Incorporating weather: a comparative analysis of Average Annual Daily Bicyclist estimation methods

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ABSTRACT

Average Annual Daily Bicyclists (AADB) is commonly used in a wide range of cycling-related research and practical applications. It is generally estimated by averaging the daily cyclist totals recorded by a long-term automatic counter, or by using such a counter to extrapolate short-term counts. The latter method is commonly referred to as the expansion factor method, and has been shown to produce estimates with considerable error. To help mitigate this error, this study proposes two AADB estimation methods, one of which uses a cycling-weather model to adjust short-term counts, and one of which is based on individual daily totals from a long-term count site (as opposed to annual averages by day or by month). These methods are compared to two more traditional expansion factor methods. The weather and disaggregate methods out-performed the traditional methods, with the latter producing an average absolute relative error of roughly 14% when based on just one day of short-term data.

1. INTRODUCTION

Average Annual Daily Bicyclists (AADB) is a valuable metric used in a wide range of practical and academic transportation applications. Among other uses, it is critical in project evaluations, such as ex-post evaluations of new cycling programs or infrastructure, safety analyses, and level of service calculations (1).

AADB is typically estimated on bicycle facilities, intersections or roadways in one of two ways. The first way is to install a permanent bicycle counter, such as an inductive loop counter, for at least one year and compute the average of the daily cyclist totals. While generally most accurate, this method is both cost and time consuming. Moreover, in some locations, such as intersections, this is currently technologically unfeasible – sensors to collect automatic bike data at intersections are not commonly available in the market. Also, this requires that a counter be installed for at least one year in all locations for which an AADB estimate is desired. Hence the use of the second method, traditionally known as the expansion factor method, which is to use long-term counting sites to extrapolate short-term counts taken at other locations. Short-term counts can be obtained manually by an observer or with temporary counter installations such as pneumatic tube counters. The strategy that many cities then employ is to maintain a set of long-term bicycle counters and to supplement those sites with short-term counts when AADB estimates are required elsewhere. Typically short-term counts are obtained for analyses which involve a relatively large number of sites, such as safety studies, cordon count studies, and so on (2,3).

Researchers have recently shown that AADB estimates obtained using temporal expansion factors are often inaccurate, and have tested and proposed ways to increase accuracy (4,5). Despite recent developments, proposed methods are based on aggregate factors, similar to the approach used for vehicular traffic. However, these methods do not adequately take into account the sensitivity of cyclist traffic to weather, events and other factors affecting volumes at the daily level. For example, if weather during a short-term count is poorly suited to cycling, then AADB estimates based on that count are likely to under-represent the true AADB. Methods that account directly for weather and can better accommodate daily variation deserve further research.

This paper proposes two alternative AADB estimation methods that are designed to account for weather-related bias and short-term (daily) variation. The first method utilizes a model which relates deviations in daily cyclist counts from average daily counts to corresponding deviations in weather conditions. The second method is a disaggregated factor method, based on the individual daily cyclist totals from long-term counting sites.

The performance (accuracy) of the proposed methods, with respect to more traditional ones, is evaluated using data from a set of long-term counting sites in two Canadian cities, Montreal, Quebec and Ottawa, Ontario. The evaluation includes exploring how the location of the short-term count site, weather, time of the count, and duration of the count affect estimated AADB accuracy. The following section presents a short literature review on the topic, followed by the presentation of the methods, the results, and finally, the conclusions.

2. LITERATURE REVIEW

The most common incarnations of expansion factors today applied to bicycle data have been long-used to estimate annualized traffic for motor vehicles. Manuals like the The Federal Highway Administration's Traffic Monitoring Guide (6) and the Road Safety Manual (7) recommends that short-term counts be extrapolated by applying a daily and monthly expansion factor to a short-term count. The daily and monthly factors are typically equivalent to the average annual daily bicyclist count for a given day of the week or month, respectively, divided by the overall AADB. If the short-term count is less than 24-hours, an hourly expansion factor is required as well.

Two recent papers have provided the most thorough, if not only, in-depth analyses of the error associated with estimating AADB. Nordback et. al. (4) used a set of counters in Boulder, CO to test the standard expansion factor method. Focused primarily on the effect of the duration of the short-term count, they determined that at least one week of counts is optimal, and that estimates based on just one, two or three hours of data had average absolute error up to 58%. They also concluded that short-term data collected in the warmer months produced lower average error due to lower variability of daily counts. Esawey et. al (5) tested several different expansion factor methods, using data from Vancouver, British Colombia to estimate monthly average daily bicyclists. Rather than utilize the traditional method of producing daily factors by averaging over the course of the year, they produced daily factors for each month individually. They concluded that weekdays provided lower average estimation errors, and recommended against transferring expansion factors across years. They also accounted for weather by producing separate sets of expansion factors for wet and dry weather, finding that this method produced the lowest estimation error.

That weather has a significant impact on cycling has been well documented. A number of researchers have observed that, in general, counts increase with temperature (8,9,10,11). Several studies have found non-linear temperature effects, suggesting that the effect of temperature on cycling at warm temperatures is reduced or even negative (10,12,13). Increases in humidity have been associated with decreases in cycling (8). Precipitation is associated with decreases in cycling counts (8,9,11-13), and Thomas et. al. (10) found a non-linear precipitation effect. Furthermore, that researchers have been able to explain a considerable portion of the variance in hourly and daily cycle counts using weather and temporal factors suggests that such models could be used to adjust short-term counts based on weather conditions.

3. METHODOLOGY

This section introduces the steps that were followed to evaluate the four proposed AADB estimation methods. The four methods are based on the scenario in which the traffic analyst has at least one site with one year or more of daily cyclist count data, and that she or he has one or more sites with at least one 24-hour short-term count (taken within the same year as the long-term data). The analyst would like to use the long-term daily count data to estimate AADB at the sites which have short-term counts. The short-term counts can come from manual data collection methods or temporary sensor installations, such as pneumatic tubes or infra-red sensors. In theory, the short-term count could be as brief as one hour and adjusted to reflect a 24-hour total. However, to simplify the scope of this paper, only methods beginning with a full 24-hour count were considered. To see a more thorough examination of methods based upon counts shorter than a full day, see Nordback et. al (4).

The four AADB estimation methods that were evaluated in this analysis are described briefly below:

- *Traditional Method:* expansion factors for each month and day of the week are computed over a whole year of data
- *Day by Month Method:* expansion factors for each day of the week are computed for each month separately
- *Weather Model Method:* a model that relates deviations from average cyclist counts to deviations from average weather conditions is used to adjust short-term counts
- *Disaggregate Factor Method*: an expansion factor is computed for each day of the year using the raw daily counts and the annual daily average.

Simulating the scenario described in the first paragraph of this section consisted of the following steps:

1. Long-term automatic counting stations in both Montreal and Ottawa were split into those that would represent long-term count sites and short-term count sites, dubbed throughout the rest of this text as long-term test sites and short-term test sites, respectively. Of eight total stations in Montreal, one served as a long-term test site; of five stations in Ottawa, two served as long-term test sites.
2. The long-term test sites were used to develop the frameworks for each of the four AADB estimation methods.
3. For each short-term test site, the four estimation methods were applied in turn to each individual day of count data to estimate AADB. AADB was estimated separately for each year of available data at a given short-term test site.
4. The estimated AADB values were compared to the observed AADB values to evaluate and compare the accuracy of the four estimation methods.

An overview of the study locations and data is presented first. Next, the development of the weather model, which will be used in one of the AADB estimation methods is discussed, followed by a detailed description of each of the four AADB estimation methods. Finally, the manner in which the accuracy of the estimation methods will be compared is discussed.

3.1. Study Locations

The locations of the long-term and short-term test sites are shown in the maps in **Figure 1**, and the nearest intersection, along with other brief summary information, is provided in **Table 1**. With the exception of M_S5, which is located on a grade-separated cycling facility, all of the counter locations in Montreal are on on-street cycling facilities. With the exception of M_S7, which is on a unidirectional bike lane, all are bidirectional and physically separated from traffic. In Ottawa, the Laurier counter locations are on paired unidirectional, on-street bike lanes and the Rideau Canal counters are on grade-separated, bidirectional pathways.

Montreal has seven short-term test sites and one long-term test site, which was selected because it had the most contiguous period of reliable data. Ottawa has two short-term test sites on Laurier, which are associated with a long-term test site also on Laurier, and one short-term test site on the Rideau Canal path, paired with a long-term test site along the same path. The short-term test sites were paired with separate long-term test sites to examine the performance of the estimation methods at sites located at varying lengths along the same corridor. Associated long-term and short-term test sites are shown with symbols of the same shade in **Figure 1**.

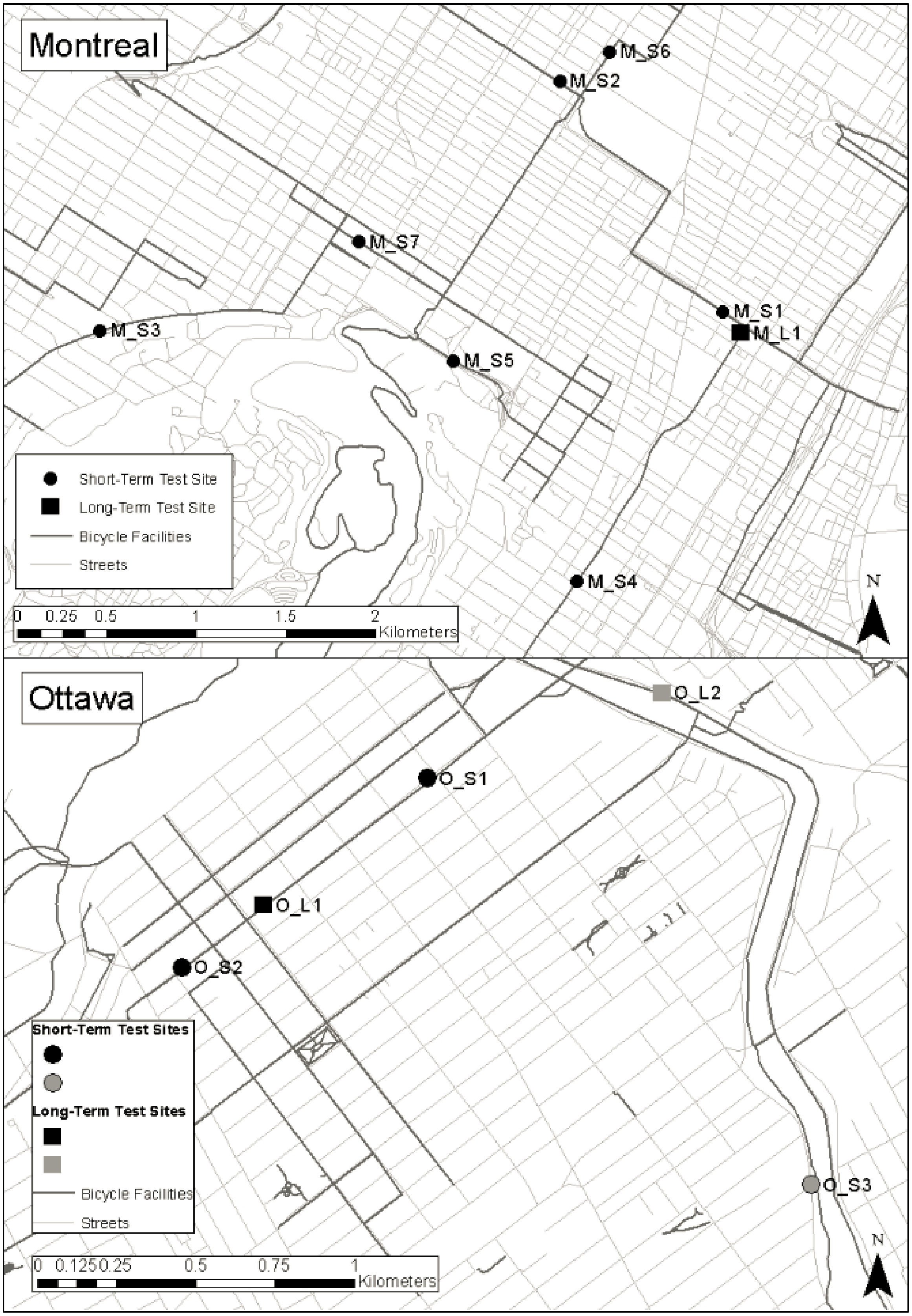

Figure 1. Montreal and Ottawa bicycle counter locations

3.2. Data

Bicycle Data

All of the bicycle data used in this study was obtained from inductive loop bicycle counters manufactured by Eco-Counter. Data from this equipment has been used in a wide range of studies, and when operating properly, the absolute error of these counters has been shown to be below 4% (8,13,14).

Weather Data

Weather data, used in the development and application of the weather model and in the analysis of the average absolute error of the estimation methods, were obtained from Environment Canada weather stations. The Montreal and Ottawa weather data came from the McTavish and Ottawa CDA weather stations, respectively, both of which are within 5 kilometers of all of the bicycle counter locations.

Data Processing

Because some of the bicycle counters are located on facilities that are not maintained in the winter, their count data becomes unreliable in the colder months. Therefore, to be consistent across as study locations, data from December through March were excluded from the analysis. The AADB values utilized throughout this study effectively average seasonal daily values. This is however still a useful metric for bicycle studies, and the methods presented here could easily be extended to full years if data are available. Furthermore, holidays were removed, resulting in a loss of roughly 2% of the data. The irregularity of traffic on holidays makes them difficult to include in the calibration and application of the weather models, and it was decided that they could be removed without significantly affecting AADB estimates. Finally, the datasets were combed thoroughly to identify missing data, which can be caused by counter malfunction, construction detours, and so on. This resulted in the loss of another 2.7% and 4% of daily observations in Montreal and Ottawa, respectively.

If more than a few days were missing over the course of a season, the entire year was discarded, as the observed AADB could not reliably be obtained. Because the number of missing days in each season was small, missing data were not estimated. The available years of data for each site are provided in **Table 1**. Again, for each short-term site, each year was treated separately, resulting in 19 test years. AADB was estimated for each year four ways, resulting in 76 different estimates. For reference, the observed AADB values computed over each site's full dataset is also provided in **Table 1**.

Table 1. Short-Term and Long-Term Test Sites

Type	Name*	Location	Years with Data	AADB
Long-Term	M_L1	Maisonneuve at Berri	2008-2012	4429
Short-Term	M_S1	Berri at Maisonneuve	2008 - 2010, 2012	3390
Short-Term	M_S2	Brebeuf at Rachel	2011	2789
Short-Term	M_S3	Cote St. Catherine at Mceachran	2012	1662
Short-Term	M_S4	Maisonneuve at Peel	2008, 2010-2012	2176
Short-Term	M_S5	Parc at Duluth	2011, 2012	2420
Short-Term	M_S6	Rachel at Papineau	2012	3838
Short-Term	M_S7	St. Urbain at Mt. Royal	2008 - 2010	1917
Long-Term	O_L1	Laurier at Lyon	2012	1015
Short-Term	O_S1	Laurier at Metcalfe	2012	1437
Short-Term	O_S2	Laurier at Bay	2012	418
Long-Term	O_L2	Rideau Canal Western Pathway at First	2012	1210
Short-Term	O_S3	Rideau Canal Eastern Pathway by Laurier	2012	1181

*In each name, L and S correspond to long-term and short-term test sites, respectively

3.3. Weather Model Formulation

As noted earlier, in addition to temporal factors, weather can have a significant effect on bicycle traffic volumes, which can in turn have a large effect on AADB estimates. In an attempt to account for that effect, a model was developed which relates deviations in daily cyclist totals from the average daily total to respective deviations in daily weather conditions from average conditions. If a researcher knew that weather conditions on the day of a given short-term count were better or worse for cycling than average, she or he could use this model to adjust their short term count accordingly. This model will be incorporated into one of the tested AADB estimation methods presented in the following subsection. The model can be represented as follows:

$$\Delta DB_{y,j} = (\beta * \Delta W_{y,j}) + (\alpha * W_{y,j}) + (\gamma * FE_{y,j}) + \varepsilon_{y,j}, \text{ where} \quad \text{(Eq. 1)}$$

$\Delta DB_{y,j}$ $= \left[DV_{y,j} - \frac{\sum_{k=j-10}^{k=j+10} DB_k}{21}\right] \Big/ \left[\frac{\sum_{k=j-10}^{k=j+10} DB_k}{21}\right]$, the relative Daily Bicyclists deviation of day *j* in year *y*, from a 21 day moving average of Daily Bicyclist totals, where *j* ranges from 1 to the number of days in the year or cycling season,

$\Delta W_{y,j}$ $= \left[W_{y,j} - \frac{\sum_{k=j-10}^{k=j+10} W_k}{21}\right] \Big/ \left[\frac{\sum_{k=j-10}^{k=j+10} W_k}{21}\right]$, a vector of deviations in continuous weather variables (temperature, dewpoint, total precipitation, etc.) from their respective 21 day moving averages on day *j* in year *y*. (Note that although the normalized version is shown above, these variables may or may not be normalized)

$W_{y,j}$ = a vector of continuous weather conditions on day *j* in year *y*,

$FE_{y,j}$ = a vector of binary variables related to temporal effects, like the day of week on which day j falls,

β, α, γ = vectors of coefficients to be estimated from the data, and

$\varepsilon_{y,j}$ = a random, independent error term for day j in year y.

Linear regression was used to calibrate the model coefficients. Multi-collinearity was checked to ensure that variables with correlation coefficients with absolute values greater than 0.5 were not included in the same model.

Note that Miranda-Moreno and Nosal (8) developed a similar model, but they calculated average cycling and weather values by month. It was found here that the 21-day moving average produced a better fit. Also note that because the response of cycle counts to weather conditions varies between weekdays and weekends (13), the model coefficients were calibrated using only weekdays. Therefore, since the average values were computed using all days, the model relates deviations in weekday cycle counts from the overall average to deviations in weather conditions.

3.4. AADB Estimation Methods

The first two methods are based on those described in the Federal Highway Administration's Traffic Monitoring Guide (6), and account for temporal variation only. The third and fourth methods are similar, but attempt to control for both temporal and weather-related variation. Note that although the AADB values reflect bicyclist counts on all days, only weekdays were used to estimate AADB.

Traditional Method

This method accounts for daily and seasonal variation in traffic volumes with individual factors for each day of the week, averaged over the whole season or year, and for each month. It has been widely used to annualize both motor vehicle and bicycle and pedestrian traffic counts.

$$\widehat{AADB}_{i,y,j} = SDB_{i,yj,d,m} * {}^{1}/_{DF_d} * {}^{1}/_{MF_m}\text{, where} \qquad \text{(Eq. 2)}$$

$\widehat{AADB}_{i,j}$ = the estimated AADB for short-term site i, and year y, based on the short-term count taken on day j, which ranges from 1 to the number of days in the cycling season or year,

$SDB_{i,yj,d,m}$ = the observed Short-term Daily Bicyclists at short-term site i on day j in year y, which falls on day of the week d in month m,

DF_d = the Day-of-the-week Factor for day of the week d.

MF_m = the Month Factor for month m.

Both DF_d and MF_m are calculated using data from a long-term test site. In this case, the DF_d is the ratio of the average daily total cyclists on a given day of the week, *d,* averaged over the entire season or year, divided by the overall AADB. MF_m is the ratio of the average daily total cyclists in month *m,* divided by the overall AADB. Both DF_d and MF_m were calculated separately for each year.

Day by Month Method

This method is similar to the traditional method, but rather than account for daily and seasonal variation with separate factors, they are accounted for by computing the DF_d separately for each month. For instance, for an 8 month cycling season there would be 56 total factors.

$$\widehat{AADB}_{i,y,j} = SDB_{i,y,j,d,m} * {}^{1}/_{DF_{d,m}}, \text{ where} \qquad \text{(Eq. 3)}$$

$\widehat{AADB}_{i,y,j}$ = the estimated AADB for short-term site *i*, and year *y,* based on the short-term count taken on day *j,* which ranges from 1 to the number of days in the cycling season or year,

$SDB_{i,y,j,d,m}$ = the observed Short-term Daily Bicyclists at short-term site *i* on day *j* in year *y*,, which falls on day of the week *d* in month *m,*

$DF_{d,m}$ = the Day-by-month Factor for day of the week *d* and month *m.*

The $DF_{d,m}$, again calculated using data from a long-term test site, is the average daily total cyclists for each day of the week, *d,* within each month, *m*, divided by the overall AADB. $DF_{d,m}$ was calculated separately for each year.

Weather Model Method

This method attempts to account for the effect of weather on daily cyclist counts and subsequent AADB estimations by using the expected cyclist count deviation, obtained from the model described in **Section 3.1**, to adjust the observed short-term count. The method is executed in two steps: first, the short-term count is adjusted based on the predicted deviation from the 21-day moving average due to weather; second, the weather-adjusted count is temporally adjusted to reflect how the 21-day average varies from the AADB. The first step can be summarized as follows:

$$\widehat{MADB}_{i,y,j} = SDB_{i,y,j,d,m}/(1 + \widehat{\Delta DB}_j) \text{ , where} \qquad \text{(Eq. 4)}$$

$\widehat{MADB}_{i,y,j}$ = the estimated Moving Average Daily Bicyclists for short-term site *i*, and year *y,* centered at day *j*, which ranges from 1 to the number of days in the cycling season or year,

$SDB_{i,y,j,d,m}$ = the observed Short-term Daily Bicyclists at short-term site *i* in year *y,* on day j, which falls on day of the week *d* in month *m.*

$\widehat{\Delta DB}_{y,j}$ = the expected deviation in daily bicyclists on day *j* in year *y,* based on the weather conditions on day *j* and obtained from **Equation 1**, after calibrating the model with bicycle data from a long-term site.

For example, if the weather on day *j* was particularly well-suited to cycling, $\widehat{\Delta DB_j}$ will be positive, and the short-term daily bicyclists count, $SDB_{i,d,m}$, will be adjusted downward. The second step can be represented as follows:

$$\widehat{AADB}_{i,y,j} = \widehat{MADB}_{i,y,j} * {}^{1}/_{MAF_j}, \text{ where} \quad \text{(Eq. 5)}$$

$\widehat{AADB}_{i,y,j}$ = the estimated AADB for short-term site *i* and year *y*, based on the short-term count taken on day *j,* which ranges from 1 to the number of days in the cycling season or year,

$\widehat{MADB}_{i,y,j}$ = the estimated Moving Average Daily Bicyclists for short-term site *i* and year *y*, centered at day *j*, as estimated using **Equation 4**.

MAF_j = $\frac{\sum_{k=j-10}^{k=j+10} DB_k}{21} / AADB$, the Moving Average Factor, centered at day *j* and calculated using data from a long-term site.

The coefficients of the weather model were estimated using data from the long-term sites. For Montreal, all 5 years of data were used to calibrate one model. If a contiguous section of data was missing, then a section spanning from ten days before to ten days after the missing data was excluded. If a single day was missing, then only twenty days were used to calculate the moving average, when applicable.

Disaggregate Factor Method

The disaggregate factor method is perhaps the simplest. For a long-term test site, each daily bicyclist total is divided by the overall AADB. Essentially, an expansion factor is created for each day of the year. It is expected that, as long as the long-term and short-term test sites experience the same weather, this method will account for deviations in weather conditions, and temporal factors like day of the week and month. It can be represented as follows:

$$\widehat{AADB}_{i,y,j} = SDB_{i,y,j} * {}^{1}/_{DF_{y,j}}, \text{ where} \quad \text{(Eq. 6)}$$

$\widehat{AADB}_{i,y,j}$ = the estimated AADB for short-term site *i* and year *y*, based on the short-term count taken on day *j,* which ranges from 1 to the number of days in the cycling season or year,

$SDB_{i,y,j}$ = the observed Short-term Daily Bicyclists at short-term site *i,* on day j in year y,

$DF_{y,j}$ = $DB_{y,j}/AADB_y$, the Disaggregate Factor for day j in year y, where $DB_{y,j}$ and $AADB_y$ are the total cyclists on day *j* in year *y* and the AADB, respectively, for the long-term count site. Again, j ranges from 1 to the number of days in the cycling season.

3.5. Evaluation of Accuracy

Each day of available count data was used to estimate AADB for a given short-term test site and year. Therefore, for each AADB estimation method, each day's estimate was compared to the observed AADB using the absolute relative error:

$$\left|Error_{i,y,j}\right| = \left|\widehat{AADB}_{i,y,j} - AADB_{i,y}\right|/AADB_{i,y}, \text{ where} \quad \text{(Eq. 7)}$$

$\left|Error_{i,y,j}\right|$ = relative absolute error for short-term site *i,* based on the AADB estimated on day j in year *y,* and calculated for each estimation method,

$\widehat{AADB}_{i,y,j}$ = the estimated AADB for short-term site *i* and year *y*, based on the short-term count taken on day *j,* which ranges from 1 to the number of days in the cycling season or year,

$AADB_{i,y}$ = the observed AADB for site *i* and year *y.*

In the results section, unless otherwise noted, the average absolute relative errors (AARE) (averaged across all sites and years) are used to compare the accuracy of the different methods.

4. RESULTS AND DISCUSSION

The results of the weather model calibration are first discussed briefly, followed by the results and discussion regarding the different AADB estimation methods.

4.1. Weather Model

The coefficients of the weather model are presented in **Table 2**, along with corresponding p-values and a description of each variable. All of the results related to the signs and magnitudes of the estimated coefficients are in accordance with previous research.

It was found that positive deviations in temperature from the average were statistically significantly associated with increases in cyclist counts. However, this effect is tempered when the temperature is above twenty and deviations from the average temperature were positive; when it is already hot, increases in temperature make cycling less appealing.

For incorporating the effects of humidity on cycling, it was found that the relative deviation in maximum daily dew point depression explained a greater amount of the variance than relative humidity. Dew point depression is the difference between the air temperature and the dew point temperature, the temperature at which water vapor will condense into a liquid. The larger the dewpoint depression, the less humid the air feels. Increases in dewpoint depression from the average were associated with increases in cyclist counts.

Precipitation was entered into the model as continuous variable. Though precipitation decreases cyclist counts, a non-linear effect was observed: the magnitude of its negative effect increases less rapidly at higher levels of precipitation. To the average cyclist, the difference between no rain and light rain is greater than the difference between moderate rain and heavy rain.

In addition to the weather-related variables, fixed effects for Tuesday, Wednesday and Thursday were significant, meaning that average ridership on those days varies with respect to Monday. A fixed effect for Friday was found to be insignificant. Finally, a constant was significant and had a positive magnitude. This reflects the fact that the dependent variable in this model is the deviation in daily cyclist counts from the overall average count (calculated using all days of the week), but the model was calibrated using only weekdays. Counts at locations used to calibrate this model are generally higher during the week than on the weekend.

Table 2. Weather Model Coefficients - Montreal

Category	Variable	Description	Coefficient	P-Value
ΔW_i	del_temp_max	Deviation of maximum daily temperature from average	0.027	0.000
	del_dpd_max	Deviation of maximum dew point depression (temperature minus dew point temperature) from average	0.023	0.000
W_i	temp_max _o20_pdev	Equal to maximum daily temperature when maximum temp. is above 20 °C and del_temp_max is positive (equal to 0 otherwise).	-0.0036	0.000
	$(\text{total\_precipitation})^2$	The square of total daily precipitation (in mm^2).	0.000065	0.000
	total_precipitation	Total daily precipitation (in mm).	-0.018	0.000
FE_d	fmon (reference)	---	---	---
	ftue	Equal to 1 if Tuesday, 0 otherwise.	0.12	0.000
	fwed	Equal to 1 if Wednesday, 0 otherwise.	0.11	0.000
	fthu	Equal to 1 if Thursday, 0 otherwise.	0.11	0.000
	constant	---	0.17	0.000
R^2 = 0.61				

4.2. AADB Estimation

With the exception of M_S7, the disaggregate method produced the lowest AARE for all sites, followed by the weather method; the traditional and day by month methods performed comparably, and produced the least accurate estimates with the highest AARE values (**Figure 2**). The magnitudes of the average absolute errors for the traditional method, which is the most comparable method, are in accordance with those obtained in other analyses (4,5). The rest of the results section is broken up to examine more specific factors that affect AARE.

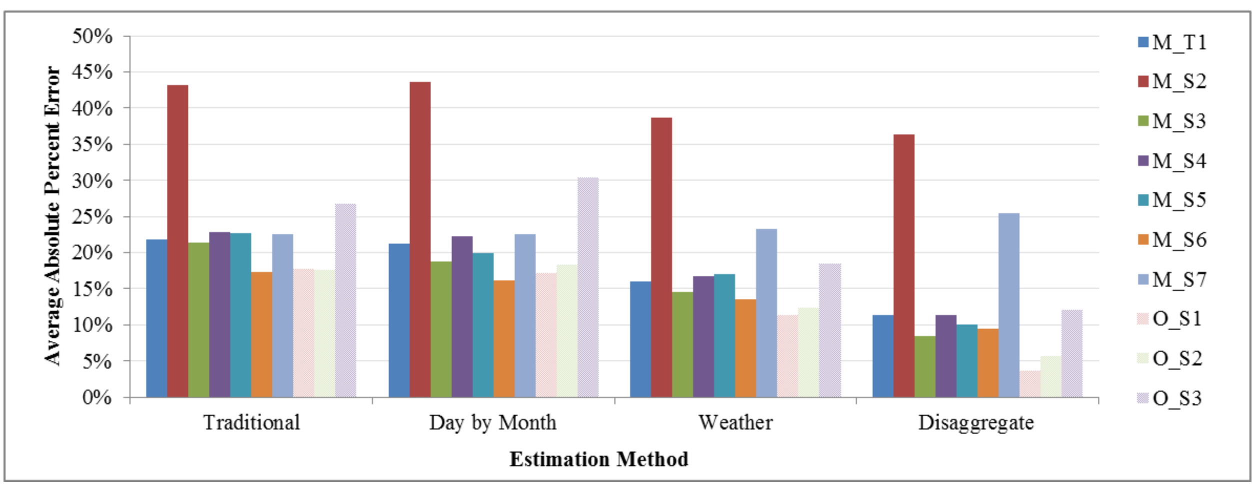

Figure 2. AARE by Estimation method and Short-Term Count Location

Location of Short-Term Site

Although an in-depth analysis of the contextual factors related to each short-term site was beyond the scope of this study, some conclusions can be drawn from a basic examination of the AARE by short-term site locations. For some sites, such as M_S2, it was not possible to produce a reasonably accurate estimate with any method (**Figure 2**). An examination of the average daily cyclists by month reveals why this is so (**Figure 3**). While the monthly traffic profiles for the other two short-term sites with data in 2011, M_S4 and M_S5, closely match that of the long-term site, M_L1, M_S2 has a very different ridership pattern. Although the monthly profile is not shown in **Figure 3**, M_S7's low accuracy can be attributed to a similar reason. This highlights the need to determine before estimating AADB whether the long-term and short-term sites have compatible traffic patterns. This in practice can be a difficult task if the analyst is not familiar with the traffic dynamics in the different corridors of the network. How to determine whether this is the case will require much further research.

The two sites with the lowest AARE are O_S1 and O_S2, which are on the same corridor as and are close to their associated long-term site, O_L1 (**Figure 1; Table 1**). Their AARE values for the disaggregate method are 6% and 3%, respectively. This suggests that the AADB of short-term sites on the same corridor or a corridor with similar traffic patterns as their long-term site can be estimated relatively easily with high accuracy. Again, this highlights the importance of matching sort-term sites to the appropriate permanent counting stations, in particular when they are not in the same corridor.

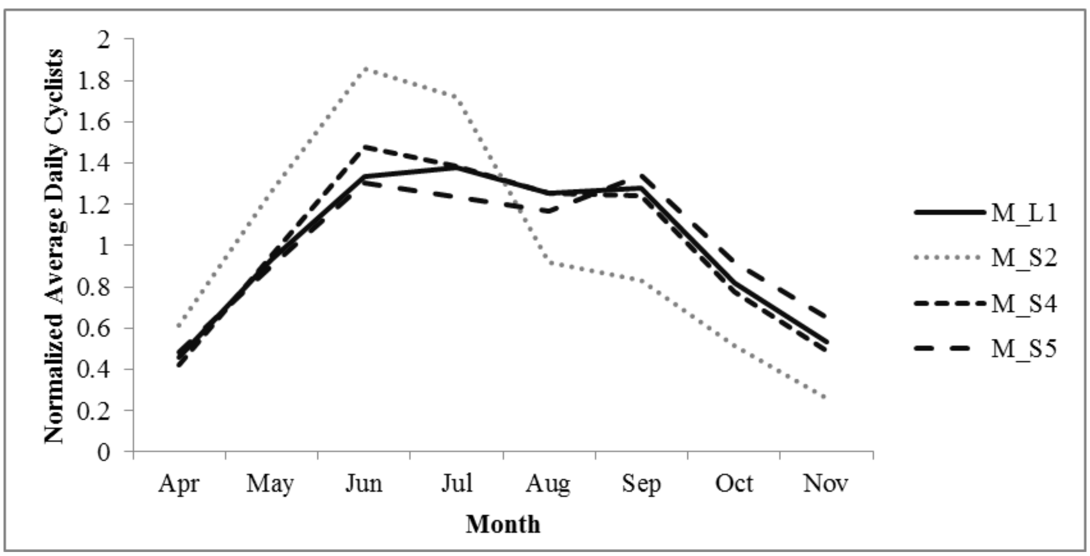

Figure 3. Average Daily Cyclists by Month in 2011

Weather Conditions

For all four estimation methods, when temperatures are warmer, estimates are more accurate (**Figure 4a**). However, the difference between estimates obtained during colder periods and warmer periods is more pronounced for the traditional and day by month methods; the traditional method produces errors that are roughly four times lower when the temperature is above 30 than when it is less than zero.

Estimates are more accurate when short-term counts are performed during dry weather (**Figure 4b**). However, for the disaggregate method, the difference in accuracy is less pronounced between dry and wet weather. This makes this method particularly attractive, as it suggests that, for instance, even days on which it rained during a pneumatic tube installation could be reliably used for AADB estimation. Perhaps surprisingly, the weather method produces a relatively large difference in accuracy between wet and dry days. This suggests that further work is needed to accurately model how precipitation affects cyclist counts.

This reinforces the recommendation that data collection campaigns for short-term counts ought to take place in good weather conditions and not during winter.

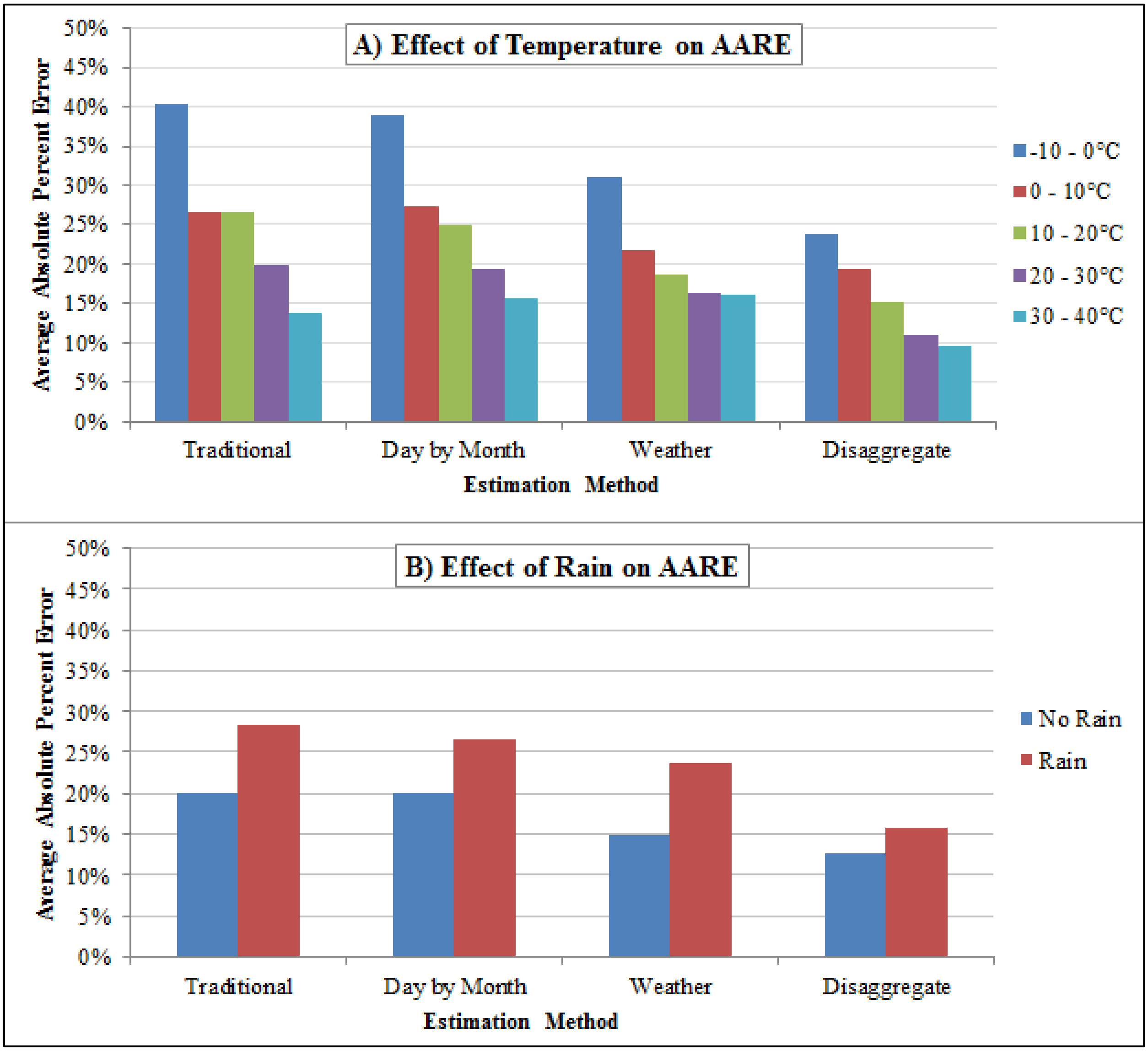

Figure 4. Effect of Weather Conditions on AARE by AADB Estimation Method

Time of Temporary Count

In general, there is not much variation in accuracy across days of the week (**Figure 5A**). For the traditional, day-by-month, and weather methods, it appears that Thursdays may be the best day on which to collect a short-term count. However, this may be specific to Montreal or to just this set of counters. Furthermore, as suggested earlier in this suggest, it is clear that more accurate AADB estimates are produced in the warmer months. It appears that, in this case, short-term counts taken in August produce the lowest AARE. This is in accordance with prior work (4,5) and should serve as a clear guideline for when is best to collect short-term data.

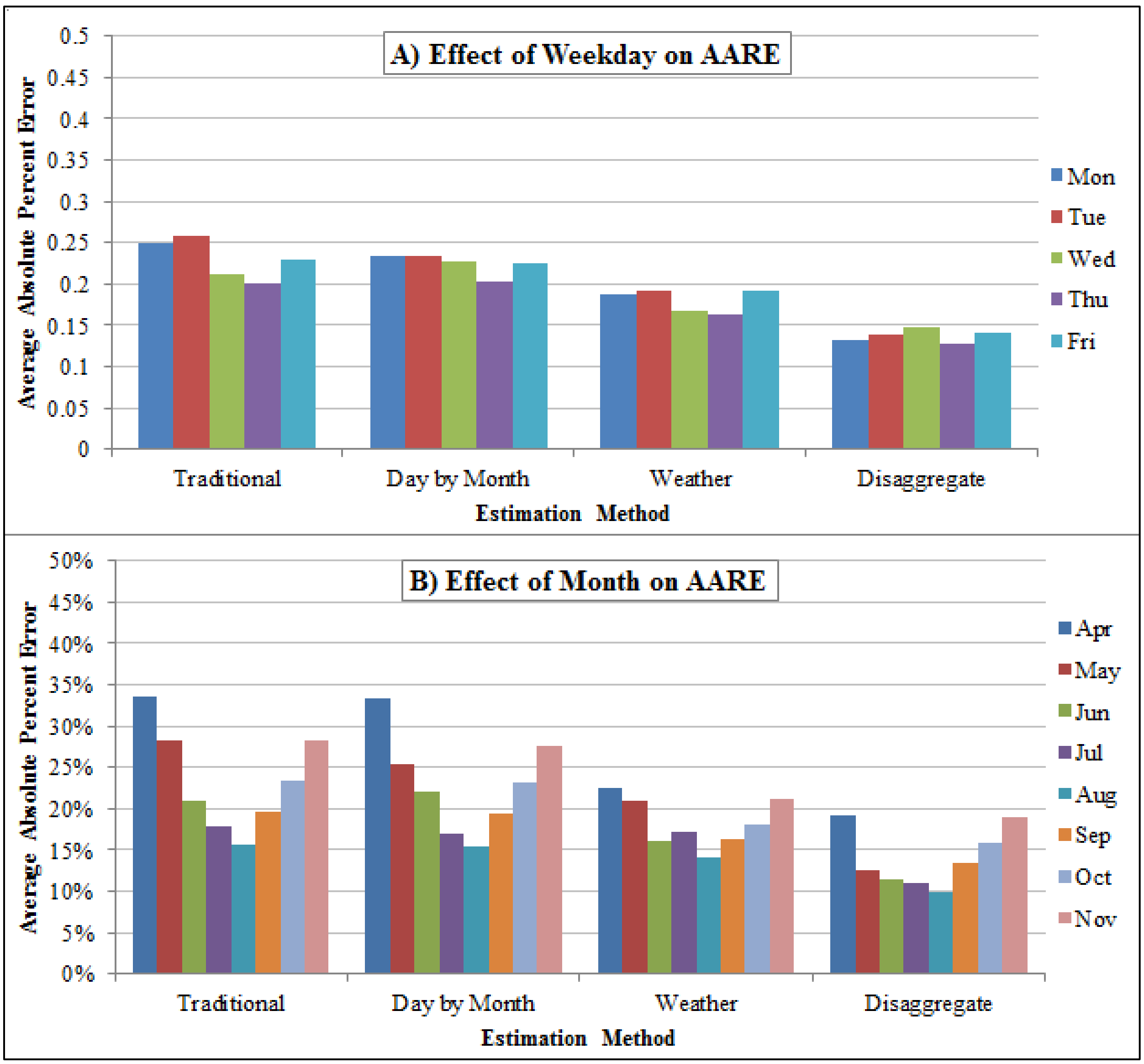

Figure 5. Effect of Time of Short-Term Count on AARE by AADB Estimation Method

Duration of Count

In order to test the effect of the duration of the short-term count on AARE, the AADB estimates obtained on contiguous weekdays were averaged, and the number of days was increased from 1 day up to 30. For the first three methods, large gains in accuracy can be obtained by increasing the duration of the short-term count (**Figure 6**); increasing the count duration from one day to five can decrease the average error by roughly one-third. For the traditional and day by month methods, the error associated with a month of counts is roughly half that of a one-day count, and for the weather method, it is roughly 60%. While gains can be made for the disaggregate method, they are less pronounced; after 5 days and 30 days, the AARE is only 15% and 34% lower than the AARE associated with a one-day count, respectively.

As more days of short-term data are included, the AARE values improve in a non-linear manner. For the first three methods and the disaggregate method, roughly 75% and 60%, respectively, of the improvement to be had by adding more data has occurred by the addition of the 10th day. Furthermore, the AARE values across the four methods converge as more data is added. After 10 days of short-term data collection, the weather method and the disaggregate method produce the same AARE, and after 20 days, all are essentially the same.

The results presented in **Figure 6** highlight the potential advantage of the disaggregate method. On average, ten days of short-term data collection are necessary for the traditional and day-by-month methods to produce estimates which are comparable in error to one day of the disaggregate method, and 5 days of data collection are required for the weather method to do so.

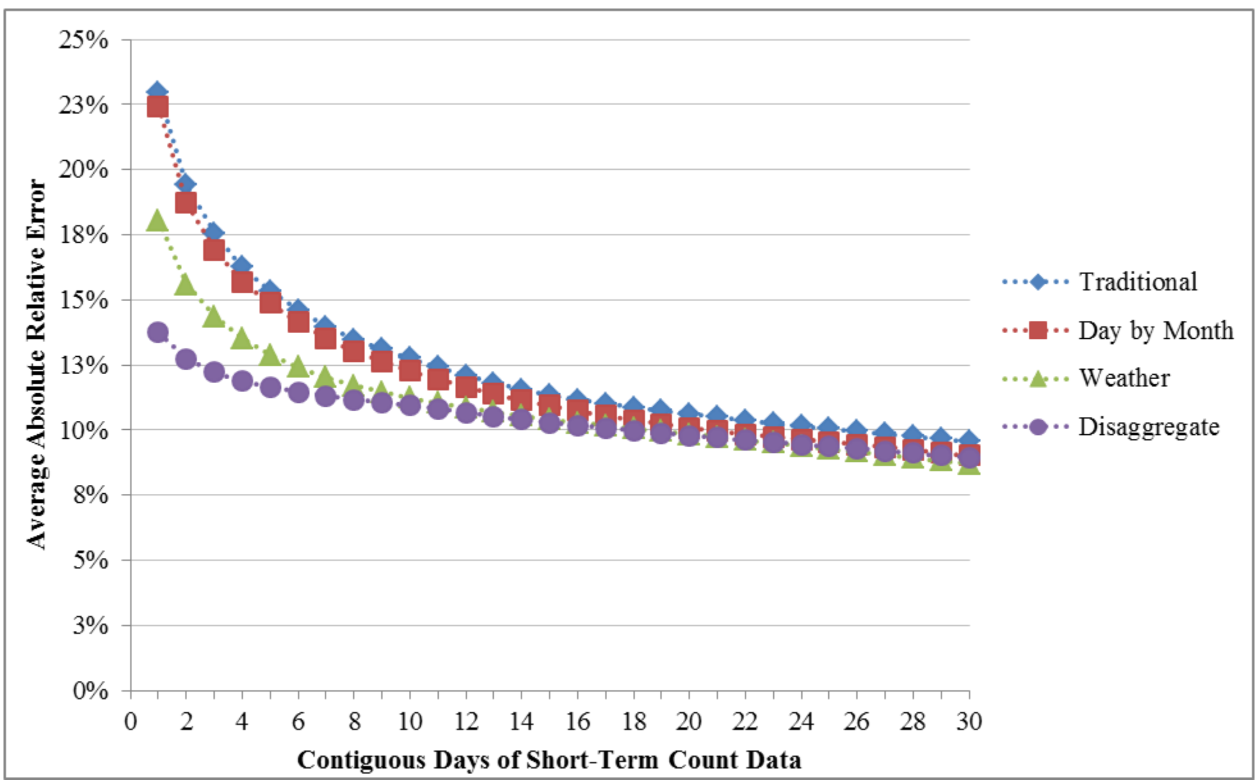

Figure 6. Effect of Duration of Short-Term Count on AARE by AADB Estimation Method

5. CONCLUSION

This paper evaluates the performance of four methods to estimate AADB from short-term counts, including two that are relatively unique. A set of long-term count sites in two Canadian cities, Montreal and Ottawa, were divided into those that simulated long-term and short-term count data sites. Using data from long-term test sites, the four methods were applied to data from the short-term test sites to estimate AADB. The accuracy of the four methods was evaluated based on the average absolute relative error between the estimated and observed AADB values.

In general, it was found that the disaggregate method performs better than the other three methods, particularly when compared to the traditional and day-by-month methods. The weather adjustment method was the second best option, performing in some cases as well as or better than the disaggregate method. It was observed that the selection of the long-term location is critical; lowest error is obtained when the traffic patterns at the long and short term sites match well. This could be even more important than the selection of the factoring method.

The effect of weather conditions, as well as the time and duration of the short-term count was also evaluated, and it was found that greater accuracy can be obtained by considering these factors when planning a short-term count. Short-term data collected on dry days in warmer periods, particularly in the month of August, produced the lowest error for this set of sites. Collecting data on Thursday also appears to improve accuracy slightly. Furthermore, increasing the number of days of short-term data reduces error considerably, albeit in a non-linear fashion. After around 10 days of data collection, further gains in accuracy are marginal.

The weather and disaggregate methods are advantageous in that they produce more accurate AADB estimates. Because of their ability to account for weather conditions, it appears that less short-term data is needed to obtain accuracy comparable to more traditional methods. However the data needs of the weather method, and the fact that both methods are only applicable to short terms counts collected in the same year as the long-term counts, reduces their utility.

Future work will include testing these methods with short-term counts less than a full day long. In addition, methods to more reliably match short-term data collection sites with representative long-term sites will be developed. Ensuring that long and short-term sites have similar traffic patterns will ensure greater accuracy. Finally, extensions of the weather model method will be developed, such as the ability to use short-term counts from different years, and the standardization of data from different years for comparative or post-project evaluation studies.

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