# Day-of-Year Scaling Factors and Design Considerations for Nonmotorized Traffic Monitoring Programs

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**General procedures, including the estimation of annual average daily traffic (AADT) from short-duration counts, have not been established for nonmotorized traffic monitoring programs. Continuous counts of nonmotorized traffic were collected at six locations on the off-street trail network in Minneapolis, Minnesota, in 2011. A new approach for estimating AADT values from short-duration counts, the use of day-of-year factors, is demonstrated. Analyses of variability in count data can be used to design a monitoring program that uses both continuous and short-duration counts of nonmotorized traffic. Five core conclusions may be useful for developing nonmotorized monitoring programs: (*a*) day-of-year scaling factors have smaller error than does the standard (day-of-week and month-of-year) method of AADT estimation, especially from short-duration counts (<1 week); (*b*) extrapolation error decreases with short-duration-count length, with only marginal gains in accuracy for counts longer than 1 week; (*c*) errors in estimating AADT values are lowest when short-duration counts are taken in summer (or spring, summer, and fall) months (April through October); (*d*) the impact of sampling on consecutive (successive) versus nonconsecutive (separate) days on AADT estimation is minimal but may reduce labor requirements; and (*e*) the design of a traffic monitoring program depends on the acceptable error, equipment availability, and monitoring period duration. Trade-offs in short-duration-count lengths and estimate accuracy will depend on resource constraints. Analysts can use day-of-year factors to improve the accuracy of AADT estimation. Analyses of variability in traffic counts can strengthen the design of monitoring programs.**

Traffic counts are the foundation of transportation planning programs. Over the past several decades, the FHWA, state departments of transportation (DOTs), and local governments have established and funded comprehensive networks for counting motor vehicles in each state. These agencies also have developed standard procedures for monitoring traffic, analyzing counts, identifying traffic patterns, extrapolating short-duration counts, and estimating traffic volumes at locations where traffic has not been counted (*1*). Estimated traffic volumes from these monitoring programs are used for many purposes, including planning, guiding investments, and establishing maintenance priorities.

In North America, similar monitoring networks have not been established for nonmotorized traffic. Despite efforts to understand nonmotorized traffic that date back to the 1970s or earlier, planners still lack the tools and data necessary to plan for nonmotorized travel (*2–4*). Most research to date has focused on site-specific effects on nonmotorized traffic such as weather, neighborhood demographics, and characteristics of the built environment (*5–9*); less research has explored traffic patterns on networks (*10*). Because efforts to develop nonmotorized transportation are growing, the need for robust, local programs that count cyclists and pedestrians across networks also is increasing (*11, 12*). For planners interested in nonmotorized travel, consistent methods of data collection and analysis that enable better descriptions of nonmotorized traffic patterns (e.g., estimates of bicycle miles traveled) are needed.

In Europe and in other countries outside North America, where the nonmotorized mode share is higher, research on nonmotorized travel has focused on similar topics. For example, researchers in Berlin have counted bicycles continuously since at least 1983 and have shown that daily bicycle traffic varies systematically with temperature, precipitation, and duration of sunshine (*13*). Studies from Australia, the United Kingdom, and New Zealand also focus on how weather and neighborhood characteristics affect nonmotorized traffic volumes (*14–16*). Studies in the Netherlands and Sweden show that bicycle crashes are inversely correlated with bicycle volumes (*17, 18*). Survey tools frequently are used to estimate mode share and explore travel behavior (*19–22*). A report from the Swedish National Road and Transport Research Institute recommends the use of both surveys and traffic counts to track two common policy goals: (*a*) mode share of bicycles and pedestrians and (*b*) trends in nonmotorized traffic volumes over time (*21, 22*).

Even though research into the monitoring of nonmotorized traffic is growing, the federal, state, and local agencies in the United States have not adopted standard methods (*23*). Key questions remain on best practices for most elements of monitoring, including methods to scale short-duration nonmotorized traffic counts to estimates of annual average daily traffic (AADT) (*24–28*). The FHWA recently published the first chapter on nonmotorized traffic monitoring in its authoritative *Traffic Monitoring Guide* (TMG) (*1*). The chapter offers standard procedures for monitoring motor vehicle traffic and recommends a combination of permanent reference sites and mobile short-duration sites to characterize spatial patterns in traffic. Automated continuous counts from reference sites are classified into factor groups and used to develop scaling factors. Two scaling factors typically are constructed for motor vehicles: month of year (ratio of

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average monthly traffic to AADT) and day of week (ratio of average day of week traffic to AADT). The scaling factors are applied to several short-duration counts to estimate traffic on a street network.

The state of Colorado and several cities, including Portland, Oregon, and San Diego and San Francisco, California, have initiated nonmotorized traffic monitoring programs based on this approach, but general factor groups and factoring procedures have not been validated. Because nonmotorized traffic varies more in response to weather than motorized traffic does and because weather varies regionally within states, extrapolation factors specific to different municipalities or regions will be needed.

Researchers recently have addressed three key issues in nonmotorized traffic monitoring: (*a*) the short-duration-count lengths needed to minimize error in extrapolation, (*b*) the identification of factor groups based on hourly traffic patterns, and (*c*) the development of adjustment factors for bicycle traffic. Nordback et al. (*27*) use data from a monitoring network in Boulder, Colorado, to develop guidance for short-duration monitoring. They show that short-duration counts of at least 1 week are satisfactory for minimizing the magnitude of error when using the standard scaling factor approach for motor vehicles (i.e., day-of-week and month-of-year factors) and that extrapolation error is minimized when monitoring occurs between April and October. They recommend that short-duration counts be at least 24 h long (preferably 1 week or longer) and corroborate findings from the TMG that data from at least five reference sites be used to develop factors.

Miranda-Moreno et al. derive four classifications (utilitarian, mixed–utilitarian, mixed–recreational, and recreational) from observing hourly bicycle traffic patterns at 37 locations in five cities (*29*). This classification scheme can be used to define factor groups for developing scaling factors. El Esawey et al. use multiple years of monitoring data from Vancouver, British Columbia, Canada, to show that the use of weekend and weekday factors produces results comparable to those of seven day-of-week factors, integrating weather considerations into factors improves estimates, and factor reliability degrades over time (*10*).

These findings are expanded by illustrating a new method for scaling short-duration counts and showing how a limited number of continuous-count sites can inform the efficient design of monitoring networks. Specifically, a day-of-year scaling factor (i.e., a scaling factor for each day of the year; applicable to that year only) is introduced as an alternative to the standard (i.e., month-of-year and day-of-week) scaling factors. The effect of the length and month of short-duration counts on AADT estimation is explored according to Nordback et al. (*27*). Also, the effect on AADT estimates of taking short-duration counts on consecutive or nonconsecutive days is demonstrated. Then, the implications for design of a comprehensive monitoring program are illustrated for a 78-mi (126-km) trail network in Minneapolis, Minnesota.

## DATA AND METHODS

Since late 2010, TrailMaster active infrared monitors have been used to collect continuous counts of nonmotorized traffic at six locations on the off-street trail network in Minneapolis. Wang et al. describe the procedures used to collect, adjust, validate, and aggregate counts (*30*). In brief, the monitors record a count any time the infrared beam is broken; therefore, counts reported here are for mixed-mode traffic (i.e., cyclists and pedestrians combined). Traffic volumes for 2011 varied by an order of magnitude across sites (Table 1).

### Example of Classifying Locations in Factor Groups

Previously published indexes were used to classify the study sites in factor groups (*29*). This classification is performed as an example; in the analyses that follow (e.g., length and month of short-duration counts), results are based on pooled scaling factors (i.e., no factor groups) because of the small sample size (i.e., six count sites) and to be consistent with the recommendation of Nordback et al. to use at least five continuous reference sites when calculating scaling factors (*27*). Furthermore, Miranda-Moreno et al. define locations according to bicycle traffic; here, their method is applied to mixed-mode trail traffic (*29*).

According to the criteria established by Miranda-Moreno et al., sites were classified as utilitarian, mixed–utilitarian, mixed–recreational, or recreational (Table 2) (*29*). Miranda-Moreno et al. use two traffic indexes: relative index of weekend versus weekday traffic (WWI) and relative index of morning (7 to 9 a.m.) to midday (11 a.m. to 1 p.m.) traffic (AMI):

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

$$\mathrm{AMI} = \frac{V_{\mathrm{am}}}{V_{\mathrm{mid}}} \tag{2}$$

where

$V_{\mathrm{we}}$ = mean daily weekend traffic volume,
$V_{\mathrm{wd}}$ = mean daily weekday traffic volume,
$V_{\mathrm{am}}$ = mean morning (7 to 9 a.m.) traffic volume, and
$V_{\mathrm{mid}}$ = mean midday (11 a.m. to 1 p.m.) traffic volume.

**TABLE 1 Descriptive Statistics for Counts of Off-Street Trail Traffic, 2011**

| Location | Valid Hours of Counts (%) | Annual Traffic (number of bicyclists and pedestrians) | AADT (bicyclists and pedestrians) | Segment Length [mi (km)] | Distance Traveled [mi (km)] |
|---|---|---|---|---|---|
| Lake Calhoun Parkway | 89 | 1,308,643 | 3,585 | 1.2 (1.9) | 1,583,458 (2,548,329) |
| Lake Nokomis Parkway | 93 | 538,448 | 1,475 | 1.2 (1.9) | 667,676 (1,074,520) |
| Wirth Parkway | 93 | 116,765 | 320 | 1.5 (2.4) | 171,645 (276,236) |
| Midtown–Cedar | 91 | 738,336 | 2,023 | 1.6 (2.6) | 1,151,804 (1,853,648) |
| Midtown–Hennepin | 96 | 720,714 | 1,975 | 1.6 (2.6) | 1,124,314 (1,809,407) |
| Midtown–West River Parkway | 91 | 333,395 | 913 | 1.4 (2.3) | 480,089 (772,628) |

**TABLE 2 Classification Criteria for Potential Factor Groups of Reference Sites**

| Location Type | WWI[a] | AMI[b] |
|---|---|---|
| Utilitarian | <0.8 | >1.5 |
| Mixed–utilitarian | 0.8–1.25 | 0.75–1.5 |
| Mixed–recreational | 1–1.8 | 0.35–1 |
| Recreational | >1.8 | <0.35 |

NOTE: Adapted from Miranda-Moreno et al. (*29*).
[a]Relative index of weekend versus weekday traffic.
[b]Relative index of morning (7–9 a.m.) to midday (11 a.m.–1 p.m.) traffic.

Both the AMI and WWI indexes are meant to identify sites where traffic is utilitarian or recreational. For example, sites with a low WWI value probably would be utilitarian because weekday traffic exceeds weekend traffic. Similarly, a location with a high AMI value also would be classified as utilitarian because higher traffic in the morning peak hour than at midday would indicate largely commute-based traffic. The AMI index uses the morning peak hour rather than the afternoon peak hour because the afternoon peak hour likely includes after-work recreational traffic.

### Month-of-Year and Day-of-Week Versus Day-of-Year Scaling Factors

The method used for extrapolating short-duration counts of motor vehicles typically involves using month-of-year and day-of-week scaling factors to estimate AADT values. A new day-of-year scaling factor is proposed to account better for the greater day-to-day variability in nonmotorized traffic. Instead of count data being averaged across the day of the week and month of the year, 365 separate scaling factors are calculated specific to each day of the year.

Importantly, day-of-year scaling factors apply to 1 year only and are not necessarily applicable across years. This approach accounts for peaks and lows specific to certain days (e.g., poor weather, holidays) that may be missed when data are averaged over long periods. This approach also should improve performance for short-duration counts because the scaling factors are day specific. One limitation of scaling factors for nonmotorized traffic is that they are applicable only to the city or region where the data are collected; different weather patterns in different regions make scaling factors difficult to transfer from one region to another. Figure 1 shows the day-of-year scaling factors (new method) as well as the day-of-week and month-of-year scaling factors (standard method) for 2011 data.

### Short-Duration Counts: Sample Duration and Month

Error associated with various lengths of short-duration counts was analyzed in AADT estimates according to Nordback et al. (*27*). Any given monitoring location will have day-to-day variability in traffic counts because of weather, individual traffic behavior, and other variables. In general, the error associated with extrapolating from short-duration counts should decrease as the short-duration-count length increases. The study analysis aims to find the point of diminishing return for estimation error as the length of the short-duration count increases.

First, count periods ($n = 50$) were randomly pulled from year-2011 counts as a basis for the analysis. An average scaling factor was calculated for each location and count period based on an average of the other five locations. Then, short-duration counts were scaled to AADT values and compared with actual AADT for that location. Mean absolute error was calculated for comparison. This analysis was repeated for short-duration-count periods of 1 day, 3 days, 1 week, 2 weeks, and 1 month. It was performed for both the standard method of deriving scaling factors and the new day-of-year method.

The impact on estimation error of taking short-duration counts during different months also was explored. For each count period length, the random sample was stratified by month to assess whether some months seemed to be better for estimating annual traffic. Again, this analysis was repeated for all count period lengths (1 day, 3 days, 1 week, 2 weeks, and 1 month) and both methods of scaling to AADT values. Then, the equipment needs associated with different short-duration-count lengths were estimated.

### Design Scenario: Planning a Short-Duration Count Campaign In Minneapolis

As a practical example of the decisions needed to implement a comprehensive monitoring program for any traffic network, a design scenario was created for a hypothetical short-duration monitoring program on the Minneapolis off-street trail network. The aim of the program is to estimate annual miles traveled for the entire trail network. The process entails choosing monitoring segments, developing protocols for count length, and scaling to estimated AADT for each segment when monitoring must be completed in a specific amount of time. In this scenario, counts are collected over 7 months at 78 locations and 125 monitoring sites (because bike and pedestrian traffic is separate at some locations). From these assumptions, the number of counters necessary to complete the monitoring campaign was calculated for different short-duration-count lengths.

Also explored was whether sampling on consecutive or nonconsecutive days (e.g., five temporally separate 1-day samples versus one 5-day sample) affected error in the estimated AADT value. AADT estimation error is presented as well as the additional labor needed to complete a sampling campaign where counters are relocated more frequently.

## RESULTS

The analysis is tailored to inform decisions on how to plan a monitoring program for the trail network in Minneapolis. Results led to five main conclusions:

1. Day-of-year scaling factors result in smaller error than the standard factors (day-of-week and month-of-year) in estimated AADT, especially for short-duration (<1 week) counts.
2. Extrapolation error decreases with the length of the short-duration counts, with only marginal gains in accuracy for counts longer than 1 week.
3. Extrapolation error is lowest when short-duration counts are taken when volumes are highest—here, in summer (or spring, summer, and fall) months (April through October).
4. The impact on AADT estimation of sampling on consecutive versus nonconsecutive days is minimal, but sampling on consecutive days likely reduces labor requirements and is more efficient.

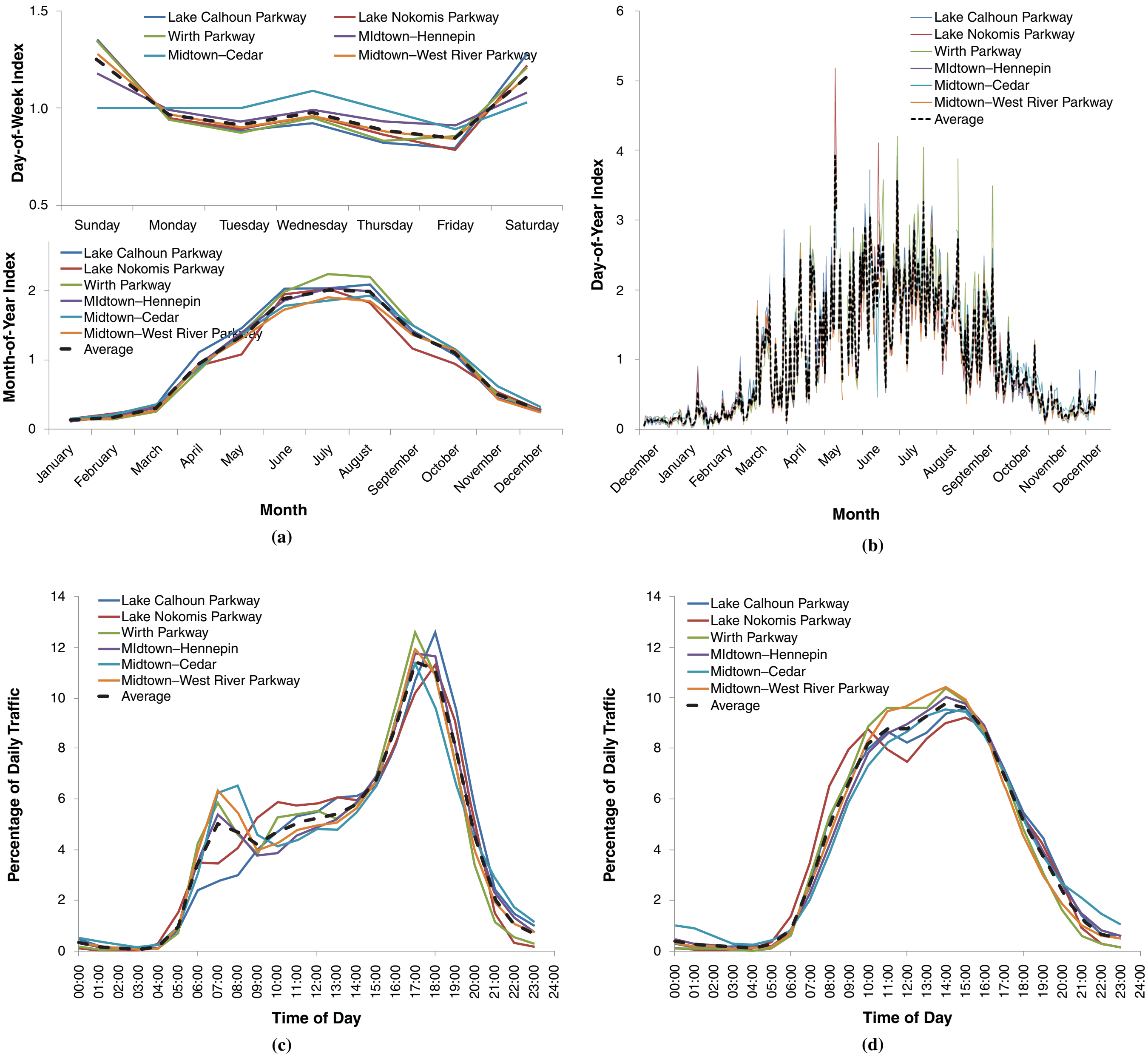


FIGURE 1 Seasonal, daily, and hourly trail traffic patterns: (*a*) month-of-year and day-of-week scaling factors, (*b*) day-of-year scaling factors, (*c*) hourly proportion of weekday traffic, and (*d*) hourly proportion of weekend traffic.

5. The design of a traffic monitoring program depends on the acceptable error, equipment availability, and monitoring period duration. Trade-offs in short-duration-count lengths and estimate accuracy will depend on resource constraints.

## Example of Factor Group Classification for Reference Sites

The WWI and AMI values were calculated for each location, and the locations fell into two categories: mixed–utilitarian and mixed–recreational (Table 3). Even though the feasibility of applying these methods separately was explored for these two factor groups, pooled results are reported for all six locations because the AMI values in these two categories overlap and because if the reference sites were

TABLE 3 Factor Groups Available at Current Sites

| Location | WWI[a] | AMI[b] | Factor Group |
|---|---|---|---|
| Midtown–Hennepin | 1.19 | 0.77 | Mixed–utilitarian |
| Midtown–Cedar | 1.02 | 0.95 | Mixed–utilitarian |
| Lake Calhoun Parkway | 1.52 | 0.50 | Mixed–recreational |
| Lake Nokomis Parkway | 1.45 | 0.65 | Mixed–recreational |
| Wirth Parkway | 1.44 | 0.74 | Mixed–recreational |
| Midtown–West River Parkway | 1.34 | 0.84 | Mixed–recreational |

[a]Relative index of weekend versus weekday traffic.
[b]Relative index of morning (7–9 a.m.) to midday (11 a.m.–1 p.m.) traffic.

separated into two groups, the minimum number of locations for factor groups (as recommended by Nordback et al.) would not be met (*27*). Even though the variation in traffic across sites is comparable (Figure 1), pooling factor groups may increase estimation error at some sites. As monitoring occurs at more sites, the use of separate factor groups may be feasible. Because monitoring has not occurred on other segments, whether any sites in Minneapolis fall in the other two categories (utilitarian and recreational) could not be determined. To establish a more robust reference site network, continuous counts should be added in five or more locations for all factor groups.

## AADT Estimation Error and Short-Duration-Count Length

As described earlier, 50 random count periods (1 day, 3 day, 1 week, 2 weeks, and 4 weeks) were used to explore the impact of short-duration-count length on AADT estimation error. Mean absolute error was calculated among locations and count periods for both methods of scaling counts to AADT (Figure 2). Results indicated that the day-of-year scaling factors had smaller AADT estimation error than the standard (month-of-year and day-of-week) factors. This effect was especially pronounced for short count periods and attenuated as the count period approached 1 month. For example, the AADT error when extrapolating from 1-day counts with the new method was slightly more than 20%; error when the standard method was used was nearly 40%. The point of diminishing return for minimizing error from extrapolation seemed to be 1 week, similar to the findings of Nordback et al. (*27*).

To illustrate the greater need for resources to implement longer short-duration counts (or the limitations associated with the availability of portable counters for short-duration counts), the number of portable counters needed to complete the short-duration counts at 78 trail locations was plotted over a 7-month monitoring period. [Assumptions: 125 monitoring sites (because of separated traffic), one visit per site for each short-duration-count length, and monitor relocation takes 1 day.] For example, if only two counters are available, then the maximum short-duration-count lengths possible in the 7-month limit would be 3 days. With this constraint, the expected estimation AADT error would be 15% with the day-of-year factors and 27% with the standard factors. Figure 2 illustrates how an analyst can estimate equipment needs to obtain desired levels of accuracy within a fixed monitoring period. For example, to achieve an error of 11%, short-duration counts would need to be 2 weeks long, and eight portable counters would be needed.

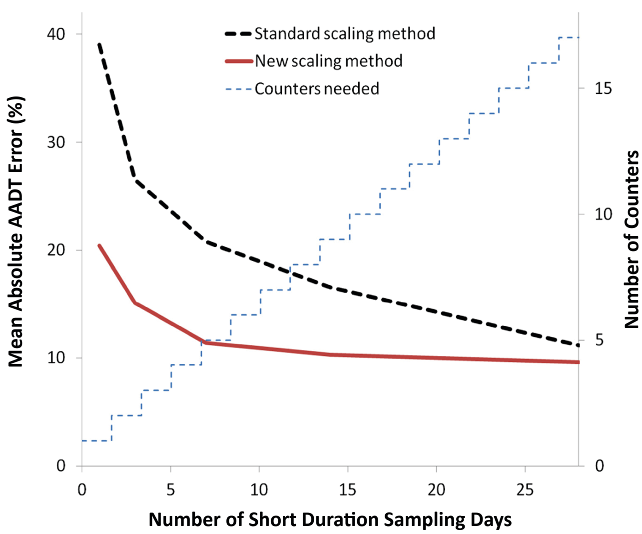


FIGURE 2 Mean absolute AADT estimation error using standard (black dashed line) and new (red solid line) scaling methods [number of counters needed to complete design scenario (7-month sampling campaign) is denoted by blue staircase-shaped plot].

## Deploying Short-Duration Counts in Different Months

The impact on AADT estimation error of sampling in different months was explored by stratifying the results from the random sample by month (Figure 3). This analysis was repeated for the standard and new methods of scaling to AADT. The day-of-year scaling factors performed better than the standard factors. The difference is larger for the shorter count periods; as the count duration increased, the difference between results using the standard and new scaling methods diminished. AADT estimation error across months was nearly equal for the two scaling methods for multiweek count durations.

For both methods, error in estimated AADT was greatest when the weather patterns were most variable in Minneapolis (early spring and late fall) and lowest in the summer and near-summer months. Use of the day-of-year scaling factors seemed to stabilize the error during summer and near-summer months to an ~10% error for the medium to long count durations. These results indicate that short-duration counts are best undertaken from April through October with the day-of-year factors. This finding corroborates the results that Nordback et al. obtained by using the standard factors (*27*).

## Design Scenario: Planning a Count Campaign in Minneapolis

For this design scenario, (*a*) segments are chosen for short-duration counts and (*b*) trade-offs are explored between short-duration-count length and labor requirements. The design scenario shows that data from some continuous-count sites can inform decisions about how and where to develop larger-scale monitoring programs for nonmotorized traffic.

### *Choosing Trail Segments for Sampling*

To locate counters and estimate AADT and miles traveled, the network must be divided into distinct segments with consistent traffic flows. Because no counts currently exist on most of the network, segments for this example were chosen using local knowledge of trail traffic (e.g., staff members at the Minneapolis Park and Recreation Board and the City of Minneapolis were consulted and the authors' knowledge of trail traffic was used). Break points typically were assigned at feeder facilities (e.g., streets with bicycle facilities) or natural generators of trail traffic (e.g., parks or beaches).

In total, 78 segments were identified that averaged 1 mi (1.6 km) in length, including sites with the reference monitors (range: 0.28 to 1.8 mi [0.45 to 2.9 km]; see Figure 4). Because users can access trails from informal access points as well as intersections and because limited information is available on traffic levels between monitoring points, whether traffic flows on these individual segments are

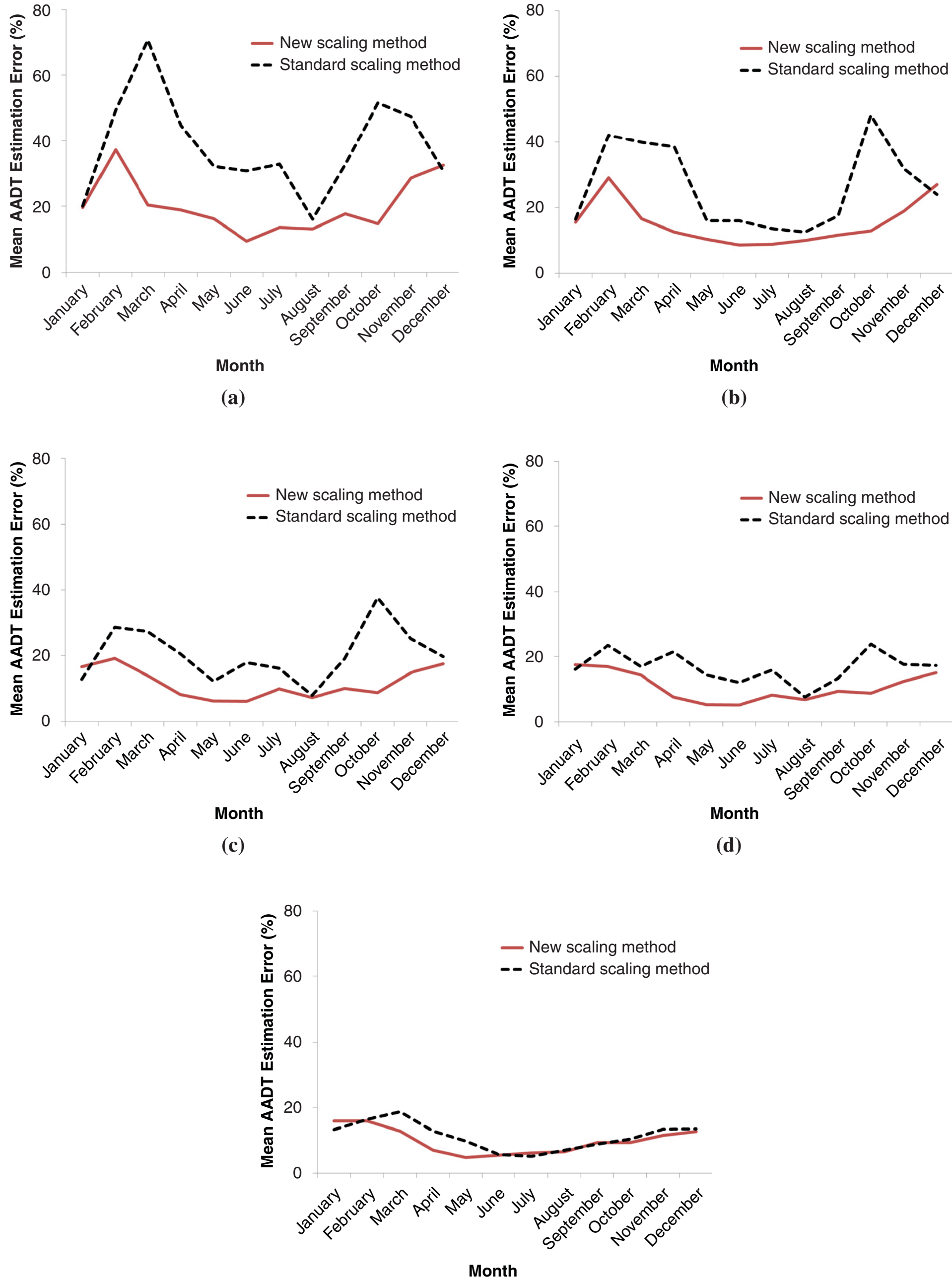


**FIGURE 3 Estimated mean absolute AADT error, stratified by month, with both methods of scaling: (*a*) 1-day short-duration count, (*b*) 3-day short-duration count, (*c*) 1-week short-duration count, (*d*) 2-week short-duration count, and (*e*) 4-week short-duration count.**

consistent and whether 78 segments is the optimal number is unknown. However, for Minneapolis, available evidence suggests that mile-long segments are a reasonable starting place.

Allocating count sites likely is best undertaken as an iterative process; future monitoring would provide more data and potentially a stronger basis for site selection. In motorized vehicle monitoring, traffic segments are determined iteratively by examining variation in traffic flow through a network link. The Minnesota DOT has established criteria for determining traffic segment breaks that consist of acceptable relative changes in traffic flow for ranges of motor vehicle AADT values (e.g., for AADT values between 1,000 and 4,999, increases in traffic along the segment of more than 20% call for a break) (*31*). On the Midtown Greenway, given that the variation in nonmotorized AADT between the Cedar and Hennepin monitoring sites is only 2%, it is reasonable to assume flow between the sites is consistent. Given the large (~120%) difference in flow between the West River Parkway and Cedar sites, subdivision into one or more segments is appropriate. Future work could usefully include field validation by monitoring different points in a segment, to determine within-segment consistency in traffic flows.

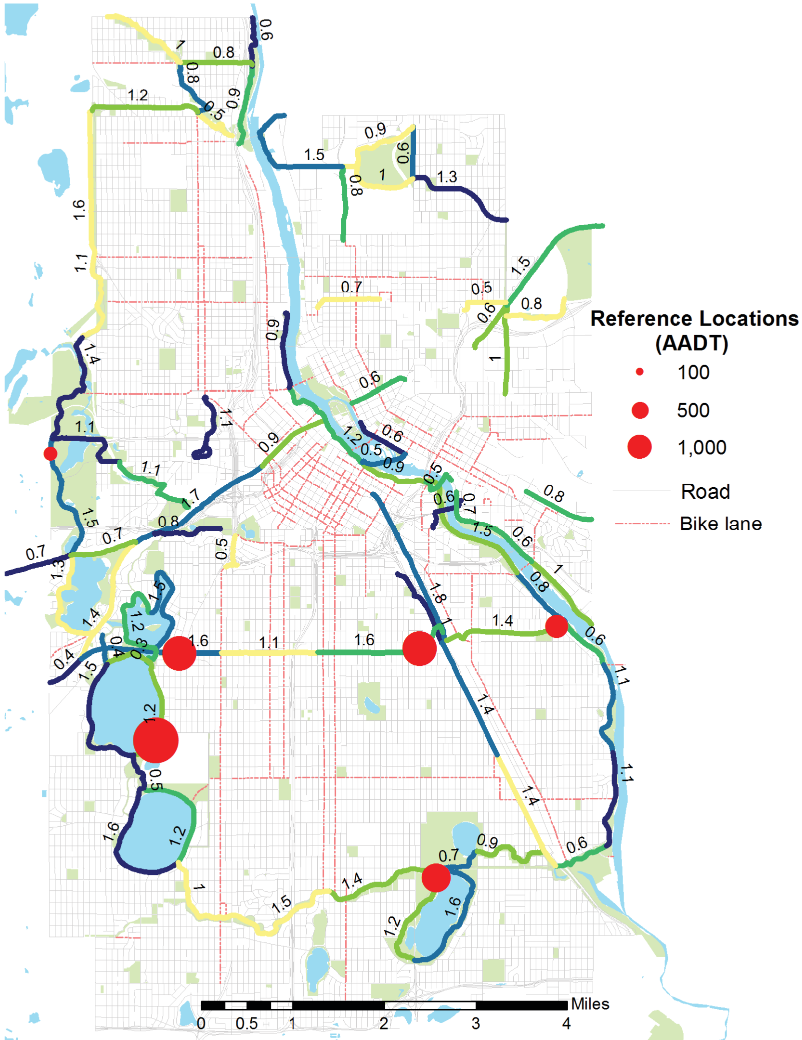


FIGURE 4 Design scenario: trail segments (78 total) for short-duration-count and continuous-count sites [reference location icons scaled by AADT: sum = 78.5 mi; mean = 1.0 mi; minimum = 0.28 mi; maximum = 1.8 mi (1 mi = 1.61 km)].

### *Estimating Feasibility of Various Short-Duration Count Lengths with Constrained Resources*

Next, a scenario analysis was performed to explore how best to implement short-duration counts and what count lengths would be possible. Calculations assume the following:

1. All 78 trail segments must be monitored at least once in a single monitoring period.
2. Sampling will occur during the months with the lowest mean AADT estimation error (April through October [210 days]) (Figure 3).
3. Six sets of monitoring equipment are available for short-duration counts in addition to the six reference locations.
4. Because bike and pedestrian traffic is separate at some locations, some segments will require multiple counters (one counter, 47; two counters, 27; three counters, 4) and a 10% subsample of the segments will be resampled for internal validation (one counter, 5; two counters, 2; three counters, 1). The total number of monitoring sites is 125.
5. The time to relocate monitors is assumed to be 1 day, resulting in 21 days lost to relocation per count cycle (i.e., time to count all segments).
6. Relocation of portable counters requires 8 h or 1 person-day.

Long-duration, consecutive-day counts require few samples per location; short-duration, nonconsecutive counts allow more temporally separate samples at each location. To determine whether long or short count periods are better, nine scenarios were constructed. For each scenario, day-of-year scaling factors are used to calculate mean AADT estimation error and the proportion of days used to relocate monitors. Count cycles (i.e., the length of time needed to sample all segments) were repeated until the 7 months expired. For example, for a 1-day count period, five count cycles could be completed in 7 months; for a 5-day count period, one count cycle could be completed in 7 months. To simulate the 1-day count period (Scenario 1), 5 days were selected at random from each reference location between April and October, and AADT was estimated on the basis of those observations. This process was repeated for each location and scenario (Table 4).

**TABLE 4 Description of Design Scenarios for 210 Total Available Sampling Days**

| Scenario | Count Period (days) | Count Days Per Cycle | Days Per Cycle (with relocation) | Number of Cycles Possible | Relocation Days | Total Days | Person Hours for Relocation |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 125 | 42 | 5.1 | 105 | 208 | 840 |
| 2 | 2 | 249 | 62 | 3.4 | 70 | 187 | 560 |
| 3 | 3 | 374 | 83 | 2.5 | 53 | 166 | 420 |
| 4 | 4 | 498 | 104 | 2.0 | 42 | 208 | 336 |
| 5 | 5 | 623 | 125 | 1.7 | 35 | 125 | 280 |
| 6 | 6 | 748 | 145 | 1.4 | 30 | 145 | 240 |
| 7 | 7 | 872 | 166 | 1.3 | 26 | 166 | 210 |
| 8 | 8 | 997 | 187 | 1.1 | 23 | 187 | 187 |
| 9 | 9 | 1,121 | 208 | 1.0 | 21 | 208 | 168 |

Figure 5 shows mean absolute AADT estimation error and time required for relocation in each scenario; scenarios compare the effect of sampling on consecutive versus nonconsecutive days (i.e., as count period length increases, counts are collected on consecutive days; short-duration-count periods are resampled at different times of year). The mean error does not differ much across scenarios, thus suggesting that the choice between consecutive and nonconsecutive days is not significant, but more labor is required to relocate the monitors multiple times for short durations (e.g., 50% of days in Scenario 1 versus 10% of days in Scenario 9) (Table 4). Furthermore, more count data are collected in Scenario 9 (1,121 count-days) than in Scenario 1 (623 count-days). This analysis does not include a margin of error that may be important for unexpected events that may arise (e.g., lost data, vandalism, or human error). To account for contingencies, the better choice may be a short count duration (e.g., 1 week) that allows for extra sampling time if needed and only slightly increases the time required to relocate monitors.

## DISCUSSION OF RESULTS

Analyses show that use of day-of-year scaling factors results in lower error in estimated AADT than are obtained with standard day-of-week and month-of-year factors, especially for estimates from short-duration counts of 1 week or less. The study analyses corroborate and generalize the findings of Nordback et al. that errors in estimated AADT are minimized when short-duration counts are taken between April and October and that short-duration samples of more than 1 week result in only marginal improvements in estimated AADT (*27*). Also, results demonstrated that short-duration counts taken on consecutive days rather than randomly selected days produce similar estimated AADT values when the day-of-year scaling factors are used, thus indicating that analysts can minimize labor costs by conducting short-duration counts on consecutive days. The results highlight the need to customize monitoring strategies for local monitoring networks. One example was illustrated for a 78-mi (126-km) trail network in Minneapolis.

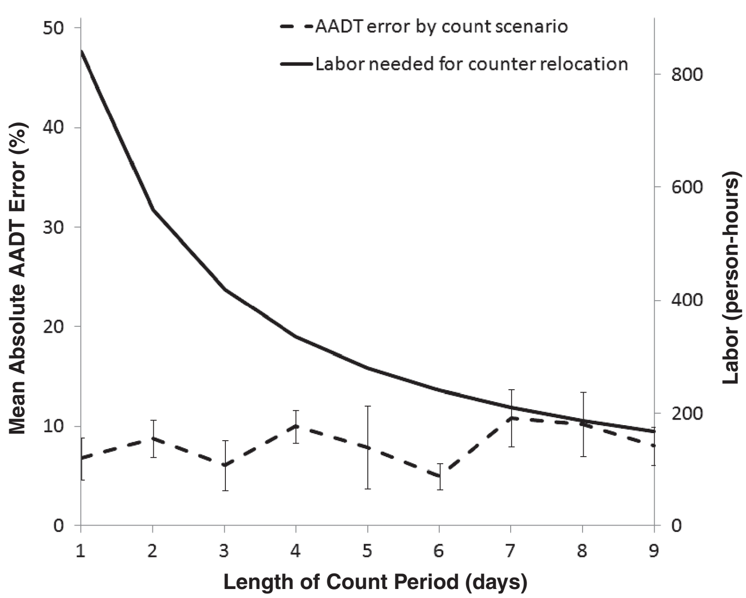


FIGURE 5 Mean absolute AADT estimation error and person-hours required to relocate monitors for each short-duration-count scenario (bars = standard error).

The proposed approach that uses day-of-year scaling factors has several limitations, including the following:

1. Day-of-year scaling factors can be used only in metropolitan areas with similar daily weather patterns and not across larger regions or states. Additional research is needed to determine the geographic scale over which day-of-year factors can be used. That scale may vary across regions within states.
2. Day-of-year scaling factors are useful only for the year for which they are calculated. Therefore, they are not as general as the factors used in the standard approach. From a practical perspective, whether it matters depends on the overall monitoring scheme and schedule for producing estimated AADT. As long as continuous monitoring sites are operating, year-specific day-of-year factors can be produced. If short-duration counts are taken annually, then AADT can be estimated accurately. In many cases, the accuracy improvements may warrant the use of day-of-year factors. If resource shortages preclude taking continuous counts in a given year, then the use of standard factors may be necessary (though less accurate).
3. Day-of-year factors only can be applied retroactively, after the end of a calendar year, when all daily reference site counts have been recorded. This aspect has practical implications. Use of the standard approach enables state DOTs to post estimated AADT values as soon as short-duration counts are available because the estimates reflect general or average traffic patterns. For example, a state DOT that verifies a 48-h count of vehicular traffic collected in April can post the updated AADT value immediately because factoring calculations are embedded in the software. Whether delay poses a problem depends on the urgency of the need for estimates and their accuracy. Trade-offs may be warranted in cases such as the allocation of maintenance resources. In addition, the use of day-of-year factors may be combined with the standard approach to produce more timely estimates that can be revised after the end of the year. This hybrid approach probably would need multiple years of continuous data to estimate the proportion-of-year factor because the length of the nonmotorized travel season will vary from year to year.

One limitation of the study example, but not the proposed method, is that day-of-year factors were estimated for combined factor groups (i.e., mixed–recreational, mixed–utilitarian) because this network currently has only six reference monitoring sites. In practice, the number of continuous reference sites needed to enable factor development for different factor groups depends on the traffic patterns that exist at other locations in the network. Factor groups only can be determined iteratively, as data are obtained from short-duration counts and analyzed and the variation in patterns is determined across sites. As data for short-duration counts are obtained, some segments may need to be combined and others broken up. Given the recommendation of five continuous monitors per factor group by Nordback et al. and the classification criteria adapted from Miranda-Moreno et al., 15 reference sites would be needed if recreational locations also exist in the network and 20 locations if both recreational and utilitarian sites exist (*27, 29*). The likely effect of pooling factor groups is to overestimate the error associated with this method of extrapolation. Error can be reduced by refining factor groups.

This scenario illustrates how analysts can work within time and equipment constraints to maximize efficiency in data collection. This approach involves maximizing the short-duration-count lengths, thereby increasing the accuracy of estimated AADT derived from those lengths. The study example included a 7-month window for short-duration counts, but the number of months or season of year appropriate for short-duration counts may vary regionally or for different weather patterns. Year-round short-duration counts may be feasible in places with arid or subtropical climates, for example; the appropriate seasons for monitoring may be different in new locations. The time required to relocate portable counters is an important figure of merit, with the common goal of reducing that time. The person-hours required for relocation were estimated but did not include other resource requirements, such as travel to monitoring sites, time addressing site vandalism, or time spent maintaining equipment performance; most (but perhaps not all) of these resource requirements may scale proportionally as the number of monitors used increases. Overall, the scenario demonstrated how an agency could monitor a 78-mi (126-km) trail network in 1 year with a few reference sites and six portable counters. As more agencies implement comprehensive monitoring programs, their results will aid understanding of program design.

## CONCLUSIONS

Use of day-of-year scaling factors results in better estimated AADT values than use of standard day-of-week and month-of-year factors because day-of-year factors better account for variations in traffic associated with daily variations in weather and other factors. Analysts with responsibility for nonmotorized traffic monitoring programs may want to consider the day-of-year factoring approach to augment or replace existing approaches. For monitoring programs of predetermined length (e.g., 1 year), analysts should monitor when volumes are highest (e.g., April through October in temperate zones) and preferably for at least 1 week [although results acceptable for some uses (e.g., ±20%) may be obtained with count durations of only 24 h]. By increasing the number of portable counters for short-duration monitoring, analysts can increase monitoring program efficiency. Future research also should focus on the validation of counting and scaling methods across regions; additional study of comprehensive monitoring programs in other regions is needed to confirm the implications of the design scenario.

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