Designing a Bicycle and Pedestrian Traffic Monitoring Program to Estimate Annual Average Daily Traffic in a Small Rural College Town

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Submission date: 11/14/2016
Word count (w/o references): 4,245 + 11 tables/figures*250 = 6,995 + 35 references (limit: 7,000)
ABSTRACT

Most bicycle and pedestrian traffic monitoring programs are implemented in urban areas and focus on specific aspects of the transportation network (e.g., off-street trails, specific corridors). We present findings from a comprehensive bicycle and pedestrian traffic monitoring campaign in a small, rural college town (Blacksburg, VA). We collected counts using three types of automated counters (pneumatic tubes [n=12], passive infrared [n=10], and radio beam [n=3]) and compared to manual validation counts (210 hours; validation $R^2$: 0.89-0.97). We selected count sites (4 reference; 97 short-duration) to be representative of pedestrian and cycling volumes across the network. Specifically, we stratified site selection by street functional class, centrality of origin and destinations, and future bicycle facility buildout plans. Our reference sites had good temporal coverage when deployed (valid days for bicycles [pedestrians]: 96% [87%]) and at least 7 days of counts were collected at nearly all short-duration sites (bicycles [pedestrians]: 98% [94%]). We imputed missing data at the continuous reference sites using negative binomial regression models; the resulting dataset was used to calculate day-of-year scaling factors to estimate Annual Average Daily Traffic (AADT) for all short-duration sites. Pedestrian volumes were higher and more variable than bicycle volumes (median [interquartile range] AADT for pedestrians: 135 [89-292]; bicycles: 23 [11-43]); traffic volumes were correlated with street functional class, presence of facilities, and distance from campus. Our work serves as a proof-of-concept for comprehensive monitoring across an entire network; we expect that our approach could be scaled to monitor bicycle and pedestrian traffic larger urban areas.
1. INTRODUCTION AND LITERATURE REVIEW

An understudied aspect of transportation systems are the spatial and temporal patterns of non-motorized (i.e., cyclists and pedestrians) traffic volumes. Design and implementation of systematic non-motorized traffic monitoring programs could aid transportation engineers and planners in multiple domains, for example, tracking performance measures, prioritizing investment in infrastructure, health and environmental impact assessments, and safety analyses (1). Recognition of these benefits has resulted in targeted funding and pilot demonstration projects at federal, state, and local levels to assess best practices for bicycle and pedestrian data collection (2).

Deploying a comprehensive monitoring program requires 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) (3-5). Key questions remain on how to implement best practices to collect bicycle and pedestrian data for an entire transportation network that can be used to estimate traffic patterns on all streets and trails where biking or walking may occur. Guidance from the National Bicycle & Pedestrian Documentation Project and the Federal Highway Administration’s Traffic Monitoring Guide have helped to provide consistency in the methods used to collect counts (6, 7). Additionally, a national count archive currently under development aims to help standardize non-motorized data collection in different locations (7, 8). Ongoing efforts are providing further guidance on counter performance (1, 9, 10, 11), developing scaling factors (3, 5, 12), identifying factor groups (3, 13, 14), and count site selection (7, 15, 16).

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. Efforts to develop standardized methods for estimating performance measures for non-motorized traffic are ongoing (3). Most non-motorized count programs (and studies of non-motorized traffic patterns) are conducted in large urban areas (e.g., Minneapolis, Portland, San Francisco, and Vancouver) (1, 7). Relatively few studies have focused on designing count campaigns in small, rural areas. Small communities may offer a unique opportunity to explore the design of comprehensive monitoring programs as the transportation network is small compared to larger urban areas, making it possible to collect a representative sample of counts across the network.

In this study, we designed a systematic non-motorized traffic monitoring campaign in a small, rural college town (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 focus on singular components of the network (e.g., off-street trails, specific corridors). 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 estimate performance measures analogous to those used in motorized traffic. Our approach may be useful to planners or policy-makers interested in comprehensive monitoring of cyclists and pedestrians. We expect that our approach could be scaled for use in larger, more complex urban areas.
2. DATA COLLECTION AND METHODS

Our approach includes mainly four steps: (1) selection and validation of automated counters, (2) site selection and data collection, (3) estimation of performance measures (i.e., AADT) at the count sites, and (4) mapping and summarization of AADT across the network (Figure 1). Here, we describe our approach to complete each step; then, summarize our results and discuss implications for implementing traffic monitoring programs for bicycle and pedestrian traffic.

![Systematic Count Program Diagram]

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

2.1. Monitoring technologies and validation counts

We used a combination of automated counter technologies and manual field-based counts (i.e., validation counts) to monitor bicycle and pedestrian traffic patterns on different road types and off-street trails. We used three automated count devices: (1) pneumatic tube counters (MetroCount MC 5600 Vehicle Classifier System), (2) passive infrared counters (Eco-Pyro), and (3) radio beam counters (Chambers RadioBeam Bicycle-People Counter). We chose automated counters based on previously reported performance, the location types we targeted for monitoring, portability, and cost. We used the pneumatic tubes to count bicycles on roads with mixed traffic, the passive infrared counters to count pedestrians on sidewalks, and the radio beam counters to 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 (i.e., the radio beam sometimes counts cyclists twice presumably due to the sensitivity of the sensor). Researchers have commonly used manual field-based validation counts to correct hourly counts obtained from automated counters (11, 17). We collected 210 total hours of manual validation counts at 8 locations to develop correction equations for each type of counter. We assessed both linear and polynomial fits for each correction equation and applied the corrections to all hourly automated counts for statistical analysis and when developing performance measures.

2.2. Site selection and data collection

Our traffic monitoring campaign included two types of count sites: (1) 4 continuous reference sites and (2) 97 short-duration count sites. The continuous reference sites provide...
continuous monitoring of bicycle and pedestrian traffic for an entire year. 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 counter were installed at the continuous reference sites; the remaining counters were rotated on a weekly basis at the short-duration sites.

Our choice of continuous reference sites was based on (1) professional judgment (perceived volumes of bicycle and pedestrian traffic), (2) street functional class and presence of a bicycle facility, and (3) surrounding land uses (i.e., proximity to the University, downtown, and residential areas). In the absence of previous traffic counts (as is the case for many jurisdictions) we based our decisions on the above existing criteria; however, once completing the first iteration of traffic monitoring it may be possible to reconfigure the reference network to better capture long-term trends.

Prior studies found that short-duration counts for at least 1 week between April and October yields satisfactory AADT estimation error (3, 4, 5). Street functional class is associated with bicycle and pedestrian traffic volumes (18). Bicycle facilities (i.e., bike lanes and paths) are associated with increased levels of bicycle commuting (19-21). Centrality (i.e., magnitude of bicycle trip potential along a segment based on the spatial orientation of the network, origins, and destinations) is correlated with bicycle traffic volume (22). Based on previous studies we selected our short-duration sites using a combination of street functional class (e.g., major roads, local roads) and centrality to span the variable space for bicycle and pedestrian traffic volumes. We sampled both existing and planned cycling infrastructure (i.e., trails, bike lanes and sidewalks) for the purpose of assessing future installation of infrastructure. Following previous studies we collected 1 week of counts during April to October (year-2015) to reduce AADT estimation error.

Our site selection approach stratified selection by street functional class while attempting to incorporate sites with high and low trip potential based on centrality. We chose sites sequentially in this order: (1) major roads (arterials or collectors), (2) off-street trails, and (3) local roads. Since there are few major roads in Blacksburg, we were able to sample all major road segments in Town limits. Specifically, 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) trails meant for transport or long distances, e.g., co-located along roads or “rails-to-trails” corridors) and (2) fragmented neighborhood (i.e., mostly subdivision) trails. We selected 10 sites from the small number of transport trail segments (n=16) to ensure good spatial coverage. We then randomly selected 10 sites among the 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).

Finally, we selected 48 count sites on local roads. We first selected sites on all roads with a planned future 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. This procedure resulted in oversampling of sites with high centrality (i.e., high bicycle trip potential). To balance our sample we also randomly added 14 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; Figure 2 shows the count sites with street functional class, bicycle facilities, and centrality.
TABLE 1. Summary of count sites by location type as compared to Blacksburg as a whole

<table>
<thead>
<tr>
<th>Location Type</th>
<th>Count locations sampled in this study</th>
<th>All street and trail segments in Blacksburg</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Centrality*: Mean (SD)</td>
</tr>
<tr>
<td>Major Roads</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bike lanes</td>
<td>10</td>
<td>54,724 (45,748)</td>
</tr>
<tr>
<td>No facility</td>
<td>19</td>
<td>44,491 (55,083)</td>
</tr>
<tr>
<td>Off-street trails</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transport</td>
<td>11</td>
<td>457,866 (395,089)</td>
</tr>
<tr>
<td>Neighborhood</td>
<td>10</td>
<td>47,001 (72,917)</td>
</tr>
<tr>
<td>Local roads</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bike buildout</td>
<td>37</td>
<td>123,755 (131,918)</td>
</tr>
<tr>
<td>Low centrality</td>
<td>14</td>
<td>588 (497)</td>
</tr>
</tbody>
</table>

*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

FIGURE 2. Location of traffic monitoring 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 purple dots.

2.3. Estimation of 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 parameters, (2) combining the 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 valid observed counts from the continuous reference sites to develop negative binomial regression models based on weather parameters. Previous studies have shown that negative binomial regression models are well suited for non-negative count data with overdispersion in the data (23-25). We developed 8 site-specific (4 for bicycles and 4 for pedestrians) negative binomial regression models to estimate bicycle and pedestrian traffic on...
each day for each continuous reference site. We used STATA 14 (StataCorp LP, College Station, Texas) and its extension, SPost 9 (26) to estimate the models. Table 2 shows the variables used during model-building with the expected sign of the coefficients: \( t_{max} \) (daily max temperature), \( t_{maxdev} \) (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 Virginia Tech.

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

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
<th>Mean</th>
<th>Expected signs</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t_{maxdev} )</td>
<td>High temperature deviation from the 30-year (1980-2010) temperature</td>
<td>0.911</td>
<td>+/-</td>
</tr>
<tr>
<td>( t_{max} )</td>
<td>Recorded high temperature (Celsius)</td>
<td>18.228</td>
<td>+</td>
</tr>
<tr>
<td>( precipitation )</td>
<td>Precipitation (mm)</td>
<td>3.412</td>
<td>-</td>
</tr>
<tr>
<td>( windspeed )</td>
<td>Average wind speed (mph)</td>
<td>4.264</td>
<td>-</td>
</tr>
<tr>
<td>( weekend )</td>
<td>Saturday or Sunday (equals 1, otherwise 0)</td>
<td>0.285</td>
<td>+/-</td>
</tr>
<tr>
<td>( university ) ( in ) ( session )</td>
<td>University in session (equals 1, otherwise 0)</td>
<td>0.436</td>
<td>+</td>
</tr>
</tbody>
</table>

After imputing missing days with 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. (3) and Nosal et al. (5) 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 followed this approach when developing scaling factors:

\[
\text{Scaling factor} = \frac{\text{Average daily traffic}}{\text{AADT}} \quad (1)
\]

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 or pedestrian day-of-year scaling factor 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.

\[
\text{AADT Estimate} = \frac{1}{n} \times \sum_{i=1}^{n} \frac{\text{Adj Count} \_i}{\text{SF} \_i} \quad (2)
\]

where, \( \text{Adj Count} \_i \) is the adjusted count on day \( i \), \( n \) equals the number of days of short-duration counts, and \( \text{SF} \_i \) 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.

### 2.4. 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 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 hours of bicycle and pedestrian traffic counts at 101 locations (~5.5% of street or trail segments) in Blacksburg, VA. Our overarching goal is to develop a method for estimating a performance measure (AADT) that can be tracked over time to measure changes in traffic patterns. Here we present findings from our approach and discuss implications for designing and implementing traffic monitoring campaigns in small communities.

3.1. Counter validation and quality control

To adjust for systematic undercounts or overcounts, we conducted field-based manual counts at 8 count sites for each counter (MetroCount: 181 hours; Eco-counter: 274 hours; RadioBeam: 29 hours) and developed correction equations to adjust all raw hourly counts from these counters; all manual counts were conducted based on different day of the week and time of the day to attempt to collect hourly intervals of varying volumes.

For MetroCount correction equations, we compared three bicycle classification schemes provided in the MetroCount software (ARX Cycle, BOCO, and Bicycle 15). 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 with the FHWA vehicle classification scheme. We found that ARX Cycle, BOCO, and Bicycle 15 schemes have similar $R^2$ (~0.89) for linear correction equations; however, the BOCO scheme has 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 counts, which is consistent with findings from other similar studies (9, 10, 17).

All automated counters were well correlated with the manual counts (MetroCount $R^2$ [absolute error]: 0.88 [38%]; Eco-counter: 0.97 [24%]; RadioBeam bicycle: 0.92 [19%], RadioBeam pedestrian: 0.92 [22%]). Figure 3 shows plots of automated vs. manual validation counts and the corresponding correction equations.
Due to invalid count days (e.g., counter malfunction, battery loss, and vandalism), we conducted quality control to flag and censor suspect data. We used a two-step process that included (1) direct cleaning of the data based on an event log 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 ± 5 × standard deviation. Overall, the continuous reference sites demonstrated good temporal coverage for the valid days of counter deployment (bicycles: 96%; pedestrians: 87%) and for the total calendar year of 365 days (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 3 summarizes the descriptive statistics for all counts at the reference and short-duration count sites.

FIGURE 3. Comparison of hourly automated counts and manual validation counts with corresponding correction equations for each type of counter.
TABLE 1. Descriptive statistics of average daily bicycle and pedestrian traffic for the reference and short-duration count sites

<table>
<thead>
<tr>
<th>Reference sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode</td>
</tr>
<tr>
<td>Bicycle</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Pedestrian</td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Short-duration sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode</td>
</tr>
<tr>
<td>Bicycle</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Pedestrian</td>
</tr>
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</table>

* IQR: Interquartile Range.

3.2. Negative binomial regression models

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

The dispersion factor \( \alpha \) in the Likelihood Ratio test for each model suggests significant evidence (\( p < 0.05 \)) of overdispersion and appropriate use of the negative binomial regression models. Higher values of McFadden’s Pseudo-R\(^2\) indicates a better overall fit (25); our Pseudo-R\(^2\) values are similar to other studies of bicycle and pedestrian traffic (23). 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 estimated (model-generated) counts with observed counts. Overall, the bicycle traffic models perform more reliably (validation R\(^2\) = ~0.70) compared to the pedestrian traffic models (validation R\(^2\) = ~0.30) likely owing to the fact that cyclists seem to be more sensitive to weather than pedestrians in our dataset which is consistent with previous research (18, 27).

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., eating, attending classes, 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. Based on previous research and for consistency across count sites, we incorporated all variables in the final models for each location.
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3.4. Mapping and summarizing AADT at the count locations

Estimated bicycle and pedestrian AADT for all monitoring sites are shown in Figure 5. Previous studies found that mixed use of land containing convenience stores, offices, or restaurants can increase bicycle activities (28-31). For our data, both bicycle and pedestrian traffic share similar findings. The downtown commercial corridor with retail and mixed uses have high cycling volumes (~70/day). Off-street trails adjacent to the University also have high bicycle volumes (~150/day). The largest pedestrian volumes (~12,000/day) are within the University area (Virginia Tech) or downtown commercial corridor. In some residential areas near off-street trails, pedestrian volumes are high compared to other outer lying areas.
Figure 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 (19-21) and cyclists show a preference to bicycle on roads with facilities compared to roads without (21, 32-35). We found that the presence of a bike 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 (“transport”) trails (mean: 112/day) compared to roads both with (72/day) and without (30/day) a bike lane as well as compared to disconnected neighborhood trails (mean: 29/day).

Pedestrian AADT is significantly higher (p < 0.01) on local roads (mean: 693/day) as compared to major roads (mean: 236/day), transport trails (mean: 162/day) and neighborhood trails (mean: 55/day). This finding is likely owing to the fact that most roads on the Virginia Tech campus are classified as local roads. To test the effect of the Virginia Tech count locations we stratified our sample by distance from campus in three categories (on campus, within 500 meters of campus, more than 500 meters from campus). We observed that when distance from campus increased, bicycle and pedestrian traffic generally declined for major and local roads but that the effect was largest for local roads.
3.5. Implications for designing non-motorized traffic monitoring programs

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. Furthermore, pedestrians were only monitored where walking facilities (i.e., sidewalks) are available, which mitigated the ability to cover the entire transportation network with pedestrian counts and AADT estimation. Our negative binomial regression models demonstrated modest performance for pedestrians (validation $R^2 = \sim 0.30$), leaving room for model improvement. Future research could explore selection of reference sites and classification into factor groups for use in annualizing short-duration counts. More work is needed to identify spatial variables (e.g., land uses) that may be useful to study both pedestrian and bicycle volumes in future research;
this may be especially important for pedestrians since they seemed to vary less by weather factors near clusters of destinations.

Our findings have practical implications for designing comprehensive count programs. Our approach combines previous research efforts on specific aspects of bicycle and pedestrian traffic monitoring, for example, validating automated count technologies, methods for site selection, and AADT estimation. Since our work was completed in a small community, we were able to systematically select a representative sample of street and trail segments on the network. Our site selection included multiple goals, such as, tracking performance measures over time as well as collecting baseline data for future infrastructure installation. 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.

4. CONCLUSIONS

This paper summarizes 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, thereby exploring whether our approach could be scaled to larger communities. 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 that 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 a representative set of count sites based on limited available information (i.e., street functional class and centrality). We found that our approach worked reasonably well in this study area; however, by initiating the effort to collect counts it is now possible to reconfigure both the reference and short-duration count location network over time. We found 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 locations 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. 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.
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