Estimating Annual Average Daily Bicyclists: Error and Accuracy

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ABSTRACT
Cities around the country are investing in bicycle infrastructure for which they seek to report bicycle use and safety improvements in order to secure additional transportation funding. A fundamental data need for performing safety studies and reporting facility use is bicyclist traffic volume. To address this need, manual bicycle counting programs have been established that count cyclists for a few hours per year at each designated location. A key issue that arises in designing counting programs (apart from the count locations) is the timing and frequency of the counts required to obtain a reliable estimate of annual average daily bicyclists (AADB). In particular, in which days of the week, hours of the day, and months of the year should counts be collected? And most important to the program cost, how many hours should be counted? This study uses continuous bicycle counts from Boulder, Colorado to estimate AADB and analyze the estimation errors that would be expected from various bicycle-counting scenarios. AADB average estimation errors were found to range from 15% with four weeks of continuous count data to 54% when only one hour is counted per year. This study finds that the most cost effective length for short-term bicycle counts is one full week, using automated counting devices specifically calibrated for bicycle counting. Seasons with higher bicycle volumes have less variation in bicycle counts and thus more accurate estimates.

INTRODUCTION

Cities around the country are investing in bicycle infrastructure and seek to report resulting increases in bicycle use and safety as well as gain additional access to transportation funds. National transportation funding, through state transportation departments, is allocated based on estimates of annual average daily motorized-traffic, but no equivalent metric is available for bicycle use. National surveys provide city-level estimates of bicycle use, but for evaluating the use and safety on specific facilities or with before and after improvements, estimates of average use are required.

Seeing the need to estimate bicycle use on roads and paths, transportation professionals have established manual bicycle counting programs with the National Bicycle and Pedestrian Documentation Project (NBPDP) even providing guidance for such programs (*1*). Such programs typically send staff or volunteers to count bicycles on roads or paths for two to twelve hours per day once or twice per year. These manual count programs are intended to facilitate an estimation of bicycle use on each facility counted. But is this enough? How many hours of bicycle counts are needed before accurate estimates of annual bicycle use can be made? This study provides an analysis of the errors in annual average daily bicyclists (AADB) estimation due to count duration and frequency and offers some recommendations.

In order for a count to be representative of actual bicycle use on a facility, it would ideally be equal to the use on an average day, but rarely is any particular day truly average. For this reason, methods for annualizing short-term counts are needed. For motorized traffic estimation, counting programs consist of a combination of continuous and short-term automated counters. Well-established methods are applied to this data to estimate annual average daily traffic (AADT) on all roadways of interest. Can motorized data collection and statistical traffic volume estimation methods be applied to non-motorized modes? Since no industry-wide accepted data collection and traffic volume estimation method exists for bicycle use, efforts are underway to establish a standardized methodology (*2*). This study informs these efforts by providing estimates of error for various short-term counting scenarios and makes specific recommendations of when and how long to count bicyclists for the most cost effective accuracy in estimating AADB.

In order to study the accuracy of estimating AADB from short-term counts, data from Boulder, Colorado were used. The city has been collecting continuous bicycle counts using automated inductive loop counters since 1998 at twelve locations around the city. These continuous counters provide the basis from which factors were computed to estimate AADB using methods outlined in the Traffic Monitoring Guide (TMG) (*3*). In order to calculate the error of AADB estimates for different count scenarios, four sets of test data, each including one complete year of counts, were extracted from the continuous count data. The error for each scenario was examined and the most cost effective short-term count scenarios are recommended.

This paper describes the current practice for estimating bicycle volumes under the State of the Practice section; details the data used in the Data section; explains the methods used to estimate AADB and to compute the error associated with each count scenario in the Methods section; presents the AADB estimation errors for each scenario in the Results section; and concludes with recommendations for most cost effective counting programs in the Conclusions and Recommendations section.

STATE OF THE PRACTICE

Much work has been done to create methods to annualize *motorized* traffic counts. For motorized counts, the state of the practice is summarized in the TMG, which is being updated to include guidance on monitoring bicycle and pedestrian volumes (*3*). The TMG gives multiple methods for establishing factor groups and estimating daily and seasonal factors for estimation of AADT for motor vehicles. Factor groups are groups of continuous count sites with similar traffic patterns used to compute temporal factors which can be applied to short-term counts in order to estimate AADT.

For non-motorized modes, the NBPDP developed a set of factors for estimating pedestrian and bicycle volumes under various conditions (*1*). It provides factors for combined pedestrian and bicycle counts on paths. While factors are provided for different climate regions, the behavior of cyclists and pedestrians varies substantially across the country, such that calculating annual bicycle and pedestrian volumes using one set of nationally calibrated factors may result in substantial error.

The NBPDP recommends that weekday short-term bicycle counts be taken on a Tuesday, Wednesday, or Thursday during the evening peak hour, assumed to be 5:00 PM to 7:00 PM by default and that weekend counts be taken on Saturday 12:00 PM to 2:00 PM. The NBPDP suggests that both weekday and weekend counts be collected during a designated week in mid-September. Around the country, teams of volunteers or staff members are rallied to complete these counts at locations dispersed throughout the area of interest. Such efforts require substantial organization and training of volunteers and staff in order to be successful. This paper will discuss the accuracy of this widespread approach.

Recently, FHWA sponsored a thorough review of the literature and methods used for counting bicycles and pedestrians (*4*). The study found that the main reasons for counting cyclists are for evaluating projects and safety analysis and that no standard factoring method for bicycle counts has been established. They also report that the common practice of using several hours of count data to extrapolate annual counts can lead to skewed results and that over 24-hours of counts should be collected when using short-term counts to estimate annual traffic.

Internationally, a recent report from Sweden studied bicycle and pedestrian data for cities. They recommend that a harmonized approach of both surveys and count data be used to understand bicycle and pedestrian use and specifically recommend that short-term counts should include at least two-weeks of count data (*5*).

Additional work is underway through the National Cooperative Highway Research Project 8-78, which will be producing a guide for measuring bicycle and pedestrian use entitled “Estimating Bicycling and Walking for Planning and Project Development” (*6*).

To date, the errors in AADB estimation have not been systematically analyzed in a published work. This paper provides such an analysis.

DATA

The continous bicycle count dataset used in this analysis was provided by the city of Boulder. Since 1998, continuous bicycle counts have been recorded in Boulder using automated inductive-loop bicycle counters. This study uses continuous counts from twenty-six stations at twelve locations from 1999 through 2012 totaling 930,290 hourly observations. While some of the count stations record bicycles by direction of travel, this study focuses on total counts in both directions on paths and roads.

The accuracy of this dataset has been previously assessed (*7, 8*). While some data were removed for reasons of inconsistency (technical issues caused counts in some years to be significantly lower than in other years), most counts were used even if under- or over-counting was observed. As long as the inaccuracies are consistent over time, the data could still be used for this study since the relative change in the counts is of interest rather than the absolute volumes.

AADB averaged for all years at each continuous count station is shown in Figure 1, which illustrates that the stations can be roughly divided into three categories based on AADB: low (<200), medium (200 to 600), and high (>600).

The full set of continous bicycle count data was used to estimate factors for computing AADB. A subset of this data, four full years as listed in Table 1, was used to compute the error for the various short-term count scenarios. The test data were not removed from the dataset before the factors were created, and this will likely result in somewhat lower errors in estimating AADB. A full year of hourly count data was needed so that actual AADB would be known for each set of test data. Few such years existed in the dataset since many months and some years of hourly counts are missing due to various problems such as power outages and lack of staff time to collect data (*9*).

METHODS

There are four fundatinal steps to the analysis. First, the continuous count data were used to create hourly, daily, and monthly factors. Second, estimates of AADB were computed by multiplying these factors by the hourly counts in the test data under the various scenarios. Third, count scenarios to be tested were chosen and the resulting AADB estimates were compared to the actual AADB by computing percent differences and absolute percent differences. Finally, the AADB estimation errors were examined by month for one count scenario, and the AADB error is compared to the error of estimating AADT for motor vehicles.

Creating Factors

Prior to creating factors, the continuous count data were divided into two factor groups: those stations with clear commute patterns and those without. Figure 2 shows examples of stations with and without clear commute patterns. Stations with commute patterns were identified as those whose average peak morning and evening peak hours were both higher than the noon peak hour. Half of the stations showed clear commute patterns, dividing the stations evenly into two groups for factoring.

The TMG computes AADT by multiplying the 24-hours of count data by a daily, monthly (or seasonal), growth, and axle factors that are computed from the continuous counts in the factor group. Daily and monthly factors are generally computed by dividing the AADT by the daily average count for a particular day or month. State departments of transportation use different variations of exactly how these factors are computed, but their methods must be approved by the Federal Highway Administration because AADT volumes are used as part of the formula for allocating transportation funds to states.

For this study, growth factors and axel factors were not used. Since the study investigated only counts within the year of interest, growth factors were not used. Axle factors were not needed as manual counts and counts from bicycle-specific temporary automated counting equipment are typically already in terms of total bicycles.

Like motor vehicle factors, daily and monthly factors for bicycle use can be computed in multiple ways. Since many non-motorized count programs collect less than 24-hours of counts, an hourly factor is also needed to adjust the hourly count up to a day. Two methods for computing these factors were employed in this analysis. Both use the average AADB for the factor group for a given year as the numerator for most of the factors.

First, a straight-forward method for computing factors was used, computing monthly factors by dividing the AADB for that year by the average daily count for that month, computing daily factors by dividing the AADB by the average daily count for that day of the week, and computing hourly factors by dividing the AADB by the average hourly count for that hour of the day. The details of this factoring method are shown in Equation 1.

Second, a set of peak-hour specific factors were computed using a subset of the continuous count data for the peak hours of 8:00 AM to 9:00 AM, Noon to 1:00 PM, and 5:00 PM to 6:00 PM (8am, noon, and 5pm) on Tuesdays, Wednesdays, and Thursdays (TWR days) to compute the denominator of the factors. Those days are associated with the highest bicycle use at locations with commute patterns and those days are the typical days on which motor vehicle counts are collected. The daily and hourly factors were combined and the average of the three peak hours was used instead of creating separate factors for each peak hour. The details of this factoring method are shown in Equation 2.

Estimating AADB

AADB was estimated by multiplying the known short-term count by appropriate hourly, daily and monthly factors. For short-term counts of 24-hours or more in duration, only daily and monthly factors were needed. For short-term counts of a week or more in duration, only the monthly factor was applied to the average of the daily counts during that week.

Equation 1 shows how AADB was estimated for a one-hour short-term count. Such a program would estimate AADB for a location based only on one-hour of counts on one day of the year and the factors already computed for a representative factor group.

$$\mathrm{AADB}_e = c_{kh} * H_{yf} * D_{yf} * M_{yf} \qquad (1)$$

where:

AADB_e= estimated annual average daily bicyclists
c_{kh} = known count for one hour
H_{yf} = hourly factor for a given hour of the day in a given year *y* for a factor group *f*.
= (actual AADB for that year)/(average hourly bicyclists for that hour in that year)
D_{yf} = daily factor for a given day of the week in a given year *y* for a factor group *f*.
= (actual AADB for that year)/(average daily bicyclists for that day of the week in that year)
M_{yf} = monthly factor for a given month in a given year *y* for a factor group *f*.
= (actual AADB for that year)/(average daily bicyclists for that month of that year)

The second factoring approach calibrates factors specifically for a short-term count program that counts all three peak hours (8am, noon, and 5pm) on any single Tuesday, Wednesday, or Thursday (TWorR day) in a given year. The method is detailed below:

$$\mathrm{AADB}_e = c_{kp} * D_{pyf} * M_{pyf} \qquad (2)$$

where:

$AADB_e$= estimated annual average daily bicyclists
c_{kp} = known sum of three peak hour counts (8am, noon, and 5pm) on one TWorR day.
D_{pyf} = daily factor for a given month in a given year y for factor group f for the average of the three peak hour counts for all TWR days.
= (average daily count per TWR day for a given month in a given year)/(average three peak hour count per TWR day for a given month and year)
M_{pyf} = monthly factor for a given month in a given year y for factor group f.
= (actual AADB for that year)/(average daily count per TWR day for a given month in a given year)

Comparing Scenarios

Several short-term count scenarios were investigated as listed in Table 2. These scenarios were chosen because they represent reasonable or typical count programs used in the U.S. All of the scenarios assumed that counts would be collected on days and times throughout the year, regardless of weather and holidays. This assumption introduces some additional error, as the week between Christmas and New Year holidays, for example, is likely not to be representative of the whole year.

Three different one-hour count scenarios were investigated. First, a one-hour count was assumed to be collected at any hour between 7:00 AM and 7:00 PM on any day of the week including weekends, which would model the hypothetical situation where staff members or volunteer were sent to count bicycles at a different intersection every other hour. The second one-hour count scenario also assumed that one-hour counts would be collected any hour between 7:00 AM and 7:00 PM but restricted the days of counting to all TWR days. The third one hour count scenario further restricted the one hour of counts to only peak hours (8am, noon, and 5pm) on all TWR days, since those are the times when the highest bicycle counts typically occur for locations with commute patterns and because again, those are the times that are often used in motor vehicle count programs.

One two-hour count scenario was investigated. This scenario was similar to the NBPDP count program since it specifies counts from the evening peak hours (5:00 PM to 7:00 PM) on all TWR days. Because it also samples these periods year round instead of on days specifically chosen as representative, the error from this counting scenario is likely to be higher than that from NBPDP short-term counts.

One three-hour count scenario was included. This program was based on a specific turning movement count program used by the city of Boulder for signal timing purposes (primarily for motor vehicles). Because the second set of factors was developed specifically for this count scenario, this scenario may have a lower associated error. While the specific hours when turning movement counts are collected vary from program to program, this scenario is an example of one such program.

Similarly to the three-hour count scenario above, the nine-hour count scenario specifies that counts are collected during the three peak hours (8am, noon, and 5pm) for all three TWR days of a given week. While the authors are not familiar with any specific count program of this type, it could be a rational approach. The set of peak hour specific factors was used for this scenario.

Two twelve-hour count scenarios are investigated. Both require that counts are taken during the twelve hour period 7:00 AM to 7:00 PM. The first scenario allows such counts to be collected on any day of the week, including weekends, while the second scenario restricts count to just TWR days. Both were computed using the set of hourly, daily, and monthly factors.

The remaining count scenarios specify twenty-four hours or more of short-term counts. Such counts would usually be collected using an automated bicycle counting device such as a tube counter specifically calibrated to bicycles. The week-long and multi-week count scenarios are typical of the short-term count program currently used by the Colorado Department of Transportation for combined bicycle and pedestrian counts.

The count scenarios were compared by computing the average absolute percent difference error and the standard deviation of the average percent difference error between the actual AADB and that predicted for each model for the four test datasets. These two means of computing error are detailed below in Equations 3 and 4.

$$\text{Error as \% Difference} = (AADB_e - AADB)/AADB \quad (3)$$

$$\text{Error as Absolute \% Difference} = |AADB_e - AADB|/AADB \quad (4)$$

where:
$AADB_e$ = estimated AADB
AADB = actual AADB

Methods for Analyzing Error

After the error was computed for each count scenario, seasonal variation in AADB error was also investigated, holding the scenario constant. The three-peak hour count scenario was the chosen scenario for this analysis. The results are presented graphically. This paper ends with a brief comparison, based on a published source, to motorized volume estimation error for AADT.

RESULTS

Comparing Scenarios

The average AADB estimation error for each short-term count scenario is listed in Table 3 for each test dataset. The same information is graphed by hours of counts collected in Figure 3.

AADB estimation error changes substantially with the duration of the short-term counts (Figure 3). The shape of the curves in the upper graph of Figure 3 seem to indicate that one week of count data results in the most cost effective accuracy, since the reduction in error with additional hours of data beyond one week is not as large as reductions in error between twenty-four hours and one week of counts. Average error for scenarios requiring one or more weeks of counts is below 30%, while scenarios with shorter-time periods average as much as 60% error.

Figure 3 also shows that the location with the highest bicyclist traffic (Arap13) is associated with lower error and the location with lowest bicycle traffic (Arap38) with highest error. This may be due to lower greater variability in counts as a percent of total traffic at low volume locations.

There also appears to be a reduction in AADB error for counts collected on TWorR days as opposed to any day of the week including weekends. This can be seen by looking at the first two one-hour count scenarios and the two twelve-hour count scenarios in Table 2.

AADB estimates computed using the second set of factors, which were specifically calibrated to assume peak hours (8am, noon, and 5pm) on TWR days, were sometimes, but not always, more accurate. This can be observed by comparing the error for the three-hour and nine-hour count scenarios, which used the second set of factors, to the two-hour and twelve-hour scenarios. This is best observed in Figure 3, which shows a reduction in error for the three- and twelve-hour scenarios for the Arap 13th and Arap 38th locations but a slight increase or no increase in error for the other two test datasets. While the TMG seems to recommend the creation of such data-specific factors, and they do seem to reduce error in some cases, they also reduce the flexibility of adding other data sources with counts at times not included in the calibration.

Analyzing Error

In addition to errors related to the duration of short-term counts, volume of traffic, day of the week on which counts were collected, and factoring method, AADB estimation error is impacted by other elements such as seasonal variation, variation in hourly bicycle counts, and number of continuous count stations used to calibrate the factors. Since it was necessary to hold the count scenario constant in order to observe the effects of the other variables on AADB accuracy, one count scenario was chosen: counting on all three assumed peak hours (8,12,5) on any TWorR day.

The average AADB error with month is shown in Figure 4 and listed in Table 4. This shows that when AADB estimates are based on counts in the months of July through October, the error in these estimates is substantially lower than in other months. This seems plausible since these months tend to have higher bicycle volumes and thus less variability. Figure 5 shows that variation in bicycle counts is lowest overall for the months of May through October.

If this is the case, why are AADB estimates for May through June relatively poor for the Boulder data? Looking at the total hours of counts available from the permanent count stations (second column of Table 4), one can see that July through October have more hours of counts than May and June. Thus, it is a combination of more continuous counts available for calibrating AADB estimation factors (Table 4) and lower variability in summer counts (Figure 5) that result in lower error for July through October AADB estimates (Figure 4).

This finding underscores the importance of operating permanent continuous count stations. Though Boulder has thirteen continous count stations for each of the two factor groups, less than half of that data was actually available for any given month due to incidents when data were not collected or counters were not accurate. In effect, the data available were the equivalent to having about five or six permanent count stations per factor group, the minimum recommended by the TMG for motorized traffic. Had more continous count data been available, AADB error would likely have been lower. However, had the city only installed one or two permanent count stations, the error may have been higher.

Comparison to AADT

After discussing AADB error, one might wonder how it compares to error in motorized traffic volume estimates. According to an analysis of AADT estimates in Florida and Minnesota, average absolute percent differences in AADT estimates range from 5% to 83% per location and averaged 12% in Minnesota and 14% in Florida (*10*). While this AADT analysis was based on hundreds of locations and the analysis described herein is based on four locations, it provides perspective for understanding the errors observed in AADB. When a week of counts is available, the average AADB absolute percent difference error ranges from 15% to 30%, which is near the range observed for AADT. If four weeks of bicycle counts are available for each location, the average error is 15%, which is very close to the average error reported for AADT from 24-hour counts.

Why might more bicycle counts needed than motor vehicle counts to compute annualized daily volumes with the same level of accuracy? Bicyclist traffic volumes are lower and more variable due to weather and events than motor vehicle volumes; thus, the relatively smaller volume of bicycle counts means that the change in counts from day to day due to random or other variation is a higher percentage of the total count, which increase the variability of the counts and makes it harder to estimate average annual volumes.

CONCLUSIONS AND RECOMMENDATIONS

AADB estimation error is least when based on one or more weeks of hourly bicycle count data. On average the AADB estimation error for the one or more weeks of counts is less than 30%, assuming counts are taken year round. When based on only one hour of bicyclist counts, the error in predicting AADB can be prohibitively high, with average absolute percent differences of 54%.

Lower error is associated with locations with higher bicycle traffic and seasonality where calculated traffic volumes are made based on short-term counts collected from July through October. For these months, even when only three assumed peak hours of counts are known, there is less than 20% error as measured by average absolute percent difference between actual and estimated AADB. Regardless of which scenario is used by a city to count bicyclists, this work provides a report of what the error associated with the scenario might be.

As data sources, counting technologies, and calculation methods improve, AADB accuracy should increase. Increases in bicycle use may also lead to less variability in counts and thus higher AADB accuracy.

Based on this work, the following recommendations are made.

- Continuous bicycle counters are essential. AADB cannot be calculated from short-term counts without them. The TMG recommends at least five permanent automated motor-vehicle count stations per factor group to reduce error. Since bicycle volumes are more variable than motorized traffic volumes, more counters may be needed per factor group. This means that cities interested in or required to report bicycle volumes should **install multiple permanent automated bicycle counters** per factor group. A city with fewer than five operating permanent automated counters per factor group is likely to have higher AADB estimation error than those reported herein.
- **One week of continuous hourly counts is most cost effective for reducing AADB error.** Such counts can be collected using portable tube counters specifically designed for bicycle counting or similar equipment. If this is not possible, 12-hour counts on TWorR are the minimal information needed. While not ideal, they reduced average errors from 46% for a two-hour count to 30% in this study and provide information on weekday traffic pattern to determine if a commute patter is present. Estimates based on one-, two-, or three-hour counts were found to have average error of as much as 58%. With less than twelve hours of data collected, actual peak hours cannot be identified and the appropriate factor group (commute or non-commute) cannot be determined. If manual counting is the only data collection method available, the next best scenario based on this study is to collect data for at least the three peak hours on TWR at each location.

- Ideally **short-term counts should be conducted when variability in counts is lowest.** For this study, that time period was between May and October. Of course this varies based substantially with location and climate, but it can be identified after a year of continuous count data is available.

While much more work can and should be done on this topic, this paper provides a first look at how to minimize AADB estimation error and contributes to the discussions of what data collection methods should be established to quantify bicycle facility use and performance. Without an accurately calculated traffic volume statistic on which to base project evaluations, safety studies, and funding decisions, transportation professions risk losing funding and reaching inaccurate safety conclusions. Establishing such a metric and a standardized method for collecting data and computing that metric are essential for planning, designing, and funding safe, efficient, and long-term bicycle transportation facilities.

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TABLE 1 Hourly Continuous Counts Used to Compute AADB Error for the Scenarios

Station Location	Station Name	Dates	Commute Pattern	AADB	Volume
Boulder Creek Path at 13th St.	Arap 13th	January 2007 - December 2007	No	778	High
Arapahoe Path at 38th St.	Arap 38th	June 2004 - May 2005	No	86	Low
Foothills Path at Arapahoe Ave.	Foothills	June 2004 - May 2005	Yes	431	Medium
Arapahoe Path at Foothills Pkwy.	Arapahoe	June 2004 - May 2005	Yes	311	Medium

TABLE 2 Short-term Count Scenarios

Duration of Count	Time Frame	Days of the Week
1 Hour	7:00 AM to 7:00 PM	Any day
1 Hour	7:00 AM to 7:00 PM	TWorR day
1 Hour	8:00 AM, Noon, 5:00 PM	TWorR day
2 Hours	5:00 PM to 7:00 PM	TWorR day
3 Hours	8:00 AM, Noon, 5:00 PM	TWorR day
9 Hours	8:00 AM, Noon, 5:00 PM	TWR day
12 Hours	7:00 AM to 7:00 PM	Any day
12 Hours	7:00 AM to 7:00 PM	TWorR day
24 Hours	All hours	Any day
1 Week	All hours	All days
2 Weeks	All hours	All days
4 Weeks	All hours	All days

TABLE 3 Average AADB Estimation Error by Scenario

Short-term Count Scenario	Hours	Error as Average Absolute % Difference				
		Arap 13th	Arap 38th	Foothills	Arapahoe	Average
1 hour: 7am-7pm any day	1	49%	58%	56%	52%	**54%**
1 hour: 7am-7pm TWorR day*	1	41%	47%	41%	39%	**42%**
1 peak hour: 8,12,5 TWorR day*	1	36%	44%	46%	40%	**42%**
2 peak hours: 5 to 7pm TWorR day	2	41%	54%	46%	43%	**46%**
3 peak hours: 8,12,5 TWorR day average/day**	3	30%	36%	47%	46%	**40%**
3 peak hours 8,12,5 TWR day**	9	25%	31%	41%	40%	**34%**
7am-7pm any day	12	34%	47%	41%	38%	**40%**
7am-7pm TWorR day*	12	25%	38%	28%	28%	**30%**
24 hours any day	24	29%	39%	41%	42%	**38%**
1 week	168	17%	28%	20%	24%	**22%**
2 weeks	336	11%	25%	19%	19%	**19%**
4 weeks	672	7%	24%	14%	14%	**15%**

*Scenarios that use the monthly factors calibrated specifically to 8,12,5 TWR day.
**Scenarios that use the daily and monthly factors calibrated specifically to 8,12,5 TWR day.

TABLE 4 AADB Estimation Error by Month

Month	**Number of Hourly Counts Available**	**AADB Error as Average % Difference**		**AADB Error as Average Absolute % Difference**	
		Average	St Dev	Average	St Dev
1	96,000	29%	75%	63%	49%
2	77,000	42%	70%	70%	43%
3	74,000	36%	63%	58%	43%
4	63,000	26%	46%	45%	28%*
5	63,000	17%	38%*	34%	24%*
6	62,000	2%	37%*	26%	26%*
7	80,000	-5%	18%**	16%	10%**
8	90,000	-2%	26%*	20%	16%**
9	81,000	-6%	30%*	24%	19%**
10	81,000	-9%	22%*	18%	16%**
11	73,000	14%	51%	44%	30%*
12	88,000	34%	70%	65%	42%
Average	77,000	15%	46%	40%	29%

***Standard Deviation below 40%**
****Standard Deviation below 20%**

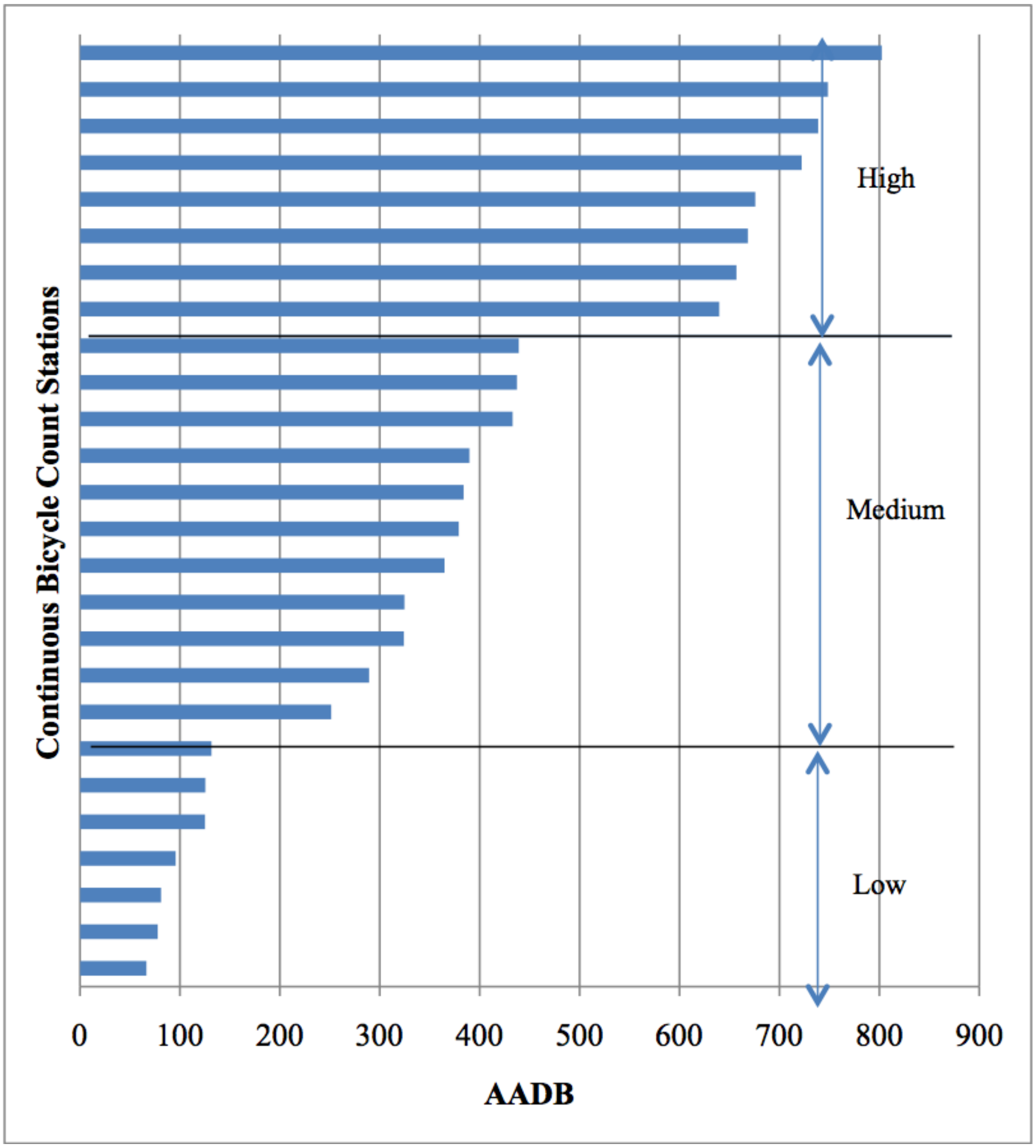

FIGURE 1 AADB averaged for all years at each continuous count station.

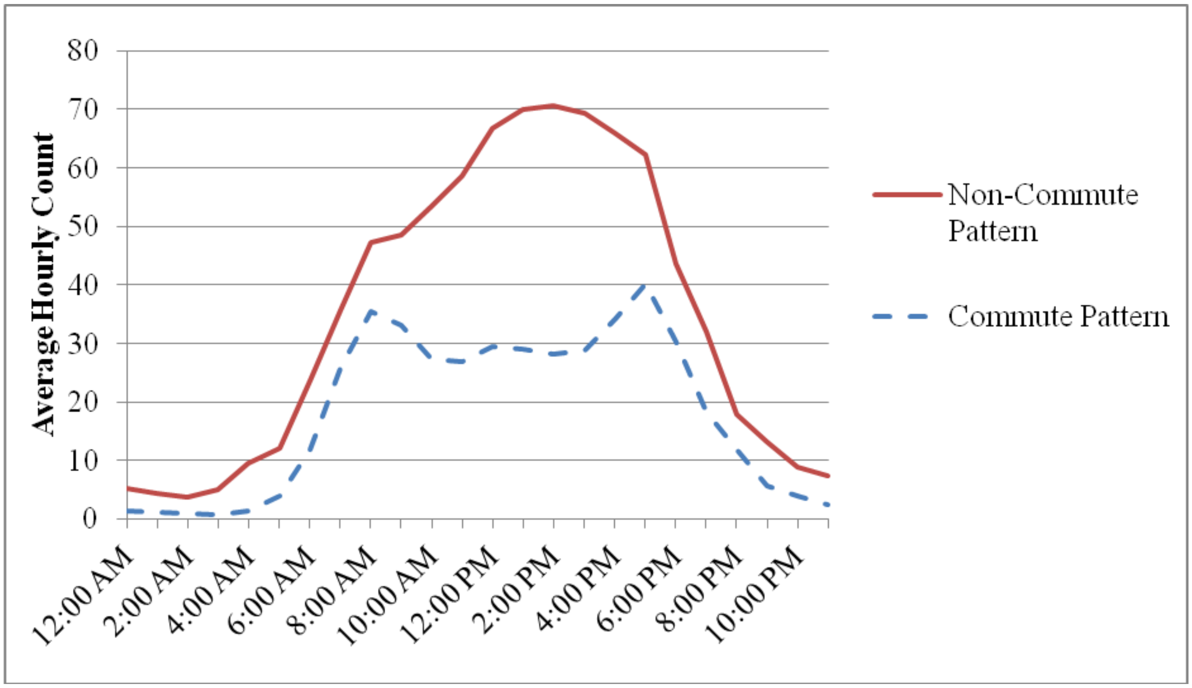

FIGURE 2 Examples of commute and non-commute patterns.

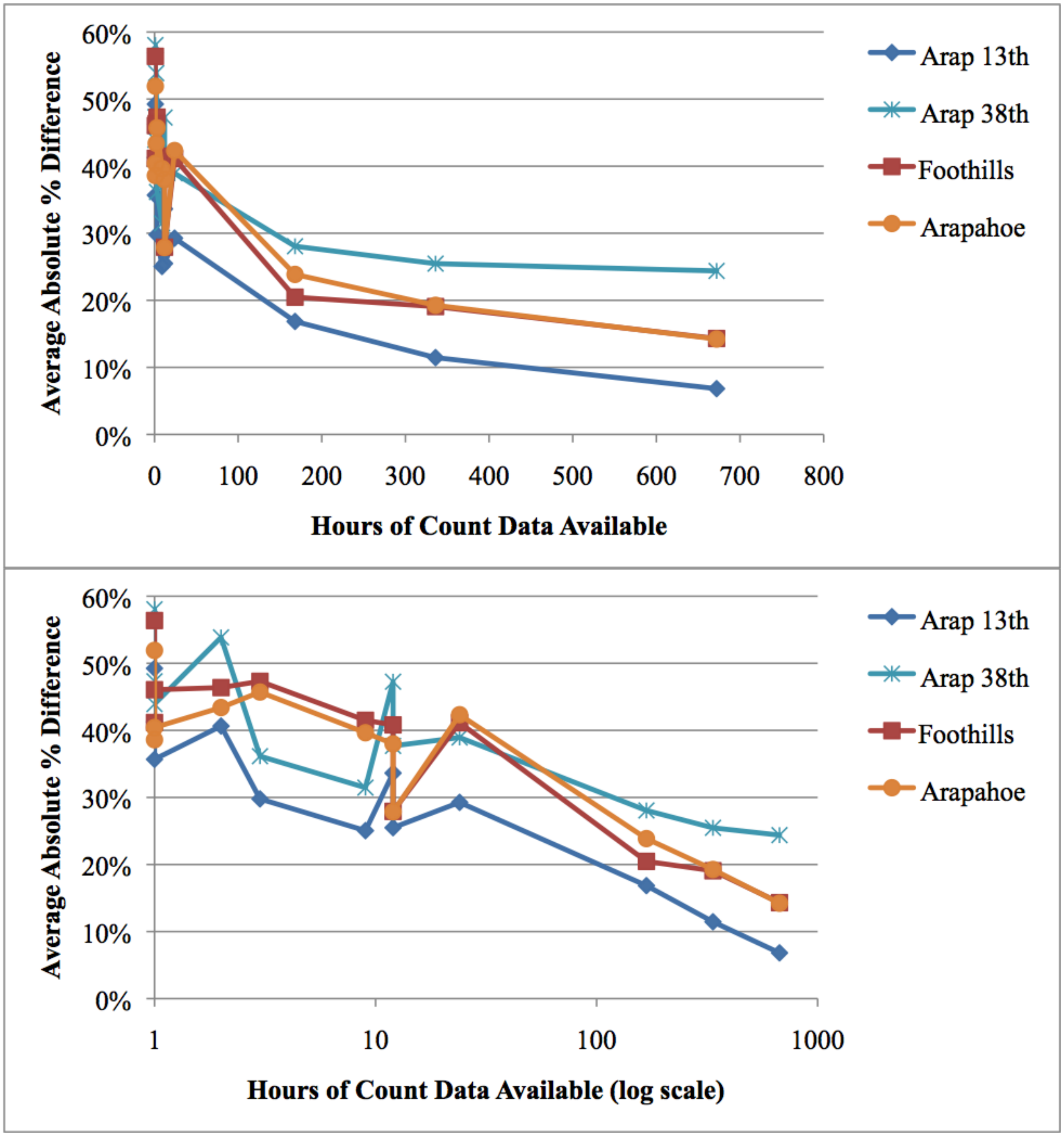

FIGURE 3 AADB error for each test dataset by short-term count duration plotted with and without log scale.

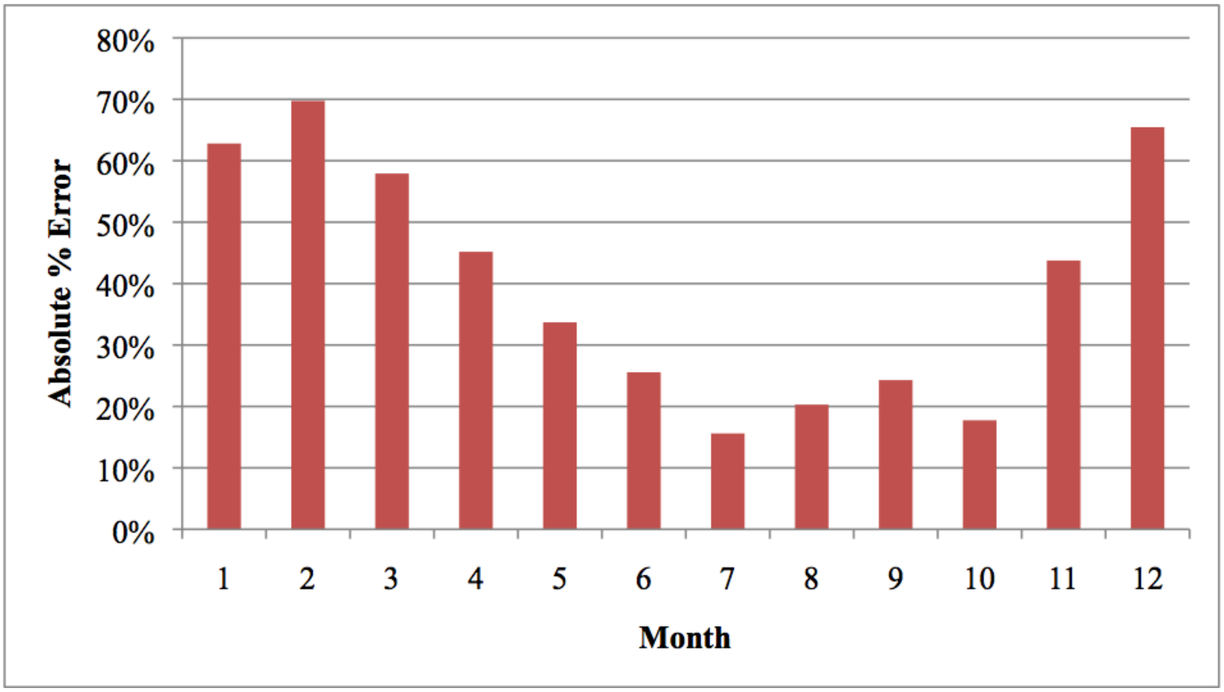

FIGURE 4 AADB error as a function of month when short-term counts were collected.

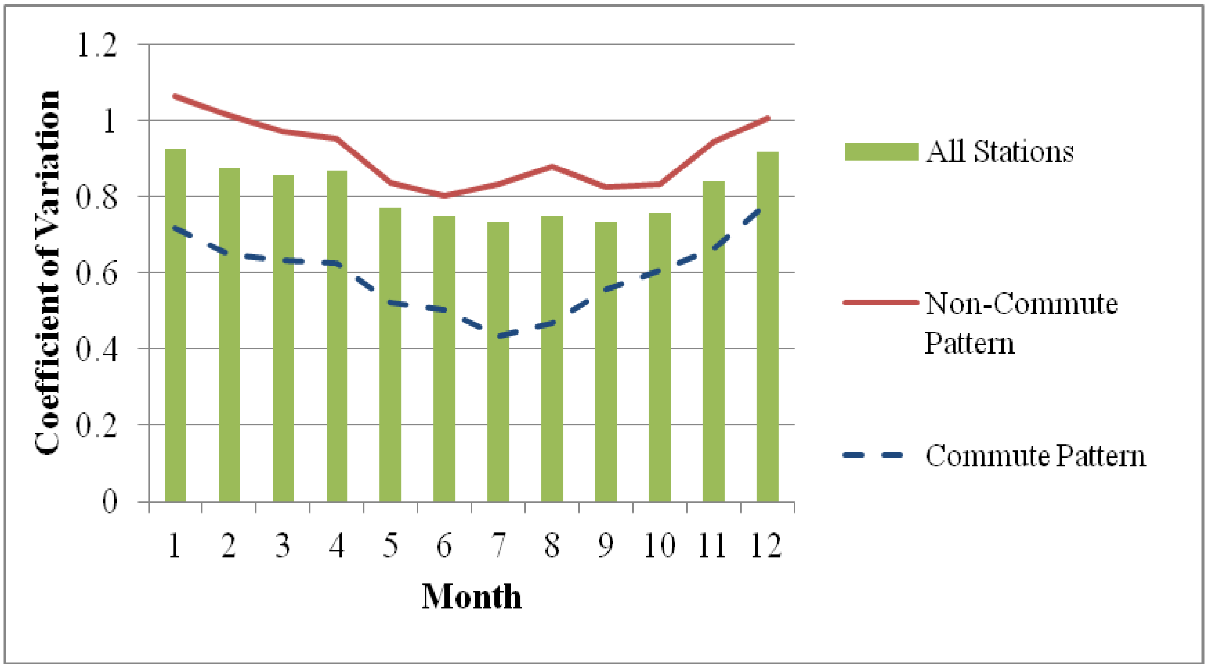

FIGURE 5 Variation in daily bicycle counts by month.