurance and quality control for bicycle and pedestrian counts, we used a two-step process to check for outliers: (1) direct cleaning of the data based on an event log that captured special events like counter malfunction, battery loss, vandalism, and football games and (2) a statistical check based on the variability of the overall count dataset. Specifically, we calculated the mean and standard deviation of the bicycle or pedestrian hourly counts for weekends and weekdays for each month. We then flagged outliers by using the following criteria: mean traffic $\pm 5 \times$ standard deviation. Our goal was to flag the hourly counts that were clear outliers while maintaining as much valid data as possible in the database.

2.4. Estimation of pedestrian and cyclist AADT

We used a four-step process to estimate AADT at each count site: (1) imputing missing days at the reference sites by developing negative binomial regression models based on weather and temporal parameters, (2) combining observed and imputed counts to calculate AADT for the continuous reference sites, (3) developing average day-of-year scaling factors among the reference sites, and (4) applying the day-of-year scaling factors to estimate AADT for all short-duration sites.

We used the observed counts from the continuous reference sites to develop negative binomial regression models. Previous studies have shown that negative binomial regression models are well suited for count data with overdispersion (Wang et al., 2014; Lindsey et al., 2013; Cao et al., 2006). We developed 8 site-specific models to estimate bicycle and pedestrian traffic on each day for each continuous reference site; we then used the models to provide daily volume estimates for the missing days. We used STATA 14 (StataCorp LP, College Station, Texas) and its extension, SPost 9 (Long, 2006) to build the

Table 1
Summary of count sites by location type as compared to Blacksburg as a whole.

	Count locations sampled in this study		All street and trail segments in Blacksburg	
Location type	n	Centrality[a]: Mean (SD[b])	n	Centrality[a]: Mean (SD[b])
Major roads				
With facility	10	54,700 (45,700)	45	80,000 (110,500)
Without facility	19	44,500 (55,100)	121	36,400 (48,400)
Off-street trails				
Connected	11	457,900 (395,100)	15	244,100 (324,000)
Fragmented	10	47,000 (72,900)	26	31,300 (56,500)
Local roads				
Future planned bike facility	37	123,800 (131,900)	976	32,700 (72,900)
Low centrality	14	588 (497)		636 (515)

[a] Centrality: magnitude of bicycle trip potential along a segment based on the spatial orientation of the network, origins, and destinations.
[b] SD: Standard Deviation

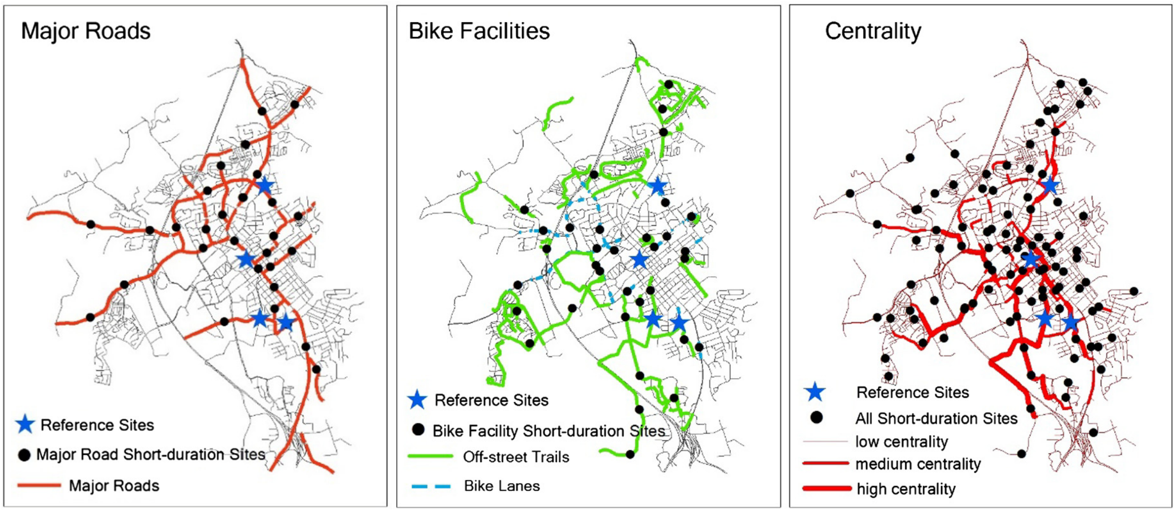

Fig. 2. Location of traffic count sites shown with each variable used in site selection: major roads (left); bicycle facilities (middle); centrality (right). Short-duration sites are the black dots; reference sites are the blue stars. Sites selected with major road and bike facility strata are shown in the left and middle panel; all sites are shown in the right panel.

models. Table 2 shows the variables used during model-building with the expected sign of the coefficients: *tmax* (daily max temperature), *tmaxdev* (the daily variation compared to the 30 years average [1980–2010]), *precipitation* (in millimeters), and *windspeed* (in mph). All data were retrieved from the National Climate Data Center of the National Oceanic and Atmospheric Administration and the National Weather Service Forecast Office. We used dummy variables (i.e., *weekend* and *university in session*) to account for day of week patterns and the academic calendar of the university (see Appendix B, Table B.1 for further details on weather and temporal variables used in the negative binomial modeling).

After imputing missing days using the negative binomial regression models we reconstructed a full year of data at the reference sites and developed day-of-year scaling factors for each reference site. 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 and month-of-year method. We only used days with valid counts to estimate day-of-year scaling factors; the imputed data was used only to calculate AADT in the denominator of Eq. (1). We followed this approach when developing scaling factors:

$$\text{Scaling factor} = \text{Average daily traffic}/\text{AADT} \tag{1}$$

We used the average day-of-year scaling factors (among all four reference sites) to estimate AADT for all short-duration sites. We matched daily counts at each short-duration site with the average bicycle and pedestrian day-of-year scaling factor of the 4 reference sites to estimate the site-specific AADT for each day of the short-duration count period (~7 days per site). Then, we averaged the daily AADT estimates to calculate a final AADT estimate for each short-duration site.

$$\text{AADT Estimate} = 1/\text{n} * \sum_{i=1}^{n} AdjC_i/SF_i \tag{2}$$

where $AdjC_i$ is the adjusted count (using the correction equations from the validation counts) on day i, n equals the number of days of short-duration counts, and SF_i denotes scaling factor retrieved from the reference site data. To compare the estimated AADT of the short-duration sites during times when the University was in session and not in session, we resampled 16 sites to compare estimates of AADT when collecting ~1 week of counts during these two time periods.

Table 2
Variables used in negative binomial regression models of bicycle and pedestrian traffic at the reference sites.

Variables	Definition	Mean	Expected signs
tmaxdev	The daily variation compared to the 30-year (1980–2010) average temperature	0.91	+/–
tmax	Recorded high temperature (Celsius)	18.2	+
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	+

2.5. Mapping and summarizing results

We mapped and summarized our AADT estimates to explore patterns of bicycle and pedestrian traffic in Blacksburg. We focused on stratifying our results by street functional class, presence of facilities (e.g., sidewalks or bicycle facilities), and proximity to campus. By using a systematic procedure to select count sites and remove temporal effects of cyclist and pedestrian traffic (via estimation of AADT) we were able to explore spatial trends in traffic patterns. We discuss how trends in these patterns could be tracked over time to evaluate planning decisions.

3. Results and discussion

We collected 45,456 h of bicycle and pedestrian traffic counts at 101 locations (~5.5% of street or trail segments) in Blacksburg, VA. Our overarching goal was to synthesize findings from the literature in a single framework to develop a method for estimating a performance measure (i.e., AADT) that can be tracked over time. Here, we present findings from our approach and discuss implications for designing and implementing traffic monitoring campaigns in small communities.

3.1. Data correction and cleaning

Our comparison of classification schemes showed that the ARX Cycle, BOCO, and Bicycle 15 schemes had similar R^2 (~0.89) for linear correction equations; however, the BOCO scheme had a slightly lower linear slope (1.26) than ARX Cycle (1.29) and Bicycle 15 (1.31), potentially indicating more accurate classification. For this reason, we chose the BOCO scheme to correct and process our bicycle counts, which was consistent with findings from other similar studies (Brosnan et al., 2015; Nordback et al., 2015a; Hyde-Wright et al., 2014). All automated counters were highly correlated with the manual

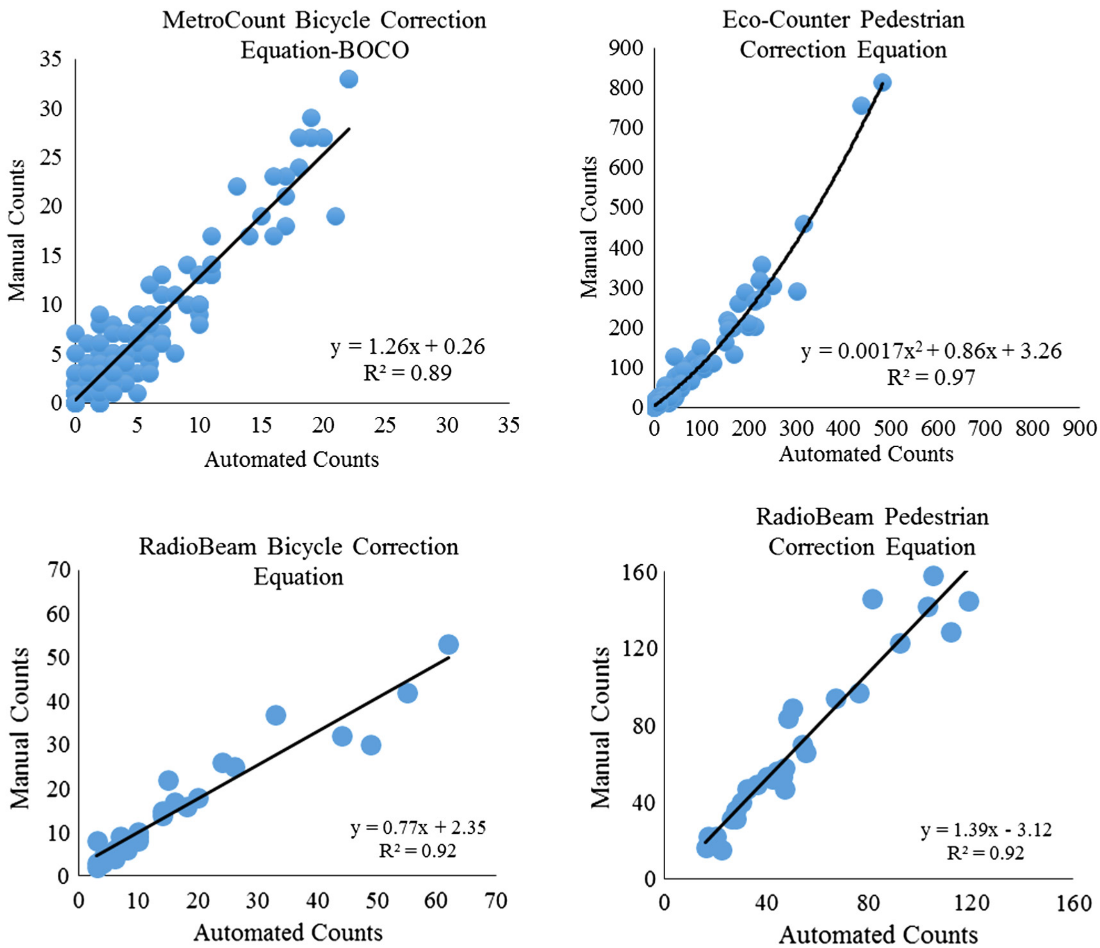

Fig. 3. Comparison of hourly automated counts and manual validation counts with corresponding correction equations for each type of counter.

validated counts (MetroCount R^2 [absolute error]: 0.88 [38%]; Eco-counter: 0.97 [24%]; RadioBeam bicycle: 0.92 [19%], RadioBeam pedestrian: 0.92 [22%]; see Appendix A, Table A.4–A.6 for a detailed comparison of schemes).

MetroCount and RadioBeam counters had a linear fit, while the Eco-counter demonstrated the need for a polynomial fit. Fig. 3 shows plots of automated vs. manual validation counts and the corresponding correction equations for each type of automated counter.

The quality assurance and quality control process resulted in censoring (bicycle: 3%, pedestrian: 8%) a small number of count days at the reference sites. Since there was not enough data to build a statistical check at each short-duration site, data was only censored if an incomplete day of data was recorded or an abnormal event was logged (e.g., vandalism, battery loss). Overall, the continuous reference sites reported valid counts for the majority of the count days when deployed in the field (bicycles: 96%; pedestrians: 87%) and for the total calendar year (bicycles: 75%; pedestrians: 87%; some reference sites were deployed in March). For the short-duration sites, 98% (bicycles) and 94% (pedestrians) of count sites had at least 7 days of monitoring data; no sites experienced 5 days or less of counts (see Appendix A, Table A.7 & Table A.8 for a detailed description of valid monitoring days). Table 3 summarizes the descriptive statistics for all adjusted counts (using the correction equations) at the reference and short-duration count sites.

3.2. Negative binomial regression models

Results of the site-specific negative binomial regression models are shown in Table 4. The dispersion factor α in the Likelihood Ratio test for each model suggests significant evidence ($p < 0.05$) of overdispersion and appropriate use of the

Table 3
Descriptive statistics of average daily bicycle and pedestrian traffic for the reference and short-duration count sites.

Reference sites				
Mode	Site name	Number of days	Mean (Median) daily traffic volume	IQR[a]
Bicycle	Draper	257	24 (24)	13–31
	College	247	62 (62)	43–79
	Giles	246	59 (52)	36–71
	Huckleberry	350	177 (174)	87–260
Pedestrian	Draper	263	103 (96)	76–123
	College	225	4,424 (4,120)	2,593–5,747
	Giles	102	168 (156)	139–184
	Huckleberry	336	514 (502)	338–659
Short-duration sites				
Mode	Site type	Number of sites	Mean (Median) daily traffic volume	IQR
Bicycle	Major Road	29	37 (33)	21–52
	Local Road	48	38 (22)	8–40
	Off-street Trail	20	79 (42)	10–112
Pedestrian	Major Road	24	198 (156)	106–243
	Local Road	24	593 (161)	106–529
	Off-street Trail	20	92 (50)	17–154

[a] IQR: Interquartile range.

Table 4
Results of the site-specific negative binomial regression models.

Model	Bicycle model				Pedestrian model			
Site	Draper	College	Giles	Huckleberry	Draper	College	Giles	Huckleberry
Constant	1.68	2.46	2.92	4.03	4.18	7.41	6.05	5.47
tmaxdev	−0.058***	−0.056***	−0.032***	−0.021***	−0.017***	−0.005	0.017*	−0.006
tmax	0.067***	0.068***	0.042***	0.059***	0.021***	0.018***	−0.036***	0.030***
precipitation	−0.009***	−0.003	−0.006***	−0.008***	−0.003*	−0.002	−0.002	−0.004*
windspeed	−0.006	−0.020**	−0.043***	−0.028***	−0.003	0.008	−0.019*	−0.018*
weekend	−0.418***	−0.115*	−0.114*	0.113**	−0.135***	0.624***	0.641	0.406***
unisession	0.221***	0.725***	0.919***	0.184***	0.211***	0.827***	0.246***	0.376***
Observations	257	247	246	350	263	225	102	336
Pseudo R^2	0.066	0.107	0.113	0.082	0.026	0.031	0.055	0.022

Note: dispersion factor α of all sites fit in LR test.
* Denotes p-value < 0.10.
** Denotes p-value < 0.05.
*** Denotes p-value < 0.01.

negative binomial regression models. Higher values of McFadden's Pseudo-R^2 indicates a better overall fit among models (Cao et al., 2006); McFadden (1979) suggested that Pseudo-R^2 values between 0.2 and 0.4 represent an excellent fit. Our pseudo-R^2 values are similar to other studies of bicycle and pedestrian traffic (Wang et al., 2014). The Chi-square tests ($p < 0.05$) also indicate reasonable goodness-of-fit. To generate validation R^2 values we used the negative binomial regression models to estimate daily traffic counts for all days with valid data. Then, we compared the model-generated estimates with observed counts (see Appendix A, Fig. A.3–A.8). Overall, the bicycle traffic models performed more reliably (validation $R^2 = {\sim}0.70$) than the pedestrian traffic models (validation $R^2 = {\sim}0.30$) likely owing to the fact that cyclists seem to be more sensitive to weather than pedestrians in our dataset. This finding is consistent with previous research (Hankey et al., 2012; Schasberger et al., 2012).

Both bicycle and pedestrian traffic counts at nearly all of the reference sites were correlated with the independent variables in the expected direction. However, there were exceptions for some sites; for example, pedestrian traffic at College Avenue was not significantly associated with precipitation or wind speed, which may be due to the consistent demand associated with retail corridors (e.g., dining or meeting friends). Walking activities at Giles Road were not correlated with precipitation or day of week (i.e., weekend vs. weekday); this finding may be due to the comparatively small number of observations for this location (102 days) due to vandalism. Considering consistency across count sites, we incorporated all variables in the final models for each location. We used the models to impute missing days in the reference site database. In total, we imputed 30% of all days among the reference network.

3.3. AADT estimation

We developed scaling factors based on data from the 4 reference sites to estimate AADT at each short-duration count site. We grouped all bicycle and pedestrian reference sites to average day-of-year scaling factors for each mode rather than developing factor groups (AADT estimates are shown in Appendix B, Table B.2–B.4). Fig. 4 shows the general temporal pattern of the bicycle and pedestrian scaling factors which reveals the seasonal and university-related impacts on traffic patterns throughout the year. In general, traffic volumes were lower in the winter (days with low temperatures), and in the summer (days when students leave Blacksburg). Table 5 shows a summary of AADT compared to average daily traffic (ADT) for all count sites. As a whole, the difference between the actual counts and AADT was larger for pedestrians than for bicycles, likely

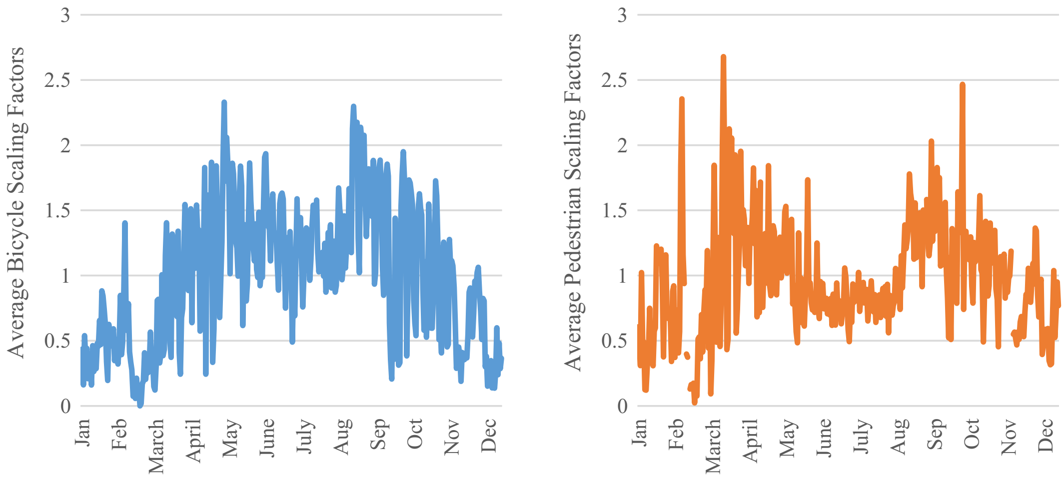

Fig. 4. Average bicycle and pedestrian day-of-year scaling factors used to estimate AADT at short-duration count sites (year-2015).

Table 5
Summary of AADT estimates compared to average daily traffic (ADT) for all count sites.

Traffic	Road and trail type	Mean ADT	Mean AADT	Percent difference	Mean absolute percent difference
Bicycle	Major road	37	32	0%	18%
	Local road	38	40	−16%	31%
	Off-street trail	79	73	−10%	23%
	All locations	46	44	0%	25%
Pedestrian	Major road	198	236	19%	23%
	Local road	593	693	7%	15%
	Off-street Trail	92	111	4%	23%
	all locations	306	371	10%	20%

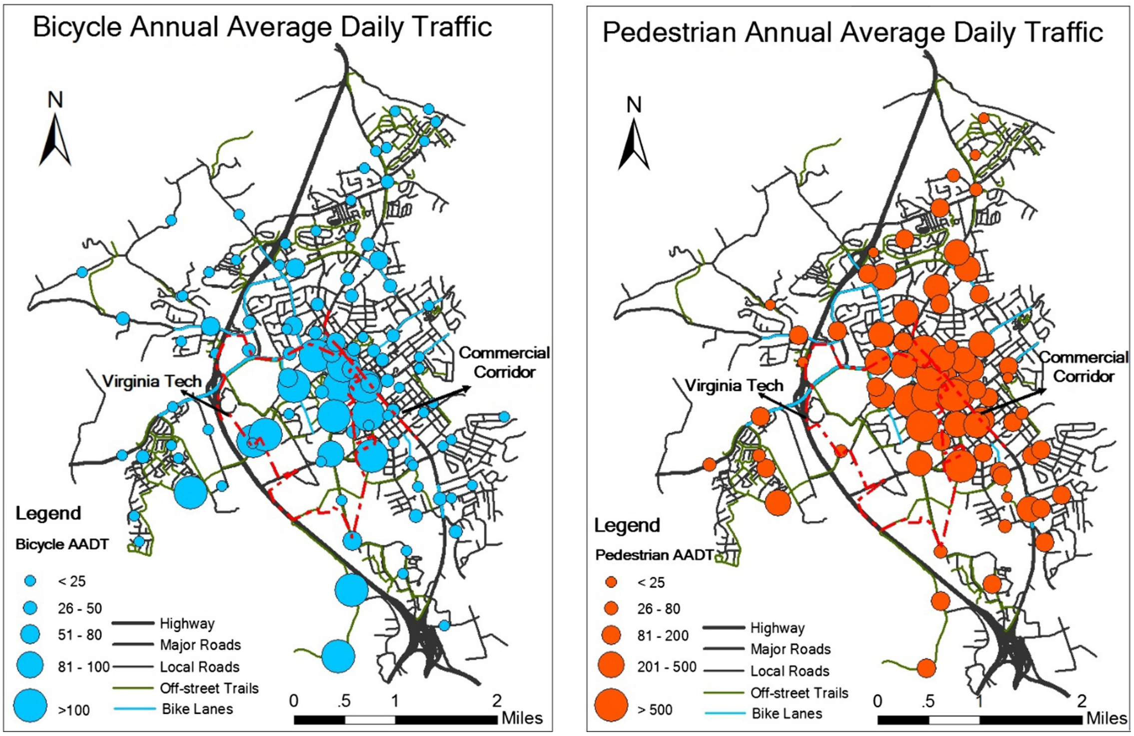

Fig. 5. Bicycle and pedestrian AADT at all monitoring sites.

owing to the fact that pedestrian volumes were generally higher and more variable by season than bicycles (likely influenced by the university population).

We resampled 16 short-duration count sites to compare the estimated AADT from counts collected when the university was in session vs. when the university was not in session. We found that the average percent error between university not in session and university in session of bicycle (pedestrian) AADT is 21% (11%), and median percent error is 6% (9%) (see Appendix B, Table B.5).

3.4. Mapping and summarizing AADT at the count locations

Estimated bicycle and pedestrian AADT for all monitoring sites are shown in Fig. 5. Previous studies found that mixed use of land containing convenience stores, offices, or restaurants are associated with bicycle activities (Pucher and Buehler, 2006; Moudon et al., 2005; Cui et al., 2004; Faghih-Imani et al., 2014). Our estimates of bicycle and pedestrian traffic are consistent with those studies. The downtown commercial corridor with retail and mixed uses have high cycling volumes (~70/day). Off-street trails adjacent to the University also had high bicycle volumes (~150/day). The largest pedestrian volumes (~12,000/day) are within the university area and along the downtown commercial corridor. In some residential areas, near off-street trails, pedestrian volumes are higher than other outer lying areas.

Fig. 6 displays the distribution of bicycle and pedestrian AADT by street functional class, bicycle facility, and distance from campus. In general, bicycle facilities are associated with increased levels of bicycle commuting (Krizek et al., 2009; Dill and Carr, 2003; Buehler and Pucher, 2012) and cyclists show a preference to ride on roads with facilities compared to roads without (Buehler and Pucher, 2012; Hunt and Abraham, 2007; Fishman et al., 2014; Sanders and Cooper, 2013; Kang and Fricker, 2013). We find that the presence of a bicycle lane is associated with higher daily cycling volumes (mean: 72/day vs. 30/day; $p < 0.01$). Similarly, bicycle AADT is significantly higher ($p < 0.01$) on long distance, connected trails (mean: 112/day) as compared to roads both with (72/day) and without (30/day) a bike lane as well as fragmented neighborhood trails (29/day).

Pedestrian AADT is significantly higher ($p < 0.01$) on local roads (mean: 693/day) than on major roads (mean: 236/day), connected trails (mean: 162/day) and fragmented trails (mean: 55/day). This finding is likely owing to the fact that most roads on the university campus are classified as local roads. To test the effect of count sites located on campus we stratified our sample by distance from campus in three categories (on campus, within 500 m of campus, more than 500 m from campus). We observe that when the distance from campus increases, bicycle and pedestrian traffic generally declines for major and local roads, but that the effect is largest for local roads.

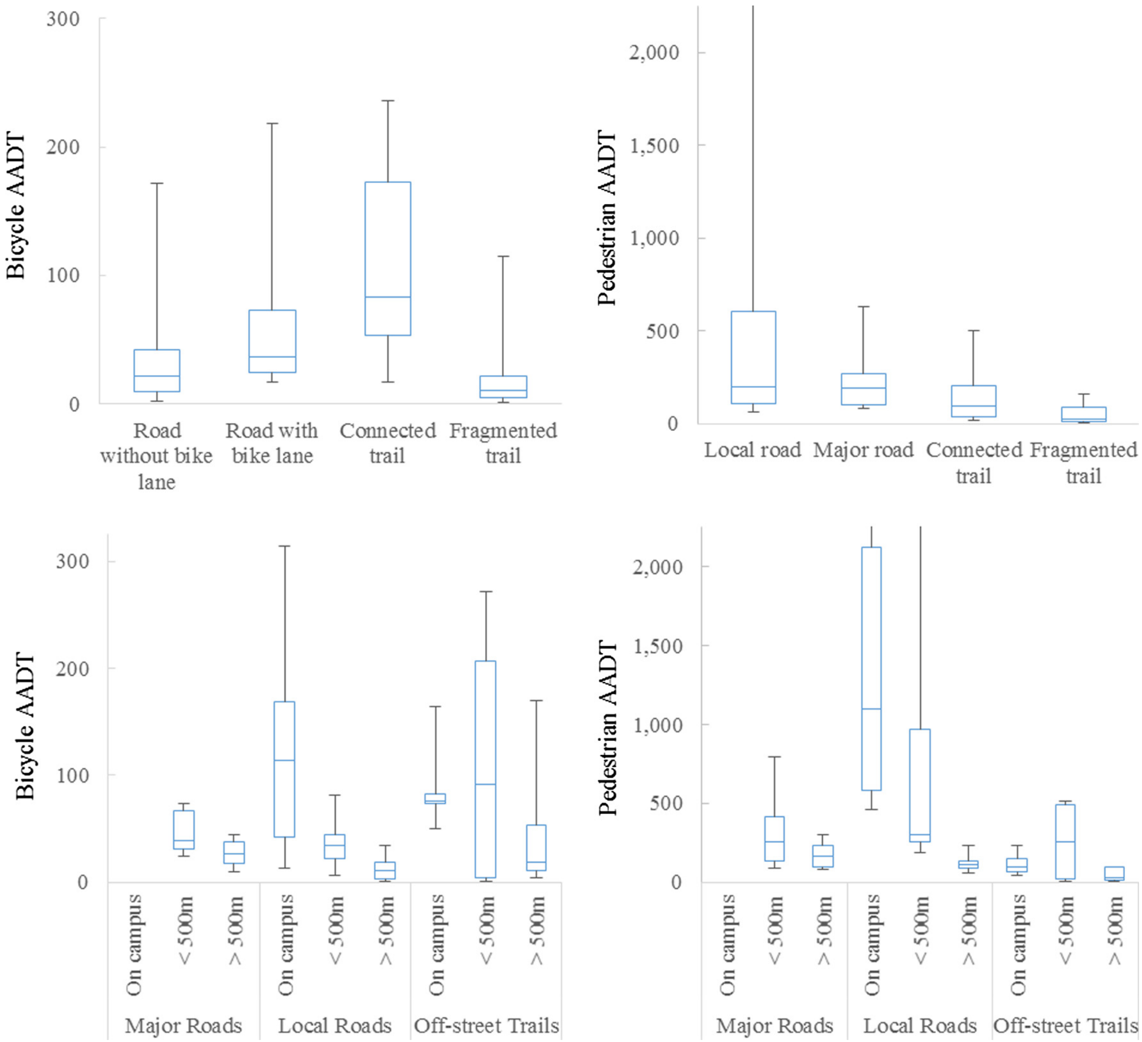

Fig. 6. Bicycle and pedestrian AADT by street functional class, bike facility, and distance from campus. The upper panels show bicycle and pedestrian AADT by street functional class and bike facility; the lower panels show AADT by distance from campus. Note: 95th percentile values were clipped from the pedestrian plots to preserve overall trends in the data.

3.5. Implications for future research and non-motorized traffic monitoring

We developed a bicycle and pedestrian traffic monitoring campaign to estimate a commonly used performance measure (AADT) in a small, rural college town. Our work synthesizes many ongoing efforts to effectively count and track non-motorized traffic patterns. For example, we used guidance on AADT estimation (e.g., length and season of short-duration count; Hankey et al., 2014; Nordback et al., 2013a, 2013b; Nosal et al., 2014), count site selection (i.e., use of a centrality metric; McDaniel et al., 2014), and data processing (e.g., use of BOCO classification and process for developing correction equations; Brosnan et al., 2015; Nordback et al., 2015a; Hyde-Wright et al., 2014) to design our count campaign. Our work offers a proof-of-concept that comprehensive monitoring programs for bicycles and pedestrians are feasible and can be designed in an efficient way to maximize limited resources. A useful extension of our work would be to test our approach in a larger jurisdiction with a more complex transportation network.

Several limitations of our work could be addressed in future studies. First, due to resource constraints, we were only able to deploy 4 reference sites to monitor temporal trends in Blacksburg. Questions remain on how best to locate reference sites and how many reference sites are sufficient to characterize a region or transportation network. The traffic volumes collected in this study could be evaluated to reconfigure the reference network to better capture long-term trends in the future. Second, pedestrians were only monitored where walking facilities (i.e., sidewalks) were available, which limited our ability to sample the entire transportation network for pedestrians. Our negative binomial regression models had modest performance for pedestrians (validation $R^2 = \sim 0.30$), leaving room for model improvement or incorporation of spatial factors that were not captured in our weather-based models. Third, with limited research for quality assurance and quality control for bicycle and pedestrian count data, we chose basic criteria to censor outliers from our dataset; however, more work is needed to assess best practices for censoring unreliable data. Fourth, we chose 1 week of data collection for our short-duration counts following previous research (Hankey et al., 2014; Nordback et al., 2013a, 2013b; Nosal et al., 2014). Bias in the AADT estimates may occur since factor groups were not developed for scaling since we were only able to deploy a small number of reference sites. Fifth, our paper described how the estimates of AADT can be calculated based on a synthesis of methods from previous research, however, we were not able to compare to actual AADT values to validate our approach. Incorporating spatial variables (e.g., land uses) into assessment and modeling may be useful to study traffic patterns of both pedestrian and bicycle volumes; this addition may be especially important for pedestrians since pedestrian volumes seemed to be less correlated with weather factors near clusters of destinations.

Our work has practical implications for designing comprehensive count programs to develop performance measures for bicycles and pedestrians. Our approach could be replicated by local planners and engineers interested in establishing a traffic monitoring program. Since our work was completed in a small community, we were able to systematically select a representative sample of street and trail segments among the entire network (~5.5% of all segments). We expect that our approach could be adopted in larger, more complex urban areas to generate analogous performance measures to motor vehicle traffic for use in decision making. Routine collection of bicycle and pedestrian counts could aid planners in evaluating infrastructure investments, safety analyses, and measuring exposure to risk.

4. Conclusions

This paper describes the design and implementation of a comprehensive bicycle and pedestrian traffic count campaign in Blacksburg, VA. Our approach focused on designing traffic monitoring programs for small communities with the goal of assessing the entire network. Our approach included four major steps: (1) selecting and validating automated counters, (2) site selection and data collection, (3) estimation of AADT, and (4) mapping and summarizing results. We found strong correlation between validation counts and automated counts and correction equations varied by counter type; this finding highlights the importance of validating counter performance prior to use in the field. We were able to choose count sites for the purpose of tracking performance measures based on limited available information (i.e., street functional class, facility, and centrality). We found that it was possible to combine methods from previous studies to estimate AADT. Namely, we (1) imputed missing counts at reference sites using negative binomial regression, (2) developed day-of-year scaling factors, and (3) estimated AADT at short-duration count sites using 1 week of traffic counts. Our work serves as a proof-of-concept for designing and implementing a comprehensive bicycle and pedestrian traffic monitoring program in a small, rural community. We found that similar approaches may be used to count bicycles and pedestrians, however, the temporal and spatial patterns of traffic differed between modes. This finding underscores the importance of monitoring and modeling modes separately. Our approach could be replicated in other jurisdictions (large or small communities) to confirm feasibility in different traffic environments.

Acknowledgements

We would like to thank the Town of Blacksburg, VA (especially Kelly Mattingly, Carol Davis, and the "Corridor" committee) and the students in a graduate course in Urban Affairs and Planning for aiding in this work. This research was supported by Mid-Atlantic Transportation Sustainability Center Regional University Transportation Center (MATS-UTC).

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.trd.2017.04.017.

References

Alta Planning and Design and the Institute of Transportation Engineers (ITE) Pedestrian and Bicycle Council, 2016. National Bicycle & Pedestrian Documentation Project Retrieved from http://bikepeddocumentation.org/index.php (Feb 10).

Brosnan, M., Petesch, M., Pieper, J., Schumacher, S., Lindsey, G., 2015. Validation of bicycle counts from pneumatic tube counters in mixed traffic flows. Transport. Res. Rec. J. Transport. Res. Board 2527, 80–89. http://dx.doi.org/10.3141/2527-09.

Buehler, R., Pucher, J., 2012. Cycling to work in 90 large American cities: new evidence on the role of bike paths and lanes. Transportation 39 (2), 409–432. http://dx.doi.org/10.1007/s11116-011-9355-8.

Cao, X., Handy, S., Mokhtarian, P., 2006. The influences of the built environment and residential self-selection on pedestrian behavior: evidence from Austin, TX. Transportation 33 (1), 120. http://dx.doi.org/10.1007/s11116-005-7027-2.

Cui, Y., Mishra, S., Welch, T.F., 2004. Land use effects on bicycle ridership: a framework for state planning agencies. J. Transp. Geogr. 41, 220–228. http://dx.doi.org/10.1016/j.jtrangeo.2014.10.004.

Dill, J., Carr, T., 2003. Bicycle commuting and facilities in major U.S. cities: if you build them, commuters will use them. Transp. Res. Rec. 1828 (1), 116–123. http://dx.doi.org/10.3141/1828-14.

El Esawey, M., Lim, C., Sayed, T., Mosa, A.I., 2013. Development of daily adjustment factors for bicycle traffic. J. Transport. Eng. 139 (8), 859–871. http://dx.doi.org/10.1061/(ASCE)TE.1943-5436.0000565.

Faghih-Imani, A., Eluru, N., El-Geneidy, A.M., Rabbat, M., Haq, U., 2014. How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (BIXI) in Montreal. J. Transp. Geogr. 41, 306–314. http://dx.doi.org/10.1016/j.jtrangeo.2014.01.013.
Federal Highway Administration, 2013. Traffic Monitoring Guide Retrieved from http://www.fhwa.dot.gov/policyinformation/tmguide/.
Fishman, E., Washington, S., Haworth, N., Watson, A., 2014. Factors influencing bike share membership: an analysis of Melbourne and Brisbane. Transport. Res. Part A Pol. Pract. 71, 17–30. http://dx.doi.org/10.1016/j.tra.2014.10.021.
Hankey, S., Lindsey, G., Marshall, J., 2014. Day-of-year scaling factors and design considerations for non-motorized traffic monitoring programs. Transport. Res. Rec. J. Transport. Res. Board 2468, 64–73. http://dx.doi.org/10.3141/2468-08.
Hankey, S., Lindsey, G., Wang, X., Borah, J., Hoff, K., et al, 2012. Estimating use of non-motorized infrastructure: models of bicycle and pedestrian traffic in minneapolis, MN. Landscape Urban Plan. 107 (3), 307–316. http://dx.doi.org/10.1016/j.landurbplan.2012.06.005.
Hunt, J.D., Abraham, J.E., 2007. Influences on bicycle use. Transportation 34 (4), 453–470. http://dx.doi.org/10.1007/s11116-006-9109-1.
Hyde-Wright, A., Graham, B., Nordback, K., 2014. Counting bicyclists with pneumatic tube counters on shared roadways. Inst. Transport. Eng. ITE J. 84 (2), 32.
Kang, L., Fricker, J.D., 2013. Bicyclist commuters' choice of on-street versus off-street route segments. Transportation 40 (5), 887–902. http://dx.doi.org/10.1007/s11116-013-9453-x.
Krizek, K.J., Barnes, G., Thompson, K., 2009. Analyzing the effect of bicycle facilities on commute mode share over time. J. Urban Plan. Develop. 135 (2), 66–73. http://dx.doi.org/10.1061/(ASCE)0733-9488(2009) 135:2(66).
Lindsey, G., Hankey, S., Wang, X., Chen, J., 2013. The Minnesota Bicycle and Pedestrian Counting Initiative: Methodologies for Non-Motorized Traffic Monitoring. Final Report. Research Services Section, Minnesota Department of Transportation, Saint Paul.
Long, J.S., 2006. Regression Models for Categorical and Limited Dependent Variables. Stata Press.
McDaniel, S., Lowry, M., Dixon, M., 2014. Using origin-destination centrality to estimate directional bicycle volumes. Transport. Res. Rec. J. Transport. Res. Board 2430, 12–19. http://dx.doi.org/10.3141/2430-02.
McFadden, D., 1979. Quantitative methods for analyzing travel behavior of individuals: some recent developments. Behav. Travel Model. Croom Helm, London.
Miranda-Moreno, L.F., Nosal, T., Schneider, R.J., Proulx, F., 2013. Classification of bicycle traffic patterns in five north American cities. Transport. Res. Rec. J. Transport. Res. Board 2339, 68–79. http://dx.doi.org/10.3141/2339-08.
Moudon, A.V., Lee, C., Cheadle, A.D., Collier, C.W., Johnson, D., Schmid, T.L., Weather, R.D., 2005. Cycling and the built environment, a U.S. perspective. Transport. Res. Part D Transp. Environ. 10 (3), 245–261. http://dx.doi.org/10.1016/j.trd.2005.04.001.
Nordback, K., Kothuri, S., Phillips, T., Gorecki, C., Figliozzi, M., 2015a. Accuracy of bicycle counting with pneumatic tubes in Oregon. Transport. Res. Rec. J. Transport. Res. Board 2593, 8–17. http://dx.doi.org/10.3141/2593-02.
Nordback, K., Marshall, W.E., Janson, B.N., 2013a. Development of Estimation Methodology for Bicycle and Pedestrian Volumes Based on Existing Counts. Colorado Department of Transportation, Denver.
Nordback, K., Marshall, W.E., Janson, B.N., Stolz, E., 2013b. Estimating annual average daily bicyclists: error and accuracy. Transport. Res. Rec. J. Transport. Res. Board 2339, 90–97. http://dx.doi.org/10.3141/2339-10.
Nordback, K., Tufte, K., Harvey, M., McNeil, N., Stolz, E., Liu, J., 2015b. Creating a national non-motorized traffic count archive: process and progress. Transp. Res. Rec. 2527, 90–98. http://dx.doi.org/10.1007/s13398-014-0173-7.2.
Nosal, T., Miranda-Moreno, L.F., Krstulic, Z., 2014. Incorporating weather: comparative analysis of annual average daily bicyclist traffic estimation methods. Transp. Res. Rec. 2468, 100–110. http://dx.doi.org/10.3141/2468-12.
Pedestrian and Bicycle Information Center, 2016a. Promote Walking and Biking: Case Studies Retrieved from www.pedbikeinfo.org/programs/promote_casestudies.cfm (Feb 12).
Pedestrian and Bicycle Information Center, 2016b. Environmental Benefits of Bicycling and Walking Retrieved from http://www.pedbikeinfo.org/data/factsheet_environmental.cfm (Feb 12).
Pucher, J., Buehler, R., 2006. Why Canadians cycle more than Americans: A comparative analysis of bicycling trends and policies. Transp. Policy 13, 265–279. http://dx.doi.org/10.1016/j.tranpol.2005.11.001.
Pucher, J., Buehler, R., 2010. Walking and cycling for healthy cities. Built Environ. 36 (4), 391–414. http://dx.doi.org/10.2148/benv.36.4.391.
Ryan, S., 2013. Establishing an automated regional non-motorized transportation data collection system to support active transportation performance monitoring. Paper prepared for Transportation Research Board 92nd Annual Meeting.
Ryan, S., Sidelinger, D.E., Saitowitz, S., Browner, D., Vance, S., McDermid, L., 2014. Designing and implementing a regional active transportation monitoring program through a county-MPO-university collaboration. Am. J. Heal. Promot. 28 (3 suppl), S104–S111. http://dx.doi.org/10.4278/ajhp.130430-ARB-212.
Ryus, P., Ferguson, E., Laustsen, K.M., Schneider, R.J., Proulx, F.R., Hull, T., Miranda-Moreno, L., 2014. NCHRP REPORT 797 Guidebook on Pedestrian and Bicycle Volume Data Collection. Institute of Transportation Studies, UC Berkeley.
Sanders, R.L., Cooper, J.F., 2013. Do all roadway users want the same things? Transp. Res. Rec. 2393, 155–163. http://dx.doi.org/10.3141/2393-18.
Schasberger, M.G., Raczkowski, J., Newman, L., Polgar, M.F., 2012. Using a bicycle-pedestrian count to assess active living in downtown Wilkes-Barre. AMEPRE 43 (5), S399–S402. http://dx.doi.org/10.1016/j.amepre.2012.06.029.
Schneider, R.J., Henry, T., Mitman, M.F., Stonehill, L., Koehler, J., 2013. Development and Application of the San Francisco Pedestrian Intersection Volume Model. Safe Transportation Research & Education Center, UC Berkeley.
Wang, X., Lindsey, G., Hankey, S., Hoff, K., 2014. Estimating non-motorized trail traffic using negative binomial regression models. J. Urban Plan. Develop. 140, 1–9. http://dx.doi.org/10.1061/(ASCE)UP.1943-5444.0000157.