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Minimizing Annual Average Daily Nonmotorized Traffic Estimation Errors: How Many Counters Are Needed per Factor Group?

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Abstract

Accurate estimates of bicycle and pedestrian volume inform safety studies, trend monitoring, and infrastructure improvements. The Federal Highway Administration's *Traffic Monitoring Guide* advises current practice for estimation of nonmotorized traffic. While methodologies have been developed to minimize error in estimation of annual average daily nonmotorized traffic (AADNT), challenges persist. This study provides new guidance for monitoring and volume estimation of nonmotorized traffic. Using continuous count data from 102 sites across six cities, the findings confirm that mean absolute percent error (MAPE) in estimated AADNT is minimized when seven-day short duration counts are collected in June through September and for 24-h counts, when data are collected Tuesdays through Thursdays (except for pedestrian-only counts). MAPE across all days (except holidays) and seasons was 34% for 24-h and 20–22% for seven-day short duration counts. The magnitude of bicycle and pedestrian volumes did not significantly affect estimation errors. For factor groups larger than one counter, the length of short duration samples may influence accuracy of AADNT estimates more than the number of counters per group, all else equal. To maximize precision of estimates of AADNT, four or more counters per factor group for bicycle and five or more for pedestrian travel monitoring are recommended. These findings provide guidance for practitioners seeking to establish or improve nonmotorized traffic monitoring programs.

Federal, state, and local agencies desire accurate estimates of demand for bicycling and walking to plan and manage transportation systems, meet people's needs for commerce, recreation, and health, and create prosperous and safe communities. The Federal Highway Administration (FHWA) Traffic Monitoring Guide (TMG) for estimating annual average daily motor vehicle traffic (AADT) informs current practice in nonmotorized traffic estimation (*1*). Estimates of AADT are produced by establishing integrated networks of monitoring locations and using ratios, or factors, derived from temporal traffic patterns observed at permanent locations to extrapolate short duration counts to estimates of AADT, or in the case of bicycling and walking, annual average daily bicycle/pedestrian/nonmotorized traffic (AADBT/AADPT/AADNT). Because bicycle and pedestrian traffic varies more across seasons and in response to weather than vehicular traffic, standard methods for monitoring and for extrapolating short duration vehicle counts must be adapted to nonmotorized modes. Although researchers have made progress in developing methods that minimize error in estimates of AADNT, methodological challenges remain.

This paper contributes to the literature on traffic monitoring by providing new guidance for monitoring and extrapolating nonmotorized traffic counts. Drawing on an extensive continuous count dataset of 102 monitoring sites in Arlington, VA; Boulder, CO; Mt Vernon, WA; Portland, OR; San Diego, CA; and Seattle, WA, the study validates previous findings about optimal timing

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and duration of short duration counts and presents new findings about other aspects of monitoring, including the number of sites needed in factor groups to produce more reliable estimates of AADNT.

Background

Researchers working to adapt principles of traffic monitoring to nonmotorized traffic have addressed challenges ranging from the validity of counts from various technologies (*2*, *3*) to the validity of estimates of AADBT from short duration counts of different length (*4*) to quality assurance and quality control (*5*, *6*). The present study focuses on recent research analyzing the magnitude of error associated with use of different temporal factors to extrapolate short duration counts and approaches to classifying temporal traffic patterns to create categories of monitoring sites, or factor groups, for development and application of factors.

Researchers have completed at least 14 studies analyzing the error in AADNT associated with use of different factors, including (Table 1):

- Day-of-week; month-of-year (19 factors; i.e., traditional, motorized)
- Day-of-week-of-month (84 factors)
- Disaggregate, day-of-year (365 factors)
- Seasonal factors
- K (design-hour) factors
- Statistical modeling approaches (weather, correction factors)

Most relevant to this study, these studies have shown that error in AANDT or AADBT can be minimized by (Table 1):

- Using daily factors that are disaggregated by weather conditions (*7*);
- Conducting short-duration counts during months with higher traffic volumes (e.g., April–October;) for at least seven days (*4*, *8*);
- Using monthly rather than seasonal factors (*9*, *10*);
- Using weather-based regression equations to correct factors (*11*, *12*);
- Using day-of-year rather than traditional factors (*8*, *12–14*); and
- Imputing missing values using methods that account for weather and information from similar, nearby sites (*15–17*).

Because comprehensive monitoring programs remain relatively rare, fewer studies have analyzed the range of temporal traffic patterns for entire local networks and established factor groups that can be used to improve the accuracy of AADNT estimates (Table 2). Grouping procedures have included visual inspection (*4*, *18*), creation of temporal indices (*8*, *14*, *19*, *20*), cluster analysis (*20*), and spatial or geographic variation (*20*). Most studies have identified at least three basic types of factor groups which include a commuter or utilitarian group, a recreational group, or a mixed group, but many different names for these have been used. For example, the papers in Table 2 name at least 14 different factor groups:

1. Commuter
2. Commute/school
3. Mixed commuting
4. Non-commuter
5. Mountain non-commute
6. Post-secondary commuter
7. Recreational
8. Mixed recreational
9. Recreational/utilitarian
10. Utilitarian
11. Mixed utilitarian
12. Mixed
13. Multipurpose
14. Mixed multipurpose

Many of these names refer to the same pattern. For example, “commuter” and “utilitarian” both refer to patterns with weekday morning and afternoon peaks that exceed midday traffic volumes. Similarly, both recreational and multipurpose refer to patterns where weekend volumes exceed weekday volumes and both weekend and weekday patterns follow more or less bell-shaped curves.

The approach first proposed by Miranda-Moreno et al. (*14*) is perhaps the most common. Their approach involves construction of two indices: the weekend/weekday index (WWI) and the average morning/midday index (AMI):

$$\mathrm{WWI} = \frac{V_{we}}{V_{wd}} \tag{1}$$

where:

WWI = weekend/weekday index;
V_{we} = average weekend daily traffic;
V_{wd} = average weekday daily traffic.

$$\mathrm{AMI} = \frac{\sum_{7}^{8} v_h}{\sum_{11}^{12} v_h} \tag{2}$$

where

AMI = average morning/midday index;
v_h = average weekday hourly count for hour (*h*) where hours are given as starting time of the hour.

Table 1. Factors and Approaches Used to Estimate AADNT, AADBT, and AADPT

Author	Types of factors used or tested	Findings
Nordback (18)	• TMG model • Statistical model	• Statistical model not significantly more accurate than TMG model if continuous counts used to establish factor groups
El Esawey (7)	• Day-of-week, Month-of-year • Weekday-weekend, Month-of-year • Day-of-week (weather groups), month-of-year	• MAPE for daily factors lower if computed with harmonic mean rather than average • MAPE for daily factors only slightly lower for weekday-weekend factors • MAPE reduced 3 to 8% with weather-based factors • MAPE with 2010 factors to estimate 2009 volumes was 23%; use of 2011 factors for 2009 volumes increased MAPE to 25%
Nordback et al. (4)	• Day-of-week; month-of-year	• Error in estimated AADBT ranges from 15% with four-week short duration counts to 54% with 1-h short duration counts • Most cost-effective length for short duration counts is seven days • Conducting short duration counts in months with highest volumes reduces variation and increases accuracy of AADBT estimates
El Esawey (9)	• Day-of-week; month-of-year • Seasonal	• Error in estimated AADBT was 23% using daily and monthly factors together • Disaggregate analyses showed 15% of estimation error attributed to daily factors and 11% to monthly factors • Use of seasonal rather than monthly factors increased error to 23%
Figliozzi et al. (11)	• Day-of-week, month-of-year • Weather-based regression (statistical) correction equations	• MAPE in AADBT ranges from 7.8 to 19.1% depending on length of sample count (1–14 days) and season of count (April–October versus year-round) • Use of correction equations reduces range of error to 7.9 to 15.6%
Hankey et al. (8)	• Day-of-week, month-of-year • Day-of-year	• Day-of-year factors rather than traditional method reduce MAPE in AADNT from 40 to 20% for one-day counts and from >20 to 12% for seven-day counts
Nosal, Mirando-Moreno et al. (12)	• Day-of-week, month-of-year • Day-of-week-of-month • Weather model (departures from average) • Day-of-year (disaggregate)	• Day-of-year factors produce lower AADBT error than traditional, day-of-month, and weather model methods • MAPE in AADBT for one-day counts was 12–13% for day-of-year factors and nearly 22% for traditional factors. For seven-day counts, MAPE was 10% for day-of-year factors and 13% for traditional factors
Beitel et al. (21)	• Three steps: validation, classification, disaggregate weekend and weekday • Peak/non-peak season ratio (PPI)	• Both approaches reduce AADBT estimation error
El Esawey and Mosa (10)	• K (design hour) factors • Day-of-week, month-of- year • Weekend-weekday factors	• MAPE in AADB for K-factors calculated as ratio of daily peak hour volume to AADB is 16.6% • MAPE for daily factors (28.3%) lower than weekend-weekday factors (28.9%)
El Esawey (13)	• Day-of-year factors • Monthly and weather factors • AASHTO method	• Confirmed superiority of performance of day-of-year factors • MAPE varies from 17.5% for day-of-year factors to 24.5% for monthly and weather-specific factors to 30% for AASHTO factors
Beitel et al. (22)	• Day-of-year for four factor groups (adapted Miranda-Moreno et al. (14)) • K-means clustering to sort short-duration counts into factor groups	• Quality of short-duration counts can be characterized by duration of count, average bicycle demand, time of year, stability of count, and correlation with the reference count • Average relative error ranges from 3% for highest quality counts to 13.5% for lowest quality counts

(continued)

Table 1. (continued)

Author	Types of factors used or tested	Findings
Budowski (*23*)	• Day-of-year (seven-day samples) • Day-of-year (2-h counts) • TMG (2-h counts) • NBPDP (2-h counts)	• Confirmed superiority of performance of Day-of-Year, disaggregate factors • MAPE varies from 7% for Day-of-Year (seven-day) to 18% for Day-of-Year (2-h) to 32% for TMG (2-h) to 80% for NBPDP (2-h) methods
El Esawey (*16*)	• Day-of-week, month-of-year • (effects of missing data, imputing values)	• Random missing counts have minimal effects on estimation accuracy of AADB (<5%); with 50% random loss of data, maximum error is 14% • For non-random missing counts, average error ranged from 1.5 to 21.1% for periods of one week and four months, respectively. • Use of multiple imputation methods can reduce estimation error to <3%
El Esawey (*17*)	• Day-of-week, month-of-year • Weekend-weekday	• Use of simple averages to impute missing daily counts associated with MAPE of 36.9 to 59.4% • Use of count-based regression models to impute daily counts associated with 20 to 34% MAPE (average MAPE = 25.8%) • Autoencoder neural network models reduced average MAPE for imputed daily counts to 10%

Note: AADNT = Annual Average Daily Nonmotorized Traffic; AADBT = Annual Average Daily Bicycle Traffic; AADPT = Annual Average Daily Pedestrian Traffic; TMG = Traffic Monitoring Guide; MAPE = mean absolute percent error; NBPDP = National Bicycle and Pedestrian Documentation Project; h = hour.

Monitoring stations with higher counts on weekends than weekdays (i.e., WWI greater than one) can be easily grouped together as having recreational patterns. Stations with higher morning than midday counts on weekdays have an AMI greater than one, which implies hourly commute patterns. Although the approach enables systematic classification and seems to match classifications from visual inspection of hourly patterns, it does not eliminate the need for examination of patterns in the data for days and hours outside of those included in these indices.

None of these studies systematically analyzed how the accuracy of AADNT is affected by the number of monitoring locations in a factor group.

Data

Continuous count data were obtained from Arlington, Boulder, Mt Vernon, Portland, San Diego, and Seattle from 2002 to 2016. The data were uploaded and stored in Bike-Ped Portal, Portland State University's online bicycle and pedestrian count data archive (*26*, *27*).

To determine actual AADNT for a given year for a given site, at least one complete day (i.e., 24 h) of counts for each day-of-the-week in every month was needed. From this dataset, 141 locations had sufficient data for the analysis, totaling over a million hourly observations. Of these locations only 102 had sufficiently high quality to be used in analysis. Table 3 summarizes the data used by each city, including notes on data quality.

Quality checking was conducted in three phases. First, the raw data was manually checked by visual observation of graphs of volume by day and hour. Data with more than one day of zero counts or suspiciously high peaks were removed as detailed in a related report (*26*). Spikes in volume below 1,000 per hour for just a few hours were considered actual events. However, if such a spike were followed by a data gap or repeating zeros, it would be excluded because of being more consistent with counter malfunction patterns. If high volumes (>200 per hour) were observed late at night or continued for days, these were considered likely to be a malfunction, insect activity, or vandalism and were excluded from the analysis. In the future, automation could be used to identify suspicious data more quickly and consistently in the first phase of quality checking.

Second, data for years without sufficient observations to compute AADNT (at least one of each day of the week in each month) and data for years with AADNT values below three were removed because such low volumes may be erroneous and produce high error because of inherent variability. Third, data with months of zeros or multiple suspiciously high peaks which had not been removed in the first or second phases were removed. The second phase of data quality checking was performed using automated checks in Excel, while the first and third used visual observation.

Table 2. Classifications and Factor Groups Used for Estimation of AADNT, AADBT, and AADPT

Author	Classification methods	Factor groups	Findings
Nordback (*18*)	• Visual inspection	• Commuter • Non-commuter	• Use of factor groups improves accuracy
Turner et al. (*24*)	• Visual inspection	• Commute/school • Recreational/ utilitarian • Mixed	• Colorado monitoring program should include permanent references site for factor groups
Miranda-Moreno et al. (*14*)	• Temporal indices (daily and hourly patterns)	• Utilitarian • Mixed utilitarian • Recreational • Mixed recreational	• Indices can be used to establish factor groups • Recreational: weekend-weekday Index $>$ 1; morning peak–midday index $<$ 1 • Utilitarian: weekend-weekday index $<$ 1; morning peak–midday index $>$ 1
Nordback et al. (*20*)	• Visual inspection • Cluster analysis • Indexes • Spatial variables	• Mountain non-commute • Front-range non-commute • Commute	• Weekend-weekday traffic volume ratios ($>$1) can be used to identify recreational sites • Professional judgment can be used to differentiate geographic groups (e.g., mountain, front-range) • More monitoring needed to identify other factor groups
Hankey et al. (*8*)	• Temporal indices (daily and hourly patterns)	• Utilitarian • Mixed utilitarian • Recreational • Mixed recreational	• Adapted Miranda-Moreno et al. (*14*) indices; used different break-points for six permanent trail counters • Two mixed-utilitarian, four mixed-recreational, and zero utilitarian and recreational sites analyzed
Budowski (*25*)	• Ward's minimum-variance clustering method • Analyst's judgment	For daily volume expansion • Commuter • Post-secondary commuter • Recreational • Mixed For SADT expansion • Winnipeg • Winnipeg post-secondary	• Different factor groups are needed for different expansion purposes. • For expanding from hours to days, one set of patterns is relevant, but for expanding from 24 h or a week of data to estimate seasonal average daily traffic (SADT), only two travel patterns were needed in the study city, Winnipeg
Lindsey et al. (*19*)	• Temporal indices (daily and hourly patterns; adapted Miranda-Moreno et al. (*14*); Hankey et al. (*8*)	• Commuting • Multipurpose • Mixed commuting • Mixed multipurpose	• Four factor groups exist on multiuse trail network based short-duration samples • Data for all factors groups not available among six reference sites • Renamed recreation multipurpose to reflect broader purposes for trips

Note: AADNT = Annual Average Daily Nonmotorized Traffic; AADBT = Annual Average Daily Bicycle Traffic; AADPT = Annual Average Daily Pedestrian Traffic; h= hour.

Methods

Figure 1 shows the steps in the analysis. First, jurisdictions with continuous count sites with at least one year of data per site were identified and their data obtained in Excel or csv files, by online access through a web portal or application programming interface. Next, the data were checked for quality using visual inspection of graphs as described previously.

For the data that passed the quality check, key metrics were computed for each continuous count site: MADT, AADNT, and WWI. The steps in factor creation generally followed procedures from the 2013 TMG. Although the 2016 TMG has a new, more advanced AADT estimation method, with advice from the experts in the field, the team chose the older method because it is more tractable and more widely used in practice. After the index

Table 3. Summary of Data Used

Community	Time period	Type of counters	Number of sites included in analysis: Bikes only	Peds only	Bike-ped undifferentiated	Total # of sites	Data quality notes
Arlington, VA	2012–2016	Passive infrared and inductive loop combination	18	11	NA	29	Suspect data (primarily repeated zeros) were removed prior to analysis. Before the team received the data, it had been cleaned by the equipment manufacturer at Arlington's request, to fill in gaps in data or replace known erroneous data with imputed data based on count patterns from nearby counters.
Boulder, CO	2002, 2004, 2007, 2008, 2010, 2012, 2016	Inductive loops	15	NA	NA	15	Some data had been removed from the dataset for known quality problems prior to this team's use in previous analyses (*18*)
Mt Vernon, WA	2010–2011	Passive infrared	NA	NA	5	5	Since the raw data had not been checked prior to this team's use, numerous data quality issues were encountered. Repeating zeros and unusually high counts were excluded from the analysis.
Portland, OR	2009–2015	Passive infrared, inductive loops, pneumatic tubes	3	5	15	23	The data from one counter had been cleaned prior to our use, but the data from all the others had not. Issues included unusually high and low counts, daylight saving time discrepancies, repeated zeros and data gaps.
San Diego, CA	2014–2015	Passive infrared and inductive loop combination	10	6	NA	16	This dataset had not been checked prior to the team's use. Spikes and repeated zeros were the most common data quality issues encountered.
Seattle, WA	2014–2016	Passive infrared and inductive loop combination, pneumatic tubes	10	4	NA	14	Data had not been checked prior to the team's use. Issues included unusual patterns, repeating zeros and low counts.
Total			56	26	20	102	

Note: NA = not available (denotes no data of a given type).

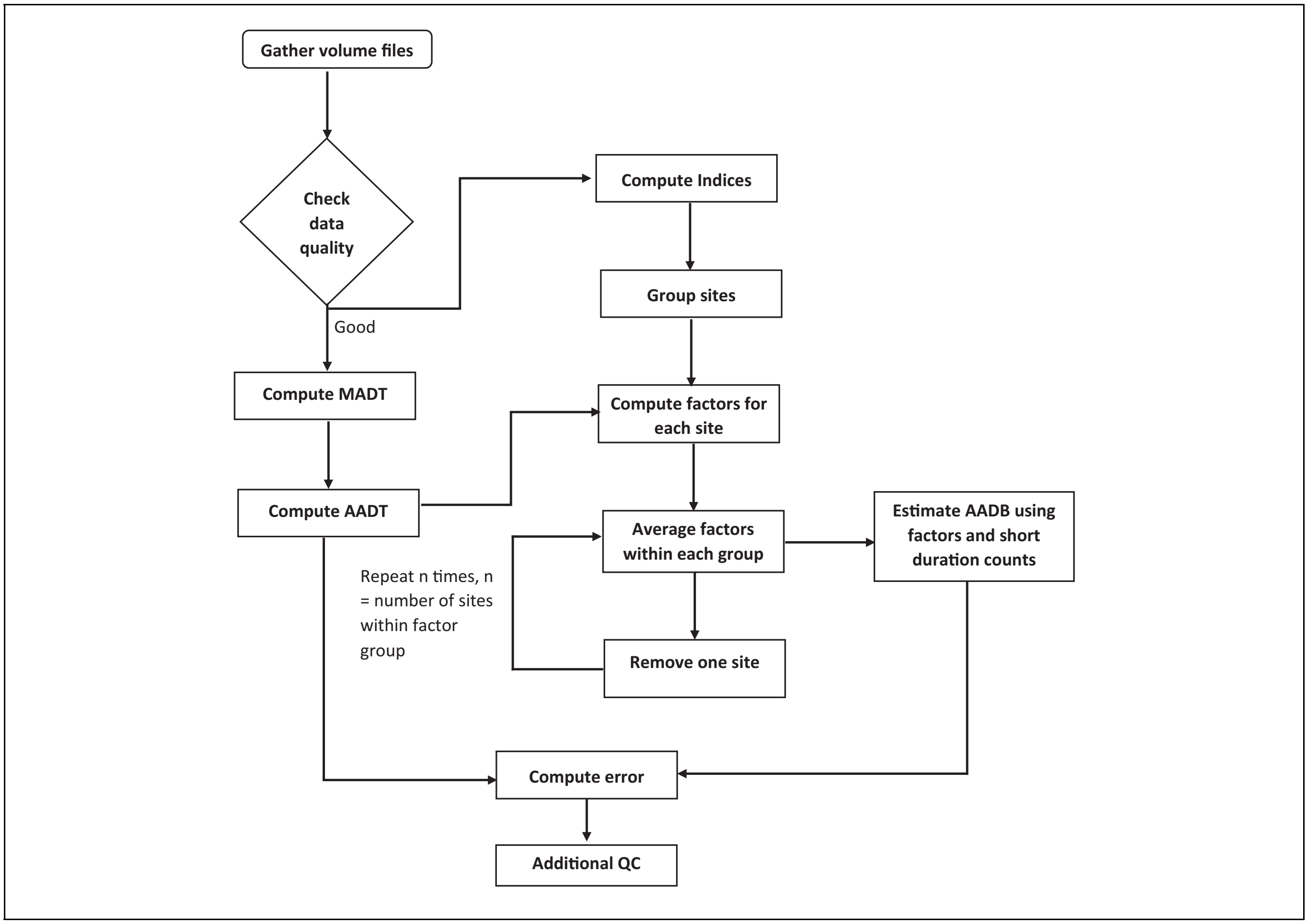

Figure 1. Flowchart showing analysis steps.

(WWI) was computed, the sites were grouped by city, mode, and travel pattern for the day-of-week-of-month factors, and by city and mode for the monthly factors. Factors for each site and average factors for each group were computed.

Next, a trial site in each group was identified and removed from the group. This trial site was then used to simulate a short duration site. For example, a 24-h count at the trial site on a non-holiday weekday was divided by the average factor computed using data from the other continuous counters in the group to estimate AADNT at the trial site. Since the actual AADNT at the site is known, it was thus possible to compute the error for the estimated AADNT at the trial site. The process was repeated in two ways, first by rotating through each member of the group as the trial site, and next by randomly removing additional sites from the factor group until only one site was left in the group from which to create factors. This second process was repeated twice for each factor group. Because of the extensive dataset and the iterative analysis, Bike-Ped Portal, the national nonmotorized data archive, which contained all data that was used for analysis, was utilized (*27*).

MADT and AADNT Computation (Ground Truth)

Next, the monthly average daily nonmotorized traffic (MADT) was computed for each day of the week for each month in each year for each segment and mode using the following formula.

$$\mathrm{MADT}_{smy} = \frac{1}{7}\sum\nolimits_{j=7}^{1}\left[\frac{1}{n}\sum\nolimits_{i=1}^{n} V_{ijsmy}\right] \tag{3}$$

where

V_{ijsmy} = total nonmotorized traffic volume for ith occurrence of the jth day of the week at site (s) within the mth month, for year (y)

n = the count of the jth day of the week during the mth month for which traffic volume is available (a number from one through five) at site (s)

As stated in the TMG, MADT was only calculated for months that had “at least one Monday, Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday” counts available (*1*).

Next, AADNT is computed.

$$\mathrm{AADNT}_{ys} = \frac{1}{12}\sum_{m=1}^{12} \mathrm{MADT}_{smy} \tag{4}$$

where

m = month of the year, y

AADNT*ys* = annual average daily nonmotorized traffic for year (y) at site (s)

Establishing Factor Groups

Factor groups are used to create the temporal and geographic adjustment factors which can be applied to short duration counts. The goal is to group sites with similar travel patterns using a method that can also be applied to the short duration count sites where little data are available. For this study, the team assumed that at least one week of data would be available at each short duration count site. This made it possible to consider travel patterns over the week when grouping sites.

Steps in factor groups creation included visual inspection of graphs of daily, weekly, and yearly temporal variations of traffic volumes for some of the sites, examination of histograms of WWI values for the sites, and discussion of alternatives with experts. The team ultimately decided to group sites for day-of-week-of-month factors into three groups by WWI values for each mode in each city. WWI values were grouped using the following criteria: Weekday Commute (Average WWI < = 0.8), Weekly Multipurpose (0.8 < Average WWI < = 1.2), Weekend Multipurpose (Average WWI > 1.2).

The monthly factors were not divided by weekly travel pattern, because the sites across a given city were observed to have the same variation over the year. Sites for monthly factors were grouped by mode and city.

For this analysis, each of the six cities was considered a distinct unit. Even though three of the cities are in the Pacific Northwest, these were not grouped together. There are six cities, three types of modes (bicycle, pedestrian and undifferentiated) and three travel pattern groups, but not all the modes were collected in each city and not all the patterns were observed in each city, so only 19 of the possible 54 day-of-week-of-month factor groups are included in the analysis.

Daily patterns such as morning, noon, and evening peaks were not considered in the grouping because it was assumed that at least a full 24 h of data (midnight to midnight) would be available for each site. If the daily volume is known, the weekly pattern is most relevant to grouping.

Factors

Two sets of factors were computed: day-of-week-of-month factors and monthly factors. Both factors are computed as a percentage of AADNT for a given year. Thus, both are values by which the short duration count should be divided, not multiplied, to estimate AADNT.

Holidays are excluded from the numerator of the factor because it is assumed that short duration counts would not be collected during holidays, as such days are known to be highly variable, and it is standard practice for motor vehicle traffic monitoring to not count on such days or weeks. For this analysis, holidays are defined as all federal holidays plus the week of Thanksgiving and the last seven days of each year. Holidays are included in the denominator, AADNT, because the intent is to estimate average daily travel over the entire year, including holidays.

Day-of-Week-of-Month Factors

Day-of-week-of-month factors (84 per year) were computed for each site as

$$F_{jmsy} = \frac{V_{jmsy}}{\mathrm{AADNT}_{sy}} \tag{5}$$

where

F_{jmsy} = factor for jth day of the week within the mth month, for site (s) and year (y).

V_{jmsy} = average total traffic daily volume for jth day of the week within the mth month, for site (s) and year (y), excluding holidays.

AADNT*sy* = the AADNT computed previously for that site (s) for year (y). It includes holidays.

Monthly Factors

The monthly factors (12 per year) are computed for each site. While the holidays are removed from MADT_{fsmy}, the holidays are included in AADNT_{sy}. MADT_{smy} is used as a step in computing AADNT, while MADT_{fsmy} is only used for computing factors. Monthly factors are calculated as

$$F_{msy} = \frac{\mathrm{MADT}_{fsmy}}{\mathrm{AADNT}_{sy}} \tag{6}$$

where

MADT_{fsmy} = monthly average daily nonmotorized traffic (MADT not including holidays) for factor computation for a given site (s) in a given month (m) and a given year (y) excluding holidays.

Precision Interval

To examine the variation in the factors for each site within a given group, the precision interval for each of the 28 groups was computed based on the method provided in the TMG, page 3–26 (*1*).

$$D = T_{1-\frac{d}{2}, n-1} \frac{C}{\sqrt{n}} \tag{7}$$

where:

D = precision interval as a proportion or percentage of the mean;

C = coefficient of variation of the factors;

T = value of student's T distribution with level of confidence $1–d/2$ and $n–1$ degrees of freedom;

n = number of locations;

d = significance level (5% in this case).

Because the TMG states that precision interval as a percentage of the mean is expected to be less than 10% with 95% confidence, this analysis used a 95% confidence in computing the precision interval.

AADNT Estimates

Next AADNT is estimated for the trial "short duration" site, using the following formulas.

For estimating AADNT from 24 h of counts using day-of-week-of-month factors:

$$\text{Estimated AADNT}_{yid} = \frac{V_{yid}}{F'_{jmyg}} \tag{8}$$

where

V_{yid} = total traffic volume for day (d) in year (y) for the trial site i;

F'_{jmyg} = the day-of-week-of-month factor recomputed for the trial factor group (the one without site, i, but which does include other sites in i's factor group) for day of week (j), month (m), year (y) and group (g).

For estimating AADNT from one week of counts using day-of-week-of-month factors:

$$\text{Estimated AADNT}_{yiw} = \frac{1}{7}\sum_{j=1}^{7} \frac{V_{jmwyi}}{F'_{jmyg}} \tag{9}$$

where

V_{jmwyi} = total daily traffic volume for jth day of the week, for week (w) within the mth month, for year (y) for the trial site i;

F'_{jmyg} = the day-of-week-of-month factor recomputed for the trial factor group (the one without site, i, but which does include other sites in i's factor group)) for day of week (j), month (m), year (y) and group (g) of which site (i) is a member. This is the factor for the trial factor group (the one that does not include the trial site (i)).

For estimating AADNT from one week of counts using monthly factors:

$$\text{Estimated AADNT}_{yiw} = \frac{1}{F'_{myg}}\left(\frac{1}{7}\sum_{j=1}^{7} V_{jmwyi}\right) \tag{10}$$

where:

V_{jmwyi} = total daily traffic volume for jth day of the week, for week (w) within the mth month, for year (y) for the trial short duration site i.

F'_{myg} = the monthly factor recomputed for the trial factor group (the one without site, i, but which does include other sites in i's factor group)) for month (m), year (y) and group (g) of which site (i) is a member. This is the factor for the trial factor group (the one that does not include the trial short duration site (i)).

Error

MAPE is estimated using the following formula.

$$\text{MAPE}_{yimw} = \left|\frac{\text{Estimated AADNT}_{yimw} - \text{AADNT}_{yimw}}{\text{AADNT}_{yimw}}\right| \tag{11}$$

Because MAPE cannot exceed 100% for underestimates but can be infinitely high for overestimates, MAPE tends to favor methods that underestimate. Despite this MAPE was selected as the measure of error because it is simple to compute and commonly used for comparing AADNT estimation error.

To simulate scenarios that could be encountered by practitioners who want to estimate AADNT from short duration count sites with 24 h or one week of data, the errors were calculated for several different scenarios:

1. When 24 h of data were available for a given site and the set of day-of-week-of-month factors were applied.
2. When a week of data was available for a given site and the set of day-of-week-of-month factors were applied.
3. When a week of data was available for a given site and the set of monthly factors was applied.

Each of these will be described separately below to assess which scenarios yield the lowest error.

Table 4. AADNT Estimation Error Given 24 H of Data per Site (Day-of-Week-of-Month Factors Applied)

	MAPE for AADNT estimates (Number of sites in analysis)				
	Weekday commute	Weekend multipurpose	Weekly multipurpose	Weighted average	Standard deviation
Bicycle	**27%**	**26%**	**34%**	**30%**	**108%**
Arlington	31% (4)	38% (3)	31% (11)	32%	41%
Boulder	29% (8)	NA	39% (7)	35%	53%
Portland	17% (3)	NA	NA	17%	18%
San Diego	NA	23% (10)	NA	23%	24%
Seattle	32% (5)	33% (5)	NA	32%	301%
Bicycle & pedestrian undifferentiated	**36%**	**30%**	**27%**	**30%**	**123%**
Mt Vernon	36% (2)	79% (3)	NA	71%	544%
Portland	NA	28% (10)	27% (5)	28%	25%
Pedestrian	NA	**43%**	**40%**	**42%**	**51%**
Arlington	NA	30% (6)	26% (5)	29%	29%
Portland	NA	47% (3)	29% (2)	46%	46%
San Diego	NA	NA	58% (6)	58%	101%
Seattle	NA	NA	35% (4)	35%	51%
Weighted average	**28%**	**35%**	**34%**	**34%**	**97%**

Note: Averages are weighted by number of trials (325,285 total), which are generally proportional to the number of sites, though some sites have more years of data than others. NA = not available (no data are available for that scenario); AADNT = Annual Average Daily Nonmotorized Traffic; MAPE = mean absolute percent error; H = hour.

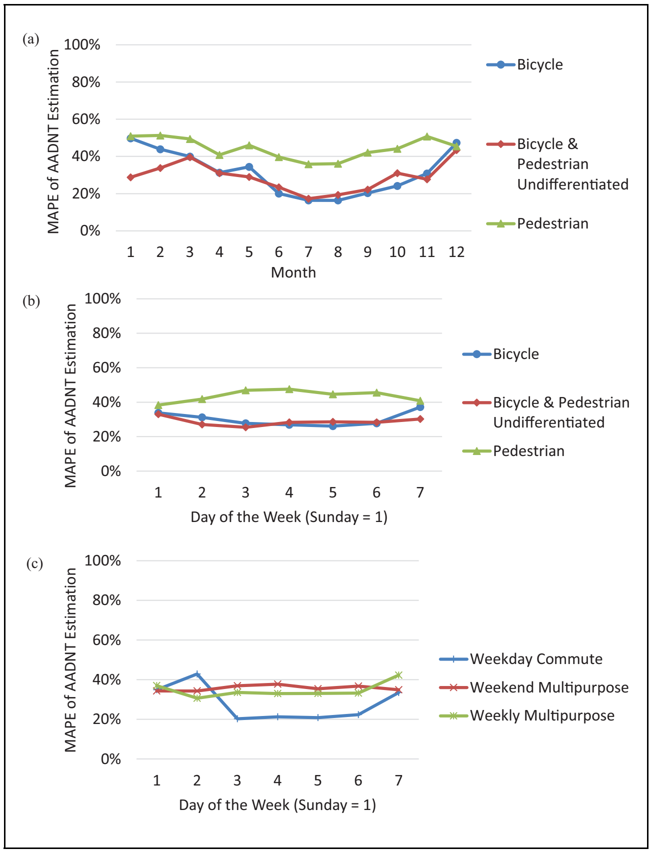

Figure 2. AADNT estimation error given 24-h short duration count with day-of-week-of-month factors applied: (*a*) mode by month; (*b*) mode by day of week, and (*c*) factor group by day of week.

Results

24-H Short Duration Count with Day-of-Week-of-Month Factors

When short duration counts of 24 h were available for a given site and day-of-week-of-month factors were applied, error varied by city and travel pattern. Portland's bicycle weekday commute pattern had the lowest error (17% MAPE), and Mt Vernon's undifferentiated bicycle and pedestrian weekend multipurpose pattern had the highest error (79% MAPE) (Table 4).

Figure 2 presents MAPE of AADNT estimates for all sites using day-of-week-of-month factors applied to 24-h simulated short duration counts: (a) mode by month; (b) mode by day of week, and (c) factor group by day of week. For all modes, extrapolation of short duration counts taken in June through September produce the lowest error (Figure 2*a*). This agrees with previous studies and standard practice which recommends counting in September (*4*, *28*). Summer months may have more predictability in travel patterns and thus less error. However, locations with different climate or higher percentage of college students may show different results if studied. Pedestrian volume estimates consistently have the highest error when compared with undifferentiated bicycle and pedestrian and bicycle only estimates.

Figure 2*b* shows that weekdays are associated with the lowest error and are thus the best days to collect 24-h counts, except for pedestrian-only counts when weekends are better. Figure 2*c* shows that error is highest for travel

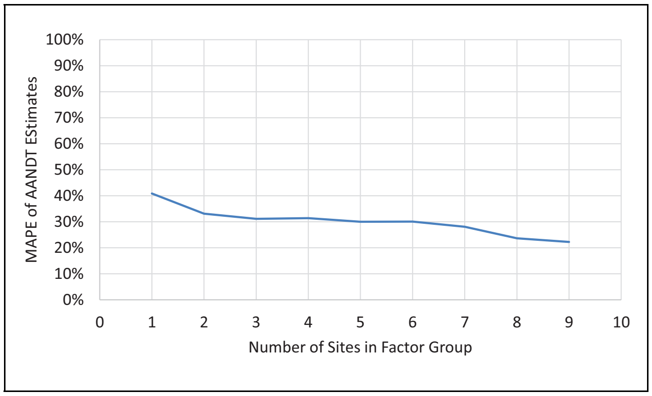

Figure 3. AADNT estimate with number of sites in factor group given 24-h short duration counts (day-of-week-of-month factors applied).

patterns when volumes are highest on weekends (Weekend Multipurpose). Even though weekend volumes are high for this pattern type, error is about the same throughout the week. Similar patterns were observed for the other two scenarios and hence they are not presented here to avoid repetition.

Figure 3 responds to the research question of how many counters are optimal for accurately estimating AADNT from 24-h short duration counts using the day-of-week-of-month factors. It shows a relatively large reduction in error when the number of counters in a factor group is increased from one to two and smaller decrease when the number of counters increases from seven to nine. The implication is that, for 24-h short-duration counts, the highest accuracy improvement (20% reduction in error from 41% to 33% MAPE) is for increasing the number of counters in a factor group from one to two, although increasing from six to eight improves accuracy by another 20% (from 30% to 24%). Another implication, which is addressed in the discussion of results, is that reliability of count data may be a more important consideration in reducing error than the number of counters per factor group. This shows the need to consider tradeoffs between (i) investments in short-duration sampling and (ii) validation and maintenance of permanent counters.

One-Week Short Duration Count with Day-of-Week-of-Month Factors

When one week of data was available for a given site and the set of day-of-week-of-month factors were applied, error is lowest for the Weekday Commute scenario for bicycles and highest for pedestrians with Weekly Multipurpose patterns, as seen in Table 5. As before, San Diego and Mt Vernon have unusually high error, likely because of data quality problems, demonstrating that data from unvalidated and poorly maintained counters may be useless.

Figure 4 shows the plot of AADNT estimation error by number of sites in factor group. The plot shows that while error decreases as the number of sites increase, the

Table 5. Error for Day-of-Week-of-Month Factors with One Week of Data per Site

	MAPE for AADNT estimates (Number of sites in analysis)				
	Weekday commute	Weekend multipurpose	Weekly multipurpose	Weighted average	Standard deviation
Bicycle	**18%**	**15%**	**22%**	**19%**	**49%**
Arlington	18% (4)	22% (3)	19% (11)	19%	27%
Boulder	18% (8)	NA	28% (7)	24%	40%
Portland	10% (3)	NA	NA	10%	9%
San Diego	NA	14% (10)	NA	14%	17%
Seattle	24% (5)	18% (5)	NA	22%	122%
Bicycle & pedestrian undifferentiated	**28%**	**20%**	**15%**	**19%**	**56%**
Mt Vernon	28% (2)	62% (3)	NA	55%	242%
Portland	NA	18% (10)	15% (5)	18%	16%
Pedestrian	**NA**	**27%**	**29%**	**27%**	**30%**
Arlington	NA	19% (6)	15% (5)	18%	17%
Portland	NA	29% (3)	20% (2)	29%	24%
San Diego	NA	NA	47% (6)	47%	68%
Seattle	NA	NA	23% (4)	23%	28%
Weighted average	**18%**	**22%**	**23%**	**22%**	**46%**

Note: Averages are weighted by number of tested scenarios (46,522 total), which are generally proportional to the number of sites, though some sites have more years of data than others. NA = not available (no data are available for that scenario); AADNT = Annual Average Daily Nonmotorized Traffic; MAPE = mean absolute percent error.

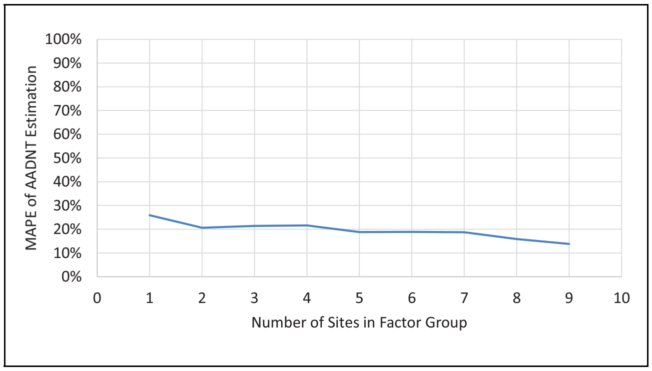

Figure 4. AADNT estimate with number of sites in factor group given one-week short duration counts (day-of-week-of-month factors applied).

decrease is not substantial beyond two counters though error does start to drop off more steeply beyond seven counters.

One-Week Short Duration Count with Monthly Factors

To test whether the day-of-week-of-month factors or the monthly factors result in lower error when one-week short duration counts are available, we also used monthly factors as suggested in the TMG to estimate AADNT. Error generally is similar regardless of whether monthly factors or day-of-week-of-month factors are used (Table 6).

In this scenario, error in estimated AADNT is reduced by about 30% (from 25% to 18%) by increasing the number of counters per factor group from two to four, but virtually no further improvements in accuracy are achieved as seen in Figure 5. Breaking it down by city, this may be a factor of the data quality. For cities with higher data quality there is not much change as additional sites are added to the factor group. Only focusing on the better data months (June through August) does not change the findings.

Discussion

AADNT estimation errors (MAPE) averaged 34% for 24-h counts, 22% for one week of counts using day-of-week-of-month factors, and 20% for one week of counts using monthly factors (Table 7). This indicates that using the day-of-week-of-month factors method yields similar error as the monthly factor method. This finding is somewhat surprising because the 84 day-of-week-of-month factors per year might be expected to capture seasonal variation better than 12 factors per year and because monthly factors were not grouped by travel pattern. Monthly factors are easier to compute and simpler to apply than the day-of-week-of-month factors because there are only 12 per year instead of 84.

The actual error varied substantially depending on city, mode, and travel pattern. To summarize,

- Extending short duration counts from one day to one week reduces error by 35% (from 34% to 22%) on average, when the day-of-week-of-month approach is used;

Table 6. Error using Monthly Factors with One Week of Data per Site

Mode and city	MAPE for AADNT estimates (Number of sites in analysis) Weighted average	Standard deviation
Bicycle	**20%**	**26%**
Arlington	19% (17)	24%
Boulder	26% (14)	36%
Portland	9% (3)	8%
San Diego	18% (10)	16%
Seattle	19% (10)	17%
Bicycle & pedestrian undifferentiated	**18%**	**21%**
Mt Vernon	27% (5)	49%
Portland	17% (14)	15%
Pedestrian	**24%**	**24%**
Arlington	15% (10)	15%
Portland	27% (5)	22%
San Diego	37% (5)	40%
Seattle	22% (4)	28%
Weighted average	**20%**	**25%**

Note: Averages are weighted by number of tested scenarios (75,952 total), which are somewhat proportional to the number of sites, though some sites have more years of data than others. AADNT = Annual Average Daily Nonmotorized Traffic; MAPE = mean absolute percent error.

Table 7. AADNT Estimation Error Summary

		MAPE for AADNT estimates (%)			
Factors	Short count duration	Weekday commute	Weekend multipurpose	Weekly multipurpose	Weighted average
Day-of-week-of-month	24 h	28%	35%	34%	34%
Day-of-week-of-month	one week	18%	22%	23%	22%
Monthly	one week	One group per city			20%

Note: AADNT = Annual Average Daily Nonmotorized Traffic; MAPE = mean absolute percent error; h = hour.

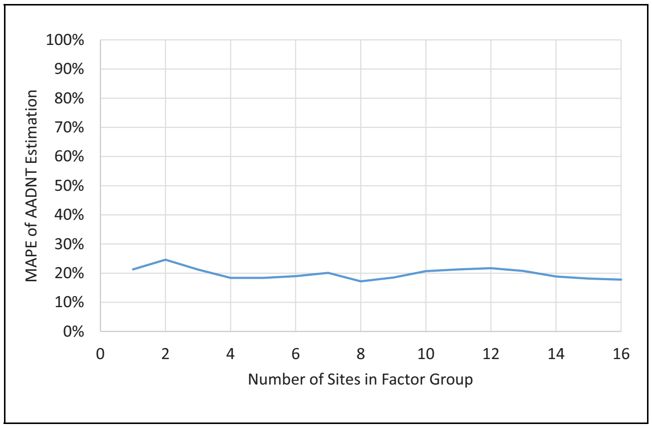

Figure 5. AADNT estimate with number of sites in factor group given one-week short duration counts (monthly factors applied).

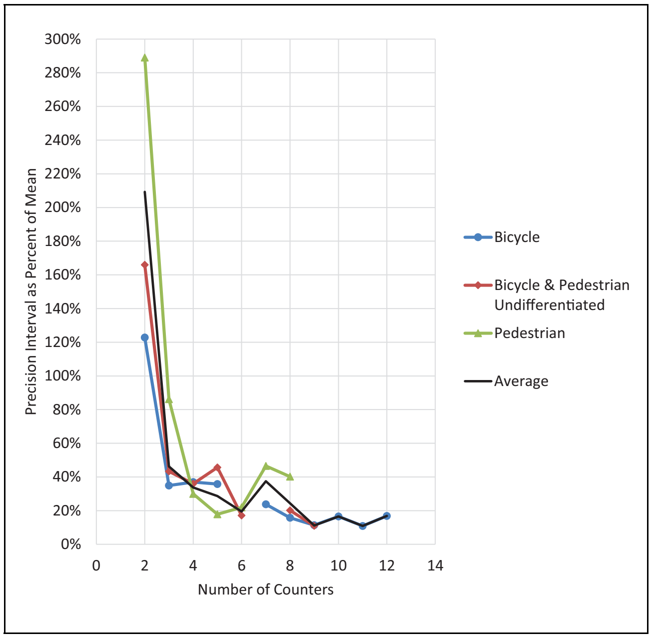

Figure 6. Precision interval as a function of the number of counters per group for day-of-week-of-month factors.
Note: Gaps in lines are because of lack of data.

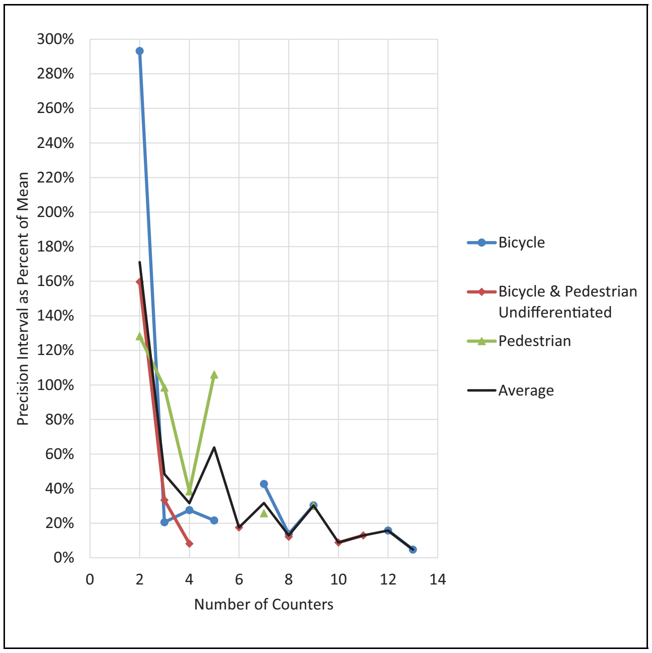

Figure 7. Precision interval as a function of the number of counters per group for monthly factors.
Note: Gaps in lines are because of lack of data.

- Focusing on length of short duration count results in higher improvements in accuracy than adding additional permanent counters in a factor group with two or more members; though, of course, the two are not mutually exclusive.

Precision Interval

In addition to the analysis of the predicted error, the precision interval was also computed for the day-of-week-of-month and monthly factors. The precision interval as defined in the TMG is computed as a percentage of the mean (see Equation 7). Thus, the precision interval is based on the variability of the factors at each count site within a factor group.

Figures 6 and 7 plot the precision interval as a percentage of the mean assuming 95% confidence is desired. The TMG recommends this approach for determining the number of counters needed to obtain the recommended 10% precision (*1*).

The TMG notes that for motor vehicles, five to eight sites per factor group is usually sufficient to attain 10% precision interval at the 95% confidence interval (*1*). More counters might be needed for bicycling and walking since such travel is known to be more variable. Figures 6 and 7 indicate that roughly 10% precision is attainable above nine or 10 counters.

There is, however, a large improvement in precision with three or more sites per group for bicycles and four or more for pedestrians when day-of-week-of-month factors are used. Similarly, for monthly factors, there is a large improvement in precision when there are three or more sites per group for bicycles and seven or more for pedestrians. As pedestrian travel is usually more variable than bicycle travel, more sites are needed for pedestrian travel monitoring.

Conclusions

Error in estimated AADNT is associated with the length and timing of the short duration sample, the method of extrapolation, the type of traffic pattern or factor group, mode, and the number of counters in a factor group. With respect to error associated with the sample, error is lower for:

- Week-long (seven-day) counts than 24-h counts;
- Short duration counts collected June through September; and
- Counts taken Tuesday through Thursday even for sites with high weekend volumes except for pedestrian-only counts, for which weekend counts may reduce error.

With respect to factor group and mode, MAPE is lower for:

- Commuter traffic than weekly or weekend multi-purpose traffic;
- Bicycle-only and undifferentiated, mixed-mode counts.

With respect to number of counters per factor group, MAPE is substantially lower when

- Using two rather than one permanent counters per group;
- Having eight or more counters in a group when day-of-week-of-month factors are used.

Data variability and quality of counts may also affect accuracy. Arlington and Portland generally had lowest error and Mt Vernon, Washington had the highest. This outcome was likely because of better data quality and less variability in Arlington and Portland's data. Surprisingly, traffic volume was not a large contributor to reducing error.

Including three or more bicycle counters and four or more pedestrian counters per factor group greatly tightens the precision interval of the factors, but not enough to achieve the desired 10% precision at 95% confidence level recommended by the TMG. If monthly factors are used for pedestrians, as many as seven per group are needed to greatly tighten the precision interval (three or more for bicycles).

Recommendations

These outcomes lead directly to a number of recommendations for practice that will help to reduce error in AADNT:

- For short duration sampling, plan for counts of at least seven days in the months with the lowest variability (e.g., avoid December, January, and February). If counts must be limited to 24 h, plan for monitoring Tuesdays through Thursdays, even at sites with high weekend volumes. Avoid use of short-duration sample counts of less than 24 h.
- For extrapolation, use day-of-week-of-month factors for 24-h short-duration counts and for week-long short-duration counts monthly factors can be used. Use mode-specific (e.g., bicycle only, pedestrian only, and undifferentiated, mixed-mode) factors.
- When planning permanent sites that will be used in factor groups, plan for at least four counters per factor group for bicycles and five or more counters for pedestrians. This recommendation includes redundancy that can help to avoid loss of accuracy when maintenance problems or vandalism, which are inevitable, result in temporary loss of data from a counter in a factor group. If a jurisdiction has the budget and staff to maintain them, using eight or more counters per group is encouraged to further reduce error and increase precision.

The results also show that tradeoffs are involved in decisions related to monitoring and analysis. In addition to tradeoffs between numbers of counters, length of short-duration samples, and accuracy, it is clear that data quality also matters and that counters need to be validated and maintained. Additional analyses are needed, for example, to determine whether resources might be better spent in maintaining and validating existing count equipment than in increasing the number of counters per factor group above the recommended numbers.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: KN; data collection and processing: DJ; analysis and interpretation of results: KN, SK, GL, SR, JR; draft manuscript preparation: KN, SK, GL. All authors reviewed the results and approved the final version of the manuscript.

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