Challenges in Monitoring Regional Trail Traffic
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ABSTRACT
This study reports traffic monitoring results at 30 locations on a 972-mile shared-use trail network across the east-central United States. We illustrate challenges in adapting the principles in the Federal Highway Administration's *Traffic Monitoring Guide* to a regional trail network. We make four contributions: (1) we use factor analysis and k-means clustering to implement a stratified random process for selecting monitoring sites; (2) we illustrate quality assurance procedures and the challenges of obtaining valid results from a multi-state monitoring system; (3) we describe variation in trail traffic volumes across five land use classes in response to daily weather and seasons; and (4) we report two performance measures for the network: annual average daily trail traffic and trail miles traveled. The Rails to Trails Conservancy deployed passive infrared traffic monitors in 2015 through 2017. Site-specific regression models were used to impute missing daily traffic volumes. The effects of weather were consistent across land use classes but the effects of temporal variables, including weekend and season-of-year, varied. A plan for short duration monitoring is presented. Results confirm the FHWA monitoring principles and the difficulties of implementing them regionally.

Keywords: trails, traffic monitoring, bicycles

INTRODUCTION

Transportation planners need information about demand for multiuse trails to plan new facilities, assess safety of facilities, prioritize investments in projects, and operate and maintain existing facilities. Despite progress, assessments of comprehensive monitoring programs remain rare, and managers need examples of approaches to designing monitoring networks, data collection and management, and interpretation.

This study reports the results of traffic monitoring at 30 locations between 2015 and 2017 on a 972-mile multiuse trail network in Ohio, Pennsylvania, New York, and West Virginia by the Rails to Trails Conservancy (RTC) and the Industrial Heartland Trails Coalition (IHTC). Our objective is to illustrate challenges in adapting the Federal Highway Administration's *Traffic Monitoring Guide* (*TMG*) to a regional trail network (*1*).

CHALLENGES IN NON-MOTORIZED TRAFFIC MONITORING: LITERATURE REVIEW

In 2013, in response to pioneering efforts by engineers and advocates, the FHWA added a chapter on nonmotorized traffic monitoring to the *TMG*, the guidance document that establishes national monitoring principles. Chapter 4 Traffic Monitoring for Nonmotorized Traffic builds on the principles of monitoring motorized traffic but notes nonmotorized traffic is more variable and requires different procedures (*1*). The basic approach, however, is analogous:

- Establish monitoring objectives,
- Determine modes of traffic to be monitored,
- Select monitoring sites, including permanent and short-duration stations,
- Determine the type(s) of devices to be deployed,
- Implement monitoring following recommended guidelines,
- Follow recommended analytic procedures to ensure validity of data, and
- Use factors derived from permanent monitoring stations to extrapolate short duration counts and estimate annual average daily bicyclists (AADB), pedestrians (AADP) or mixed-mode, undifferentiated nonmotorized traffic.

The TMG also lists steps in implementation of permanent and short-duration monitoring programs. This approach presents new analytic challenges and are the focus of research. This review summarizes research that informs choices in program implementation and advances procedures used to analyze counts.

Program Design and Evaluation

Several recent publications inform monitoring implementation. Griffin et al. (*2*) provide an overview of considerations in nonmotorized traffic monitoring. The Institute for Transportation Research and Education (ITRE) at North Carolina State University, in collaboration with the North Carolina DOT, is leading one of the largest state-level bicycle and pedestrian data collection programs in the U.S.(*3,4*). Minge et al. (*5*) recently published a guide to bicycle and pedestrian data collection for the Minnesota Department of Transportation (MnDOT). Progress in institutionalizing nonmotorized traffic monitoring in Colorado, Minnesota, and Oregon has been described (*6*), and other states, including Washington and Vermont have initiated programs. Much of the implementation is by regional and local governments, such as San Francisco and New York City, and is described on websites and in the professional literature. The Delaware Valley Regional Planning Commission (DVRPC) manages one of the largest regional monitoring programs in the U.S. and makes estimates of AADB and AADP available through its website (*7*). The Mid-Ohio Regional Plan Commission (MORPC) maintains a network of monitors on the regional trail system and has reported estimates of annual average daily trail traffic (AADTT) and trail miles traveled for the network (*8,9*). The City of Vancouver, British Columbia has implemented monitoring and is reporting bicycle traffic volumes (*10*).

Monitoring Site Selection

The *TMG* specifies three key decisions: "differentiating between pedestrian and bicycle traffic", "selecting representative permanent count locations," and "selecting optimal installation locations" (*1*). With respect to selecting locations, the *TMG* cautions against selecting sites with heaviest volumes but, other than recommending review of existing count data, does not specify how to determine representative locations. Agencies have approached this challenge differently. In North Carolina, researchers completed a study to determine the number and location of counters to obtain valid, reliable estimates of AADB. Because the cost exceeded available funds, ITRE and NCDOT established the objective of developing permanent stations at locations in urban, rural, and near-university areas believed to have commuting, recreation, and mixed traffic patterns (*3,4*). ITRE inspects potential locations and conducts field tests before permanent counters are installed. Their goal is to implement a dozen or more counters per region. The Minnesota Department of Transportation (MnDOT) incorporated existing counters, and established at least one bicycle monitor on streets and one mixed-mode monitor on trails in each administrative region. These sites serve as index sites to illustrate trends and demonstrate how counts can inform planning and engineering (*11*). Sites were selected with local partners to ensure results had practical significance.

Each of these approaches has involved stratified systematic and/or purposeful selection of locations, absent measures of actual representativeness for the networks of interest. Davis et al. (*12*) demonstrated the feasibility of a stratified, randomized site selection for purposes of estimating regional bicycle miles traveled, but their approach was not designed to be augmented with short-duration counts to characterize network flows. Randomization of site selection typically has not been implemented by public agencies.

Monitoring Equipment Selection

A National Cooperative Highway Research Program (NCHRP) report, "Methods and Technologies for Pedestrian and Bicycle Volume Data Collection", has become the authoritative guide to monitoring technologies (*13,14*). This report has been augmented by research papers. Nordback et al. (*15*) and Brosnan et al. (*16*) have evaluated the performance of inductive loops and pneumatic tubes, respectively. In general, tradeoffs among types of technologies are understood – they involve the need for mode-specific information, accuracy, cost, labor for data collection, capacity for remote reporting, and vendor support. Trends in deployment are becoming clear: inductive loops are being used to count bicycles at permanent installations; pneumatic tubes are used for short-duration bicycle counts; infrared sensors are used to count pedestrians and trail users, sometimes with inductive loops. Automated video processing remains the Holy Grail of monitoring, but it has not been implemented widely.

Data Quality Management

Questions in data quality management include validation of counters, whether to correct for systematic error associated with sensors (e.g., undercounts due to occlusion), how to implement quality assurance / quality control (QAQC) procedures, and whether to impute missing counts. Analysts have addressed these questions in different ways, and standard procedures are being developed.

All vendors recommend in-field validation of equipment following installation, but the duration of validation and periods for re-validation vary. Personnel deploying integrated inductive loop and infrared sensors at permanent stations may observe traffic for one to two hours following installation, while personnel deploying portable equipment may validate less than an hour. Some researchers have adjusted all hourly counts to correct for occlusion (*17,18,19)*. Judgment must be exercised in applying correction factors, however, to avoid changing counts when inappropriate (e.g., for zero counts).

The *TMG* describes the importance of applying QAQC procedures to nonmotorized counts, but notes that new checks need to be developed because of the variability of nonmotorized counts (*1*). Development of QAQC protocols for nonmotorized counts is an active area of research. Turner and Lasley (*20*) recommend, at minimum:

- Visual inspection of data;
- Use of pre-specified criteria to identify potential outliers;

- Assessment of zero counts; and
- Use of professional judgment to censor counts believed to be invalid.

Based on their North Carolina experience, Jackson et al. (*4*) recommend several protocols: weekly visual inspections to ensure prompt identification of problems, development of hourly data checks, interquartile checks to identify outliers, and automated procedures for flagging suspect data. Minge et al. (*5*) illustrate application of QAQC procedures on data from 12 sensors in Minnesota and the effects of censoring counts on estimates of annual average daily traffic. They show that many outliers may be valid counts associated with events and that it is difficult to differentiate valid and invalid hourly zero counts, particularly in winter. For low volume sites (e.g., less than 100 counts per day), the cost of implementing checks must be weighed against the practical significance of changes in estimates of volumes that might result from application of checks.

One approach to missing observations is to ignore them and estimate the statistics of interest with available data. Another approach is to estimate values for missing days from existing data. This can be done by assuming the volumes are the same as the volumes for closely related days with valid counts or by more sophisticated statistical methods. For example, a missing count for a Thursday in March could be estimated as the mean of existing counts for Thursdays in March. This approach controls for day of week and season but not weather. An alternative approach is to estimate a regression equation that controls for day of week and weather, obtain weather data for the days with missing counts, and use the equations to estimate missing values (*9,17,19*). This procedure involves the judgment that errors associated with imputing are preferable to errors caused by the missing values.

Determination of Pattern Groups

The *TMG* observes that nonmotorized traffic can be classified as commuter, recreational, or mixed (i.e., multipurpose) traffic based on day of week and hourly relationships and that it is important to take traffic patterns into account when extrapolating short-term counts. Miranda-Moreno et al. (*21*) illustrate how weekend-weekday and a.m.-noon hour traffic ratios can be used to classify traffic as (1) utilitarian, (2) mixed-utilitarian, (3) mixed-recreational, and (4) recreational. Analysts in Colorado established a separate factor group for cycling in mountain regions because patterns associated with seasons diverge from those in urban areas. In general, most programs focus on three factor groups based on some variation of the ratios illustrated by Miranda-Moreno (e.g., North Carolina (*3,4*); Minnesota (*5*)). Nordback et al. (*22*) recommend a minimum of five permanent monitors per factor group to minimize error in extrapolation; data are not available to assess how many programs are consistent with this recommendation.

Computation of Adjustment Factors

The *TMG* illustrates procedures analogous to those used in motorized traffic monitoring for computation of adjustment factors used in extrapolation of short duration counts (i.e., hour-of-day, day-of-week, and month-of-year factors). Nordback et al. (*22*) described error in estimating AADB associated with the length of the short-duration counts and the season when short duration counts were taken. They recommended counts of at least one week between April and October. Hankey et al. (*17*) and Nosal (*23*) simultaneously developed an alternative approach called day-of-year factoring that reduced error in extrapolation compared to the standard approach. El Esaway (*24*) subsequently demonstrated the day-of-year factoring approach is preferable because it better captures the effects of weather. Jessberger et al. *(25)* recently published an alternative to the standard approach that holds promise.

Estimation of Performance Indicators

A purpose of the *TMG* is to guide implementation that produces two performance indicators: annual average daily traffic and annual miles traveled. State (e.g., North Carolina, Colorado, Minnesota), regional (e.g., DVRPC, MORPC), and local (e.g., Vancouver, BC) agencies now are routinely reporting AADB and AADP for permanent monitoring locations, but fewer have implemented the short-duration counts required to characterize networks. Estimates of AADT have been reported for urban trails in Minneapolis, MN, Columbus, OH, and Chicago, IL (*9,26*).

Implications for Practice

This review shows that principles of motorized traffic monitoring are being applied to nonmotorized traffic monitoring, that state, regional, and local agencies are implementing monitoring programs, but that additional research is needed to improve program quality. Tradeoffs among objectives in monitoring are inevitable. Because most monitoring programs are new, a gap in the literature is the absence of evaluations of programmatic initiatives. Additional studies of monitoring programs can inform future initiatives.

THE INDUSTRIAL HEARTLAND TRAIL MONITORING INITIATIVE: APPROACH, METHODS, AND RESULTS

The IHTC is a coalition of more than 100 public and private, nonprofit organizations supported by the RTC, the National Park Service, and the Pennsylvania Environmental Council in work to establish a 1,400 mile trail network across 48 counties in Pennsylvania, Ohio, New York, and West Virginia. Nearly 1,000 miles of trail already exist. In 2015, RTC initiated a regional monitoring program to support the initiative.

Program Design and Evaluation

RTC established three objectives for the program:

- Document use on existing trails using procedures consistent with *TMG* principles;
- Inform comprehensive regional monitoring efforts; and
- Develop tools to support trail planning, including factors for extrapolating short duration counts and estimates of network use.

RTC consulted with partners, obtained a grant, and consulted with researchers about program design.

Monitoring Site Selection

Considerations in monitoring site selection included geographic variation of land uses adjacent to trails and the desire to monitor sites characteristic of different factor groups (*27*). We chose a stratified random sampling approach to avoid bias towards high volume locations, increase the likelihood of identifying different patterns, and provide a stronger statistical foundation for generalizing results. A land use typology was used because research has shown that both traffic volumes and patterns may be associated with land use.

The final classifications were based on factor analysis scores derived from 16 contextual measures that were classified using a k-means clustering approach. The contextual measures included Census data such as population and job density and remote sensing data. For logistical reasons, sample sites were selected from a subset of the entire 605 mile network. We randomly selected six locations within each class for a total of 30 monitoring sites (Figure 1). The number of sites was determined in light of budget constraints and the *TMG* recommendation that factor groups have a minimum of five sites to develop adjustment factors. RTC reviewed the locations to verify feasibility of access and counter installation.

Monitoring Equipment Selection

We selected lower-cost passive infrared monitors because this choice maximized monitoring locations and provided opportunities to engage local partners. The sensors can be adapted for future short duration monitoring as portable counters. The rationale for choosing mixed-mode over mode-specific sensors was it was more important to gain understanding of total traffic at more locations than mode-specific traffic at fewer locations. Although an integrated inductive loop-passive infrared system was installed at one location, mixed mode counts are reported here.

Data Quality Management

Challenges in data collection and management included deployment, in-field validation of counter operations, application of QAQC procedures, and management of missing observations. Although RTC confirmed monitors were operating following deployment and periodically checked monitors for specific reasons, most monitors were not systematically analyzed until the end of the monitoring period because project partners had limited time. When researchers reviewed the data in the winter of 2017, it was the first comprehensive review. Although the objective was to obtain at least one year of data at each of the 30 locations, only 22 monitors (73%) were deployed for a full-year, mainly because of logistics and delays in deployment, including coordination with partners (Table 1). The days of counts for the sites with less than one year of deployment ranged from 116 to 364.

We followed recommended QAQC procedures: visual inspection, application of a heuristic to identify potential outliers, evaluation of counts of zero, and use of judgment (*20*). Visual inspection of daily volume graphs identified sites with missing data and patterns that indicated sensor malfunction. Inspection of data (illustrated below) showed 7 monitors (23%) had missing days, apparently associated with insect infestation, vandalism, or other malfunction (Table 1). Following additional QAQC checks, outliers were censored at three locations, resulting in 19 monitors (63%) with valid counts for at least 365 days. Across locations, monitors were deployed for 11,127 days; counts were obtained for 10,951 days, 98% of the deployment periods for all counters. The total number of days with counts deemed valid was 10,698 (96% of the days of deployment). RTC decided to report published, approximate values for accuracy for passive infrared sensors rather than develop correction factors for each location.

To illustrate the problems identified during QAQC, we present daily totals for the period of record for five sites (Figure 2). Graphs A and B show “normal” patterns that reflect daily, weekly, and seasonal variation. The records appear complete, and the variation does not appear abnormal. Graph C illustrates a case with a potential outlier: most values for the period of record are below 100 but for a single day, values increase more than fourfold. Graph D is from a site where no data were recorded for a four month period. Graph E has a jump to counts of more than 60,000 per day after a 10-month period of daily counts below 1,000, an obvious error. The team used professional judgment to censor daily counts that were associated with sensor malfunction.

To identify potential outliers, we identified counts equal to or greater than three standard deviations above the mean daily count for the period of record. To decide whether to censor questionable counts, we computed the ADT with and without the potential outliers. For counters with ADT below 90, all recorded counts were retained because, even including potential outliers, the site was low-volume. The rationale for the threshold of 90 was that inclusion of the potentially invalid data would have minimal practical implications for ADT. For counters with ADT above 90, the flagged values were retained if the percentage reduction in ADT was less than 15% (an arbitrary threshold). If the reduction in ADT was greater than 15%, we assessed whether favorable weather conditions may have induced unusual use and searched for events that may have occurred. Professional judgment then was applied to retain or censor counts. We inspected days with counts of zero, but did not eliminate any zero count days.

Another challenge in data quality management involved managing the 11 sites with missing observations (which ranged from 1% to 26%). For purposes of estimating AADT, we imputed values for missing days. Research has shown that site-specific regression models including weather and day-of-week variables explain 85% of the variation in daily traffic and can be used to predict traffic with reasonable accuracy (e.g., *19*). Using only days with valid counts, we assembled weather data for each day in the period of record and estimated negative binomial weather regression models for each site. Weather data for the missing days were used in site-specific models to predict daily traffic for missing days.

To illustrate model specification and differences in response to weather across land use classes, data in each of five classes were pooled, and six additional models were estimated, one for each class and one with data pooled for all sites (Table 2). The magnitudes of some coefficients vary. For example, weekend daily traffic was statistically significantly higher than weekday daily traffic in every class.

Precipitation, which significantly reduced traffic at parks, suburban, rural, and forest sites, had no significant effect on urban traffic volumes, a departure from general patterns.

Determination of Factor Groups

The challenge in this step involved choice of criteria for establishing factor groups. Using days with counts deemed valid (i.e., excluding days with counts estimated with weather models), recommended procedures were adapted to classify sites into three factor groups (*21*). The weekend-weekday average daily traffic ratio and the a.m. (7:00 a.m. – 9:00 a.m.) – noon (11:00 a.m. – 1:00 p.m.) average hourly traffic ratio were computed to classify sites. Consistent with the *TMG*, only three factor groups were classified: recreational, commuter, and mixed. Application of these criteria identified only two factor groups: recreation (n=28) and mixed (n=2). The sites with mixed traffic patterns included one urban and one parks location.

Computation of Adjustment Factors

We computed hour-of-day, day-of-week, and month-of-year factors that could be applied to estimate AADTT from short duration counts. Because application of criteria for factor groups revealed little variation in patterns across sites, we computed factors for sites by the land use classification. The monthly average daily trail traffic (MADTT) to AADTT ratios include six sites in each class and the 30 sites pooled together (Figure 3). These graphs were computed using datasets with counts estimated for missing days. Across sites within classes, variability in MADTT/AADTT ratios is greatest with urban and forest classes. The convergence in patterns across classes, however, is evident, with the mean ratios for all classes following a general pattern. The MADTT/AADTT ratios for summer months, which reflect peak volumes and periods when short-duration sampling is most likely to occur, generally are between 1.5 and 2. The mean of means ratio for summertime months for all sites is approximately 1.5, indicating that, on average, daily summertime traffic is 50% higher than AADTT. Hour-of-day graphs for all sites could be used as adjustment factors for short duration counts (Figure 4).

Estimation of Performance Indicators

Following Davis et al. (*12*), we multiplied the mean AADTT for each land use classification by the miles of trail within the classification. This approach, which was used because short duration counts have not been completed, deviates from standard procedure of multiplying segment counts times segment length. The limitation of this approach is that it does not provide segment-specific estimates of AADTT. Nonetheless, the approach provides an order of magnitude estimate until short duration counts can be completed. Mean AADTT ranged from 40 at forest locations to 251 and 258 at urban and parks locations, respectively (Table 3). The estimate of total trail miles traveled in 2016 for the 972-mile network was approximately 29.5 million miles. Urban and park trails, which account for only about 11% of total miles, accounted for 33% of miles traveled. Forest trails, which account for nearly half the network (47%), account for less than one-quarter of the trail miles traveled. Sources of uncertainly in this estimate include the error associated in counting (i.e., systematic undercount due to occlusion, the magnitude of which may vary across sites in relation to volume), error associated with imputing missing AADTT values at some sites, and error in extrapolating mean AADTT values to the network.

Permanent and Short-Duration Site Selection

In the future, permanent and new short-duration counts will be used to refine AADTT estimates. RTC plans to retain some of the monitors permanently and to shift others to portable counts to monitor the network. To illustrate tradeoffs in establishing the short-duration monitoring program given a limited fleet of counters, we present an example in which 14 counters are retained as permanent counters and 16 are deployed for short-duration counts. To determine which sites would be retained as permanent monitoring sites, we considered factor group (i.e., recreational, mixed), land use classification, volume, land use, and location within the region, with a goal to include all factor groups and retain 3-4 monitoring locations in each land use classification. Thus, this example includes both sites with mixed traffic patterns and meets the TMG recommendation for recreational patterns but falls short for mixed patterns. With respect to land use, four urban, two suburban, two rural, three park and three forest monitoring sites were chosen for permanent monitoring. Fewer sites for suburban and rural were selected because their AADTTs were very close (87 and 81, respectively) and their weekend and weekday traffic patterns were similar. A second decision in planning short-duration counts involved determining segments. We assumed it would not be feasible given resource limitation to sample each mile of trail, so the decision was made to vary segment length by land use, which is associated with volume. We assumed segments of 5 miles for forest trails, 2 miles for rural and suburban trails, and 1 mile for urban and park trails, which have the highest volumes and, potentially, greatest variation along consecutive segments. This approach resulted in a maximum of 539 potential sampling points (Table 3). With a May to October monitoring period, 16 counters, and 10 days for each seven-day short duration count, monitoring of all sites could be completed in two summers (Table 3). If RTC decides to retain more permanent counters, or obtains funding for portable counters, this plan could be revised. This example illustrates the feasibility of completing monitoring in the network and the tradeoffs required to achieve this objective.

CONCLUSIONS AND IMPLICATIONS FOR PRACTICE

Management of a monitoring program requires application of engineering principles and use of professional judgment, subject to economic constraints, in diverse geographic and socio-political settings. Managers must make tradeoffs in pursuit of data. Jackson et al. (*3,4*) observe that “data-wranglers” are needed to launch and manage nonmotorized traffic monitoring programs. Data-wrangling is an apt metaphor, for the challenges of monitoring require taking charge, rounding up, herding, and eventually, producing results.

This study illustrates the nature of data-wrangling and some of the tradeoffs required in launching a trail monitoring program on a multistate network. Consistent with the monitoring objectives, budget constraints, and logistics of installation and maintenance, RTC installed 30 counters, but complications resulted in less than one year of data for nearly one-quarter of the monitors. Application of QAQC procedures revealed missing data, erroneous counts likely associated with counter malfunction, and outliers judged invalid and censored. Valid counts for a one-year period were obtained for only 19 (63%) of the 30 sites. Overall, however, valid counts were obtained for 96% of days deployed, indicating more days were missed getting the program running than because of problems following deployment.

These results led to analytic choices that involved tradeoffs among sources of error in subsequent estimates. For example, regression models were used to estimate missing counts for 11 sites prior to computing monthly adjustment factors. We could have computed these factors for only the 19 sites with complete, year-long records or for only sites with, for example, 300 or more days of valid counts (n=24). The tradeoff involved whether to keep sites but accept the error associated with imputing missing counts or to reject sites and rely on fewer sites with complete records. The objective of characterizing traffic at as many locations as possible led to the decision to impute missing values.

Each of these judgments has implications for the validity of the performance measures. One approach to assessment is whether the results are consistent with theory and make intuitive sense. Since volumes are highest at parks and urban locations, lower in suburban and rural areas, and lowest in more remote forest areas, the results reflect population density gradients and meet this criterion. Most of the network occurs in rural and remote areas, thus, the volumes are substantially lower than AADTTs reported for urban networks measured with essentially the same approach (*9,26*). Because the randomized selection of locations avoids bias associated with purposeful selection of sites with high volumes, there is reason to believe these measures are representative.

Several features of this initiative are distinctive and inform practice. First, use of advanced geo-spatial analytics to classify potential sampling points in the network and implement stratified-randomized selection of monitoring locations provided insight into volumes of trail use at sites that likely would be ignored in a more purposeful sampling approach. Estimates of AADTT for the network therefore reflect sections of trail with very low volumes. Second, studies of new or best practices often do not document or quantify problems in ways that facilitate comparison across programs. We report problems in implementation and indicators of the reliability and validity of counts produced for the first year of a permanent monitoring program for a large region. Systematic application of QAQC procedures identified missing and invalid counts that were censored from the dataset. Ultimately, valid counts were obtained for 365 days at only 19 (63%) of the 30 locations. Percentages for initiatives of comparable size are not available, but it may be that the geographic scale of this initiative contributed to this outcome.

Third, we show that trail traffic on this network in the east-central U.S. varies in relation to land use but that patterns converge. Monthly traffic patterns varied more within urban and forest classes than within parks, suburban, and rural classes, but mean ratios across classes were similar. Use of standard metrics indicated 28 sites were characterized by recreational traffic; no locations reflected commuter traffic. Fourth, these results complement previous estimates of AADTT and miles traveled on urban trail networks and contribute to our understanding of variation in trail traffic across the country. Fifth, we illustrate how counters could be redeployed to complete monitoring of the entire network within a two year period.

Overall, this study illustrates that the principles in the TMG can be adapted for regional trail monitoring. The study also illustrates that, given resource constraints and practical limitations, challenges will be encountered, and tradeoffs will be required in each step of the monitoring process. Decisions in implementation, from selection of sites to application of QAQC procedures to determination of factor groups, affect estimates and decisions based on those estimates. Additional studies of ways in which data wranglers meet these challenges can help inform practice.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: TH-L, GL, JW; data collection: EO; analysis and interpretation of results: GL, LS-B; draft manuscript preparation: GL, LS-B. All authors reviewed the results and approved the final version of the manuscript.

REFRENCES

1. Federal Highway Administration (FHWA), U.S. Department of Transportation. (2013). *Traffic Monitoring Guide: Chapter 4 Traffic Monitoring for Non-motorized Traffic V1*, Retrieved from https://www.fhwa.dot.gov/policyinformation/tmguide/tmg_fhwa_pl_13_015.pdf .
2. Griffin, G.., Nordback, K., Götschi, T., Stolz, E. and Kothuri, S. (2014). Monitoring Bicyclist and Pedestrian Travel and Behavior: Current Research and Practice. *Transportation Research E-Circular*, (E-C183).
3. Jackson, K. N., Stolz, E., & Cunningham, C. (2015). Nonmotorized site selection methods for continuous and short-duration volume counting. *Transportation Research Record: Journal of the Transportation Research Board*, (2527), 49-57.
4. Jackson, K. N., O'Brien, S. W., Searcy, S. E., & Warchol, S. E. (2017). Quality assurance and quality control processes for a large-scale bicycle and pedestrian volume data program. *Transportation Research Record: Journal of the Transportation Research Board*, (2644), 19-29. DOI: 10.2141/2644-03.
5. Minge, E., Falero, C., Lindsey, G. Petesch, M., and Vorvick, T. (2017). Bicycle and Pedestrian Data Collection Manual. MnDOT Report No. MN/RC 2017-03. Retrieved from http://www.dot.state.mn.us/research/reports/2017/201703.pdf.
6. Lindsey, G., Nordback, K., & Figliozzi, M. (2014). Institutionalizing Bicycle and Pedestrian Monitoring Programs in Three States. *Transportation Research Record: Journal of the Transportation Research Board*, (2443), 134-142. DOI: 10.3141/2443-15.
7. Delaware Valley Regional Planning Commission. (2017). *Pedestrian and Bicycle Counts.* Retrieved from http://www.dvrpc.org/webmaps/pedbikecounts/.
8. Lindsey, G., Wu, X., Wu, C., Ciabotti, J., and Edwards, R. (2015). *Technical Memorandum 1. COG Trails: Traffic Monitoring Results*. Mid-Oho Regional Planning Commission. Columbus, OH.
9. Wang, J., Hankey, S., Wu, X., & Lindsey, G. (2016). Monitoring and Modeling of Urban Trail Traffic: Validation of Direct Demand Models in Minneapolis, Minnesota, and Columbus, Ohio. *Transportation Research Record: Journal of the Transportation Research Board*, (2593), 47-59. DOI: 10.3141/2593-06
10. El Esawey, M., Lim, C., & Sayed, T. (2015). Development of a cycling data model: City of Vancouver case study. *Canadian Journal of Civil Engineering*, *42*(12), 1000-1010. https://doi.org/10.1139/cjce-2015-0065.
11. Lindsey, G., Petesch, M., Vorvick, T., Austin, L., and Holdhusen, B. (2017). The Minnesota Bicycle and Counting Initiative: Institutionalizing Bicycle and Pedestrian Monitoring. MnDOT Report No. MN/RC 2017-02. Retrieved from http://www.dot.state.mn.us/research/reports/2017/201702.pdf.
12. Davis, G. A., & Wicklatz, T. (2001). Sample-based estimation of bicycle miles of travel (BMT). Retrieved from the University of Minnesota Digital Conservancy, http://hdl.handle.net/11299/742.
13. Ryus, P., Ferguson, E., Laustsen, K. M., Schneider, R. J., Proulx, F. R., Hull, T., & Miranda-Moreno, L.(2014). Guidebook on Pedestrian and Bicycle Volume Data Collection, *The National Academies Press.* DOI: 10.17226/22223.
14. Proulx, F. R., Schneider, R. J., & Miranda-Moreno, L. F. (2016). Performance evaluation and correction functions for automated pedestrian and bicycle counting technologies. *Journal of transportation engineering*, *142*(3), 04016002.
15. Nordback, K., Piatkowski, D. P., Janson, B. N., Marshall, W. E., Krizek, K. J., & Main, D. S. (2011). Using inductive loops to count bicycles in mixed traffic. *Journal of Transportation of the Institute of Transportation Engineers*.
16. Brosnan, M. (2014). *Validation of Bicycle Counts from Pneumatic Tube Counters in Mixed Traffic Flows.* Lecture presented at 94th Annual Meeting of the Transportation Research Board, Washington, D.C.

17. Hankey, S., Lindsey, G., & Marshall, J. (2014). Day-of-year scaling factors and design considerations for nonmotorized traffic monitoring programs. *Transportation Research Record: Journal of the Transportation Research Board*, (2468), 64-73. DOI: 10.3141/2468-08
18. Lindsey, G., Wilson, J., Rubchinskaya, E., Yang, J., & Han, Y. (2007). Estimating urban trail traffic: Methods for existing and proposed trails. *Landscape and Urban Planning*, *81*(4), 299-315. https://doi.org/10.1016/j.landurbplan.2007.01.004.
19. Wang, X., Lindsey, G., Hankey, S., & Hoff, K. (2013). Estimating mixed-mode urban trail traffic using negative binomial regression models. *Journal of Urban Planning and Development*, *140*(1), 04013006.
20. Turner, S., & Lasley, P. (2013). Quality Counts for Pedestrians and Bicyclists: Quality Assurance Procedures for Nonmotorized Traffic Count Data. *Transportation Research Record: Journal of the Transportation Research Board*, (2339), 57-67. DOI: 10.3141/2339-07.
21. Miranda-Moreno, L., Nosal, T., Schneider, R., & Proulx, F. (2013). Classification of bicycle traffic patterns in five North American Cities. *Transportation Research Record: Journal of the Transportation Research Board*, (2339), 68-79. DOI: 10.3141/2339-08.
22. Nordback, K., Marshall, W., Janson, B., & Stolz, E. (2013). Estimating annual average daily bicyclists: Error and accuracy. *Transportation Research Record: Journal of the Transportation Research Board*, (2339), 90-97. DOI: 10.3141/2339-10.
23. Nosal, T., Miranda-Moreno, L. F., Krstulic, Z., & Eng, P. (2014). Incorporating weather: a comparative analysis of Average Annual Daily Bicyclist estimation methods 2. *Transportation Research Record*, 100–110. DOI: 10.3141/2468-12.
24. El Esawey, M. (2016). Toward a better estimation of annual average daily bicycle traffic: comparison of methods for calculating daily adjustment factors. *Transportation Research Record: Journal of the Transportation Research Board*, (2593), 28-36.DOI: 10.3141/2593-04.
25. Jessberger, S., Krile, R., Schroeder, J., Todt, F., & Feng, J. (2016). Improved Annual Average Daily Traffic Estimation Processes. *Transportation Research Record: Journal of the Transportation Research Board*, (2593), 103-109. DOI: 10.3141/2593-13.
26. Gobster, P., Sachdeva, S., and Lindsey, G. (2017). Up on the 606: Understanding Use of a New Elevated Pedestrian and Bicycle Trail in Chicago, Illinois. *Transportation Research Record. Journal of the Transportation Research Board*, (2644), 83-91. DOI:10.3141/2644-10.
27. Wilson, J. and Lindsey, G. (2016). Design and implementation of a method for selecting sampling locations for trail traffic monitoring. Prepared for Rails to Trails Conservancy, Inc., Yellowsprings, Ohio.

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TABLE 1 Summary Data for Counts at 30 Locations on IHTC Trail Network

Counter	Class	Trail / Location	Days Deployed	Days with Counts (Pre-QAQC)	Days with Valid Counts (Post-QAQC)	Days with Valid Zero Counts (Pre-QAQC)	Maximum Valid Daily Count	Minimum Valid Daily Count	ADT: Days with Counts (Pre QAQC)	ADT: Days with Valid Counts (Post QAQC)	% Change in ADT after QA/QC
1	Urban	Ohio & Erie Canal Towpath (OH)	346	257	257	0	724	26	235	235	0%
7	Urban	Ohio & Erie Canal Towpath (OH)	443	443	443	0	801	3	101	101	0%
15	Urban	Wheeling Heritage Trail (WV)	364	328	328	0	842	1	244	244	0%
16	Urban	Three Rivers Heritage Trail (PA)	241	241	235	0	2901	8	402	268	-50%
17	Urban	Three Rivers Heritage Trail (PA)	116	116	116	0	650	4	123	123	0%
25	Urban	Mon River Trail (WV)	369	369	369	0	905	8	324	324	0%
5	Suburban	Portage Hike & Bike Trail (OH)	392	392	225	0	391	2	820	138	-493%
9	Suburban	Ohio & Erie Canal Towpath (OH)	444	442	362	2	928	0	6284	81	-7628%
12	Suburban	Mill Creek Metro Parks Bikeway (OH)	458	458	458	0	826	1	189	189	0%
19	Suburban	Panhandle Trail (PA)	353	351	351	0	461	2	54	54	0%
27	Suburban	West Fork River Trail (WV)	442	442	442	22	276	0	31	31	0%
29	Suburban	North Bend Rail-Trail (WV)	442	442	442	15	330	0	28	28	0%
8	Rural	Ohio & Erie Canal Towpath (OH)	444	444	444	3	1376	0	140	140	0%
10	Rural	Western Reserve Greenway (OH)	393	393	393	0	297	1	74	74	0%
11	Rural	Western Reserve Greenway (OH)	401	359	359	1	522	0	154	154	0%
14	Rural	Brooke Pioneer Trail (WV)	364	364	364	10	172	0	35	35	0%

TABLE 1 Summary Data for Counts at 30 Locations on IHTC Trail Network Continued

Counter	Class	Trail / Location	Days Deployed	Days with Counts (Pre-QAQC)	Days with Valid Counts (Post-QAQC)	Days with Valid Zero Counts (Pre-QAQC)	Maximum Valid Daily Count	Minimum Valid Daily Count	ADT: Days with Counts (Pre QAQC)	ADT: Days with Valid Counts (Post QAQC)	% Change in ADT after QA/QC
18	Rural	Montour Trail (PA)	353	352	352	11	561	0	60	60	0%
20	Rural	Armstrong Trail (PA)	353	353	353	34	256	0	20	20	0%
2	Parks	Ohio & Erie Canal Towpath (OH)	368	368	368	0	1137	5	254	254	0%
3	Parks	Ohio & Erie Canal Towpath (OH)	368	368	368	0	2988	10	596	596	0%
4	Parks	Ohio & Erie Canal Towpath (OH)	368	368	368	0	2466	10	422	422	0%
6	Parks	Ohio & Erie Canal Towpath (OH)	368	368	368	0	731	11	175	175	0%
23	Parks	Oil Creek State Park Trail (PA)	367	367	367	9	452	0	65	65	0%
24	Parks	Oil Creek State Park Trail (PA)	379	378	378	50	326	0	34	34	0%
13	Forest	Little Beavercreek Greenway (OH)	240	240	240	3	534	0	63	63	0%
21	Forest	Armstrong Trail (PA)	241	241	241	29	99	0	15	15	0%
22	Forest	Allegheny River Trail (PA)	382	379	379	33	3064	0	94	94	0%
26	Forest	Mon River Trail (WV)	442	442	442	55	435	0	21	21	0%
28	Forest	North Bend Rail-Trail (WV)	442	442	442	171	93	0	4	4	0%
30	Forest	Ohio & Erie Canal Towpath (OH)	444	444	444	1	323	0	54	54	0%

TABLE 2 Pooled Regression Models of Daily Counts by Land Use Class

	Urban (n=1,740)	**Suburban (n=2,227)**	**Rural (n=2,184)**	**Parks (n=2,184)**	**Forest (n=2,193)**	**All Sites (n=10,528)**
Dependent Variable: ADT	216	87	81	258	42	137
Average Dew Point (ºF)	**-0.014*** **	-0.003	**-0.021*** **	0.001	**-0.024*** **	**-0.014*** **
Average Wind Speed (Knots)	**-0.045*** **	**0.068*** **	0.007	**0.070*** **	**-0.018** **	**0.012*** **
Maximum Temperature (ºF)	**0.073*** **	**0.069*** **	-0.010	**0.081*** **	**0.077*** **	**0.054** **
Maximum Temperature Squared ($^oF^2$)	**-0.0004*** **	**-0.0003*** **	**0.0004*** **	**-0.0005*** **	-0.0001	**-0.0001*** **
Precipitation (inches)	0.079	**-0.587*** **	**-0.349*** **	**-0.795*** **	**-0.361*** **	**-0.444*** **
Weekend (dummy)	**0.165*** **	**0.333*** **	**0.538*** **	**0.672*** **	**0.850*** **	**0.526*** **
Spring (dummy)	**0.552*** **	**0.665*** **	**0.568*** **	**0.648*** **	0.093	**0.458*** **
Summer (dummy)	**0.615*** **	**1.057*** **	**0.512*** **	**1.158*** **	0.019	**0.532*** **
Fall (dummy)	**0.349*** **	**0.705*** **	**0.522*** **	**0.623*** **	0.020	**0.387*** **
Constant	**2.686*** **	0.280	**3.242*** **	**-0.802** **	**1.573*** **	**1.714*** **
Pseudo R2	**0.039**	**0.049**	**0.037**	**0.039**	**0.046**	**0.028*** **
*p<.01 **p < .005 ***p<.001						
Modeling approach: negative binomial regression.						

TABLE 3 Performance Indicators for IHTC Trail Network (2016)

				Performance Indicators			**Measurable Results**		**Proposed Permanent Counters**		**Proposed Short Duration Counters**		
Sample Class	Number of Sample Points	Estimated Trail Miles	AADTT	Estimated Trail Miles Traveled	% of Sample Points (Miles)	% of Miles Traveled	Rec.	Mixed	Rec.	Mixed	Segment Length	Maximum Points	Per Year
Forest	497	457	40	6,700,000	47%	23%	6	0	3	0	5	157	79
Low Intensity Dev. and Rural	248	228	84	7,000,000	23%	24%	6	0	2	0	2	153	77
Parks	72	66	258	6,200,000	7%	21%	6	0	2	0	2	128	64
Suburban	196	180	90	5,900,000	19%	20%	5	1	3	1	1	36	18
Urban	43	40	251	3,600,000	4%	12%	5	1	2	1	1	65	33
Totals	1056	972	137	29,500,000	100%	100%	28	2	12	2		539	270
							30		14				

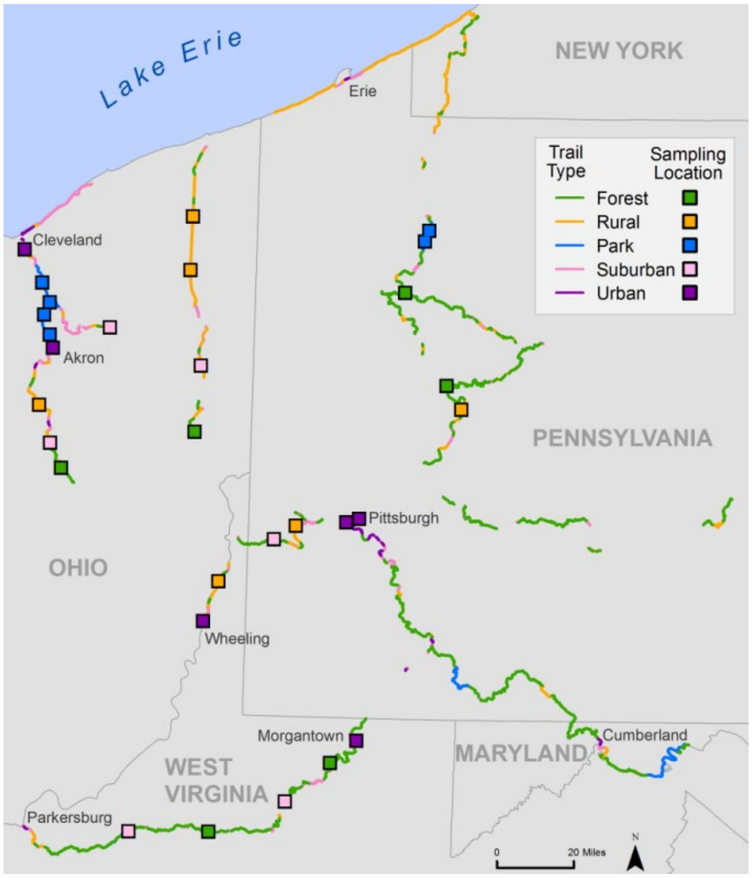

FIGURE 1 Monitoring locations in the IHTC Trail Network.

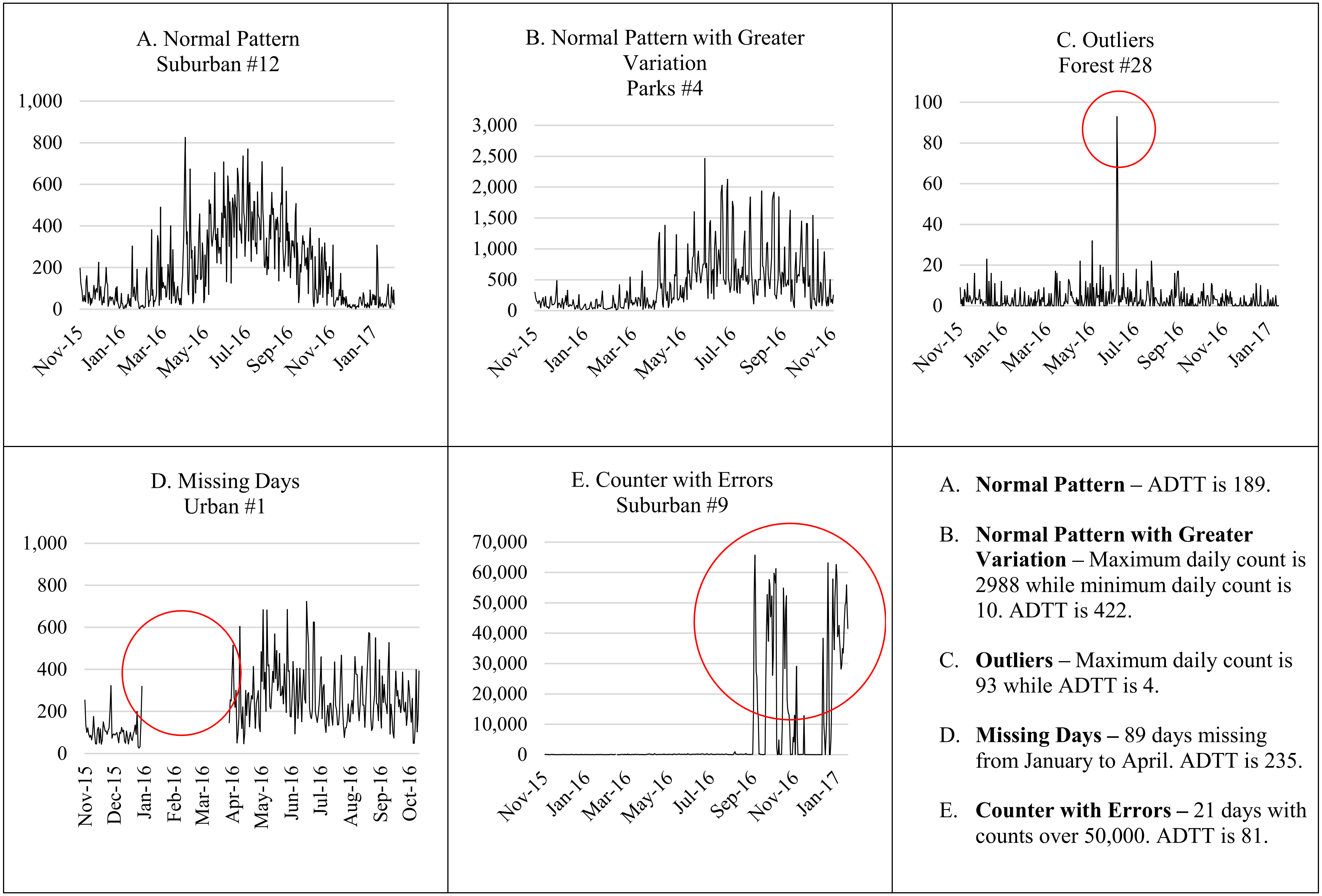

FIGURE 2 Examples of Daily Counts at Five Locations Prior to QAQC.

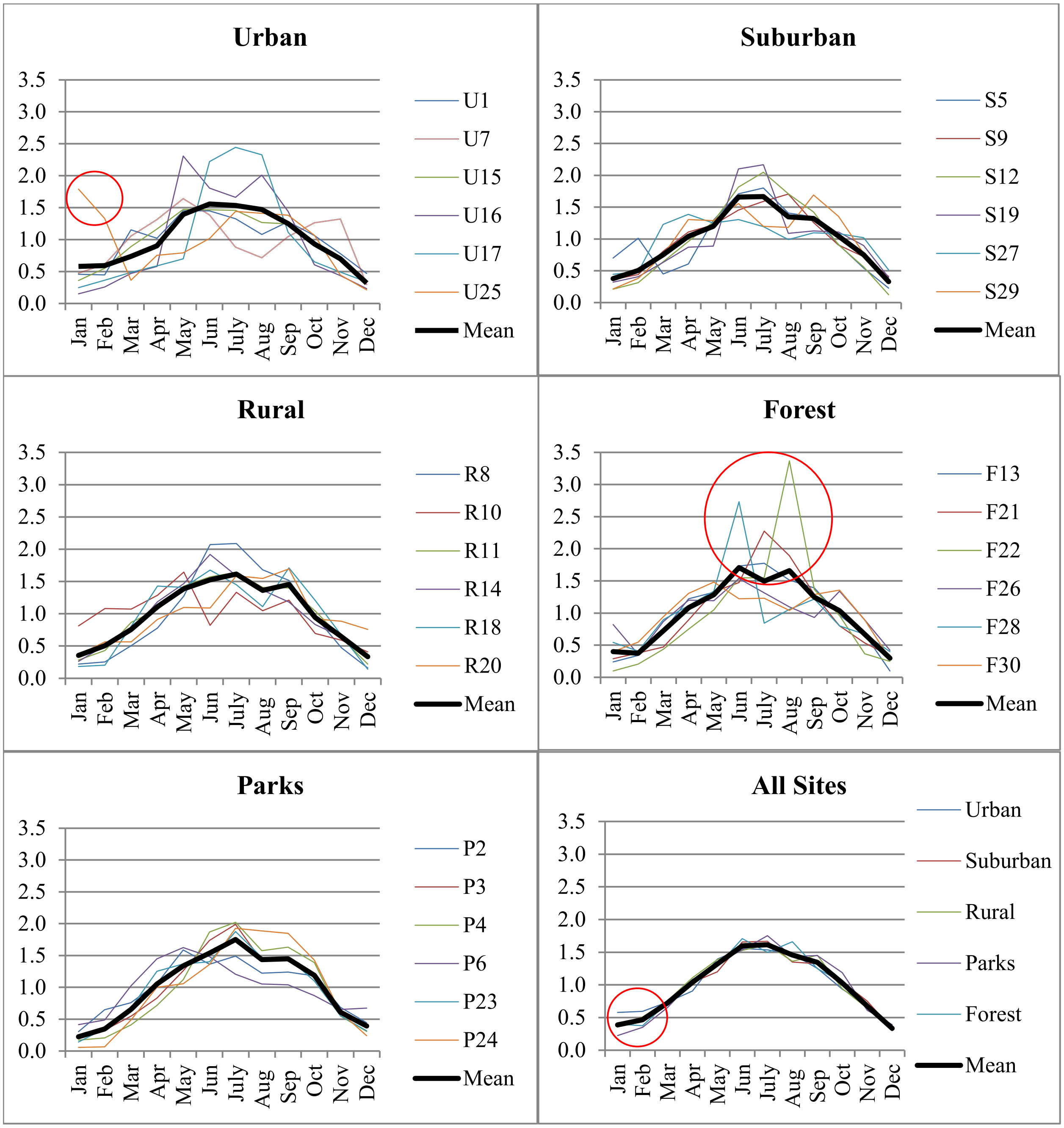

FIGURE 3 MADTT/AADTT Ratios by Land Use Classification.

FIGURE 4 Hourly Weekday and Weekend Traffic.