Methods for Improving and Automating the Estimation of Average Annual Daily Bicyclists

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ABSTRACT

Average Annual Daily Bicyclists (AADB) is commonly used by researchers and practitioners as a metric for cycling studies (demand analysis, infrastructure planning, injury risk, etc.). It is estimated in one of two ways: by averaging the daily cyclist totals measured throughout the year using a long-term automatic bicycle counter, or by using a long-term bicycle counter to extrapolate data from a short-duration counting site. AADB extrapolation is a process that can face two issues: it can produce considerable errors when using traditional factoring methods, and it is laborious as many steps in the process require manual validation. To help lessen these two problems, this study proposes a novel methodology that can reduce estimation error and facilitate automation of the AADB estimation process. The proposed methodology performs AADB estimation in a three-step process: data validation, matching and extrapolating. The data validation process can be the most laborious process, requiring a human to sift through large datasets in search for missing and erroneous values. A method is proposed for validating long-term bicycle demand data by using other available long-term bicycle demand data. Secondly, a matching process is proposed using k-means clustering and three indexes. Lastly, for the AADB extrapolation process, two novel disaggregated factor methods (DFM)s are proposed. The results are compared to the results obtained from a previously reported method, standard DFM. The first method, the DFM with filtering, improved the AADB estimation accuracy: average absolute error was 5.6% compared to 4.2%. The second method, the DFM with separate treatment of weekdays and weekends reduced AADB estimate error from 6.0% to 4.9%.

1. INTRODUCTION

Bicycle commuting and the development of bicycle infrastructure are becoming increasingly important in North America, making it necessary for researchers and transportation agencies to understand how to properly integrate cycling into an urban transportation system. Designing appropriate road treatments, estimating injury risk and evaluating the success of cycling infrastructure all require a good understanding of bicycle demand (*1; 2*). A common traffic measure, average annual daily bicyclists (AADB), is necessary to obtain at many locations throughout a bicycle network (*3-5*).

Automated bicycle counting systems, used for measuring bicycle demand, fall into two categories: long-term counters that run continuously at a single location for multiple years, and mobile counters that capture a short duration of cycling demand (typically one to 14 days). The data from long-term counters can be used to calculate the AADB when installed for more than one year, simply by averaging the daily bicycle demand throughout the year, or throughout the cycling season. Estimating the AADB with a short-duration count is possible but requires extrapolation methods using knowledge of cycling volume patterns from appropriate references - long-term counting sites. Direct measurement of AADB using a long-term counter is highly accurate but expensive. On the other hand, estimating AADB with a short-duration count and extrapolation techniques, although relatively inexpensive, produces results with varying accuracy.

Despite recent developments in literature, much work remains in improving AADB estimation from short-duration counts. The process is not trivial: it is laborious as many steps are required and can result in inaccurate measures when using traditional factoring methods. This study proposes a methodology that reduces estimation errors and facilitates automation of the AADB estimation. The proposed methodology consists of three steps: data validation, matching and extrapolating.

2. LITERATURE REVIEW

A small but growing body of work has demonstrated several extrapolation techniques with varying accuracy (*3-7*). Nordback (*5*) demonstrated that average annual daily traffic (AADT) extrapolation techniques for motor vehicle counting can be borrowed to estimate AADB. This technique uses day-of-week and month-of-year factors developed using continuous count data, taken over an entire year, from a group of counters located at similar cycling facilities. Nordback applied this method to estimate AADB at four bicycle facilities with long-term counters in Boulder, CO. The accuracy of the AADB estimates vary by time and by location. The average errors were 17% to 28% (varied by location) when a seven-day count was used and 11% to 25% when a 14-day count was used. Nordback also explored how the error in AADB estimation decreases as the duration of the short-term count increases.

Nosal (*4*) examined four methods for AADB extrapolation including two traditional methods that make use of aggregated factor groups much like the method presented by Nordback, as well as two novel approaches. Nosal applied these methods to data from long-term bike counters in Montreal, QC and Ottawa, ON. Nosal's first novel method, a weather model method was used to account for changes in cycling demand due to weather. The method relates deviations from average cyclist counts to deviations from average weather conditions to adjust short-duration counts. The weather model method had improved accuracy when compared to the two traditional methods. The average error using the weather model method, for all locations, was approximately 12% when a seven-day count was used and 11% when a 14-day count was used. When the traditional factor group methods were used (they produced similar results) the seven-day and 14-day short-duration counts yielded approximately 14% error and 12% error respectively. The second novel method, called the disaggregated factor method (DFM) produced the best results in Nosal's study. In this method, an expansion factor is computed for each day of the year using the raw daily counts and the annual (or seasonal) daily average of a long-term reference counting site. This set of factors would typically be produced using a long-term counting site in close proximity to the short-duration counting site that requires extrapolation. The idea behind this method is that the proximity of the two counting locations would ensure that weather would impact cycling demand at both locations to a similar extent. The average error using the DFM, for all locations, was approximately 11% when a seven-day count was used and 10% when a 14-day count was used.

Several other studies have demonstrated techniques to reduce AADB extrapolation error. Hankey (*6*) compared a day-of-year DFM to the more traditional day-of-week and month-of-year factor methods using data from automatic bike counters on off-street trail locations in Minneapolis. Hankey found a significant reduction in AADB extrapolation error using the day-of-year factor method, especially when the duration of the short-term count was less than one week. Figliozzi (*7*) proposed a methodology to reduce AADB extrapolation error using regression models that account for weather and non-school days, applying it to automatic count data from Portland, Oregon.

3. CURRENT METHODS AND PROPOSED IMPROVEMENTS

AADB is the standard metric used by researchers and practitioners to quantify cycling activity, referred to as volumes or flows on bicycle facilities, at intersections or on road sections (*3; 5; 8; 9*). AADB estimation from a short-duration count has the potential to be widely used as the technique makes long-term and short-duration counts comparable under one metric (see **Figure 1**). However, at present the technique suffers from two problems: it typically produces considerable errors, and it is laborious as many steps in the process require manual validation. The estimation of AADB requires three processes:

(1) Validating reference count data to identify discontinuities and anomalous data,
(2) Matching short-duration counts to appropriate long-term reference count data,
(3) Extrapolating AADB of a short-duration count using a matched reference count.

In each of these processes, inappropriate methods and/or execution can translate into a source of error. In order to improve the accuracy and ease of AADB estimation, all three processes require improvement on previously reported techniques. Namely, each process must be made more robust in handling erroneous data and must minimize the amount of manual validation required. The proposed improvements in each of the three processes will be discussed in order as follows.

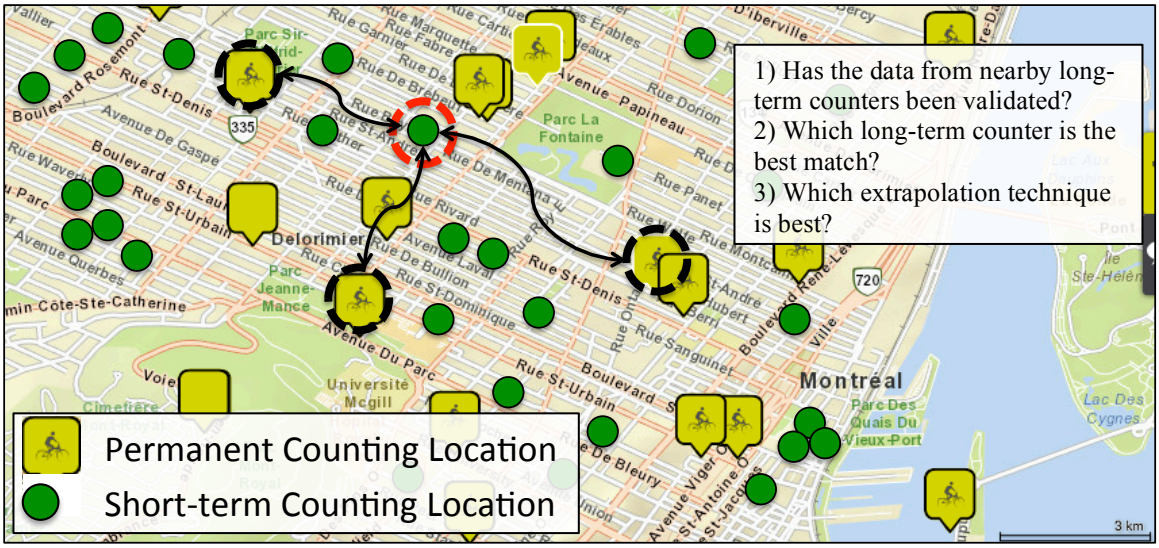

FIGURE 1: Hypothetical long-term and short-duration counting site coverage and guiding questions to help in AADB estimation process.

3.1 Validating reference count data

The first process, validating the reference count data, can be thought of as a data preparation and cleaning process. Data validation is crucial in achieving a high accuracy in AADB extrapolation, regardless of the extrapolation method used in the third process. All significant anomalies or missing values in the data must be explained and in many cases removed for the purposes of extrapolation. Nosal, when estimating AADB using counting sites in Ottawa, ON, removed all holiday data and missing data, resulting in a loss of 2% and 4% of data respectively (*4*). Although this process in Nosal's study was done manually, it would be straightforward to have the process automated.

Undercounting of the reference count data is an anomaly that can be difficult to identify and yet can have a significant impact on the accuracy of an AADB extrapolation. Undercounting can have many causes: automatic counter malfunction, temporary loss of power, construction, etc. These anomalies in the data can be difficult to detect if they result in significantly reduced, non-zero, counts. In addition to being difficult to identify, significant undercounting of the reference data can have a large impact on the accuracy of the daily AADB extrapolation of a short-term counting location because the daily bicyclist values of the reference data appear in the denominator in the estimate (see **Eq.**

5). For example, if a reference count for a particular day consists of only 25% of what would have been the total count due to a partial obstruction of the cycling facility, then the resulting AADB estimate for that day of a short-duration count would be 400% of the true estimate. In other words, AADB extrapolation is highly susceptible to error, particularly in the case where the reference experiences significant undercounting.

One method for identifying undercounting and other anomalies is to manually analyse continuous data by hourly interval. This is typically done by viewing data graphically; all anomalies that cannot be explained by local weather are then flagged or removed. This method, though quite effective, is arduous and time-consuming. Combing through multiple years of data for multiple counters can take many tens of hours to perform. However, an automated method would be significantly more time-efficient and potentially more thorough than the manual method that is currently used in research and industry.

In this study, a novel method is proposed for data validation. In the case that data from multiple reference counters are available for an entire year in a single city or region, then data validation and anomaly identification can be achieved by validating the daily factors against one another. Anomalies in count data would be easily identified as days when a counting location has a variation about its AADB that is not mirrored at other counting locations. The proposed process consists of the following three steps:

(1) Calculate the daily factors for each long-term counting location using **(Eq. 1)** below, as developed by Nosal (*4*),

$$DF_{i,y,j} = DB_{i,y,j}/AADB_{i,y}\text{, where} \qquad \textbf{(Eq. 1)}$$

$DF_{i,y,j}$ is the Disaggregated Factor for the long-term reference counting site *i* on day j of year y, $DB_{i,y,j}$ is the Daily Biyclists of day j of year y at site *i* and $AADB_{i,y}$ is the AADB for year y at site *i*.

Note that method for determining the daily factors of site *i*, was proposed and evaluated by Nosal (*4*) as part of the DFM for estimating AADB. This proposed method uses the daily factors in a different context, for validating reference data.

(2) Perform the quotient of the daily factors, using two references, for all days of the year or cycling season. Alternatively, this process could use *n* references (*n* = 2,3,4…) and would involve creating an *n* x *n* matrix, where each element is a vector of quotients of two sets of daily factors for a particular cycling season. This expanded method would allow all long-term counting sites in a city or region to be validated by all other long-term sites. For the purpose of this study, only two references were used; there is opportunity to expand this process in future work.

(3) Identify and remove all time periods with a quotient that falls outside of a threshold from the mean of all daily quotients.

3.2 Matching short-duration counts to appropriate reference

The second process, matching short-duration counts to appropriate reference count data is an important process in AADB estimation. If an inappropriate match is made between a short-duration count and a long-term reference, then the extrapolation will produce an AADB estimation with large error. All of the methods developed to extrapolate AADB from a short-duration count require the use of factor groups and the factors to extrapolate AADB can only be applied to a short-duration count if they come from a long-term counting site (or a group) that is likely to have similar daily, monthly and yearly bicycle demand patterns (*3*). The temporal variation of cycling demand on different bicycle facilities can vary widely, even between bicycle facilities in close proximity to one-another. Different temporal profiles of bicycle demand have been identified, and referred to as: utilitarian, mixed-utilitarian, recreational and mixed-recreational (*3*). Utilitarian cycling patterns have distinct demand peaks throughout the week that correspond to rush hour commuting, bicycle demand is typically greater during the week than on the weekend, and the shoulder season retention rate is high. Recreational cycling patterns have a single peak throughout the entire week, bicycle demand is greater during the weekend, and the shoulder season retention is relatively low. Mixed-utilitarian and mixed-recreational groups are characterized by temporal patterns that reflect both the utilitarian and recreational groups.

The matching process, developed by Nosal (*10*), can be completed in two stages. In the first stage, all long-term counting locations in a particular study are clustered using k-means with Euclidean distance as a dissimilarity measure. Nosal used two indices (**Eq. 2 and 3**), reflecting hourly and daily count variation. In this study, we introduce a third index (**Eq. 4**) that reflects weekly and monthly count variation. In the second stage, a short-duration count would be matched to a cluster. Investigating the performance of the second stage is not within the scope of this study.

$$I_{\frac{AM}{Midday}} = \frac{\sum_{h=7}^{10} \bar{V}_k}{\sum_{h=11}^{14} \bar{V}_k} \text{, where} \qquad \textbf{(Eq. 2)}$$

$I_{\frac{AM}{Midday}}$, known as the AMI, is the AM to midday indicator,

$\bar{V}_h$ is the average cycling volume throughout the cycling season for hour *h* of the day.

$$I_{\frac{Weekend}{Weekday}} = \frac{\bar{V}_{Weekends+Holidays}}{\bar{V}_{Weekdays}} \text{, where} \qquad \textbf{(Eq. 3)}$$

$I_{\frac{Weekend}{Weekday}}$, also known as the WWI is the weekend to weekday indicator

$\bar{V}_{Weekends+Holidays}$ and $\bar{V}_{Weekdays}$ are the average cycling volume throughout the cycling season for weekend and holiday days, and non-holiday weekdays respectively.

$$I_{\frac{Peak-of-cycling-season}{Non-peak-cycling-season}} = \frac{\bar{V}_{highest-12-weeks-of-the-year}}{\bar{V}_{following-16-weeks-of-the-year}} = \frac{\frac{1}{12}\sum_{w=1}^{12}\bar{V}_w}{\frac{1}{16}\sum_{h=13}^{28}\bar{V}_w}$$,where **(Eq. 4)**

$I_{\frac{Peak-of-cycling-season}{Non-peak-cycling-season}}$, also known as the PPI, is the peak period to non-peak period indicator,

V_w, is the weekly cycling volume on the wth highest week of cycling volume in the cycling season.

3.3 Extrapolating AADB from a short-duration count

The third process requires special consideration as a number of methods exist to extrapolate AADB from a short-duration count, all producing different estimates with varying accuracies. As mentioned previously, Nosal (*4*) and Hankey (*6*) demonstrated that the DFM, on the average, performs better than the traditional expansion factor methods developed by Nordback (*5*). The improvement in accuracy comes primarily from the fact that the DFM takes local weather fluctuations into account. However, one potential drawback in the DFM is a high sensitivity to errors in the reference count data. The traditional expansion factor method is typically applied to a large climatic region, such as an entire state, and the factors are generated using data from many long-term counting sites. By creating factors through averaging, the factors become less susceptible to count errors of the individual long-term counters. On the other hand, the DFM is meant to be applied to a small region, such as a city, that experiences uniform weather. In this application, there will not always be access to data from many long-term counting sites to aggregate into a set of factors. In fact, the DFM was tested by Nosal using a single long-term counter as a reference. In this study, we attempt to improve the DFM by making it more robust in dealing with anomalous data (more on these sources of error in the section 3.3.1 below). Developing methods that can treat anomalous data is crucial in making AADB estimation an automated process.

First, let us define the DFM as developed by Nosal (*4*). The formula for computing the daily AADB estimates is described in **Eq. 5**.

$$\widehat{AADB}_{i,y,j} = \frac{1}{n}\sum_{j=1}^{n} SDB_{i,y,j} * \frac{1}{DF_{y,j}}$$, where **(Eq. 5)**

$\widehat{AADB}_{i,y,j}$ is the estimated AADB for short-term site *i* and year *y*, based on the short-term count taken on day(s) *j = 1 to n,*

$SDB_{i,y,j}$ is the observed Short-term Daily Bicyclists for short-term site *i* and year *y*, based on the short-term count taken on day *j,*

$DF_{y,j}$, the Disaggregate Factor for day j of year y of the long term count site, is $DB_{y,j}/AADB_y$, where $DB_{y,j}$ is the Daily Biyclists of day j and $AADB_y$ is the AADB for year y.

3.3.1 Factors that degrade accuracy of AADB estimates

A number of factors can impact bicycle volumes and potentially degrade the accuracy of an AADB estimation if bicycle demand is affected in the location(s), and during the time period, used for the AADB estimation. These factors include weather variation, discontinuities and small anomalies in count data, and weekends and holidays. The impact of these factors on an AADB estimation can be mitigated by carefully verifying the short-duration and reference count data manually (with knowledge of local weather, holidays, festivals and other events) prior to extrapolating an AADB estimation of the short-duration location. However, the capability to address and treat these factors more generally is necessary to develop a robust, automated process for AADB estimation.

The impact of weather

Bicycle demand is highly sensitive to changes in weather (*11*). The traditional expansion method, a technique borrowed from vehicle counting, does not take local weather into account. By using month-of-year and day-of-month factors to extrapolate a short-term count, the method comes with the underlying assumption that all days in a month with the same day of week (i.e. all Mondays in October) experience the same bike demand. Fluctuations in local weather make this assumption problematic. The advantage of the DFM, developed by Nosal, is that it takes precise local weather, using a 24-hour base time period, into account (*4*). Since a separate factor is used for each day of the year, and the reference is close to the location of the short-duration count, the impact of the local weather for a particular day of the year on cycling demand is reflected in that day's factor. The underlying assumption in this method is that similar counting sites in close proximity to one another will exhibit similar relative fluctuations in cycling demand from one day to the next. This is a more reasonable assumption to accept than the assumption that comes with the traditional expansion method.

The impact of short-duration anomalies or discontinuities

Both anomalies and discontinuities of a short-duration or reference count can be overlooked in a manual validation process and have a significant impact on the accuracy of an AADB estimation. There are several possible causes of a short-duration count anomaly or discontinuity including loss of power, an obstruction in the bike facility (moving truck, utility vehicle or debris) or malfunction of the monitoring equipment. Special events such as street and music festivals, street closures, and large-scale open street events for cyclist (also known as cyclovia) can also have a significant short-duration impact on bicycle demand.

Short-duration anomalies can result in misleading AADB estimates. For example, as mentioned in section 3.1, if a reference count for a particular day consists of only 25% of what would have been the total count, then the resulting AADB estimate of a short-duration site, for that day, would be 400% of the true estimate. This source of erroneous data can be identified and omitted using the validation technique described in section 3.1 if access to multiple long-term counting sites in relatively close proximity to one another is possible. Alternatively, if one has access to data from only one long-term counting

site, a filtering technique can be employed after the daily AADB estimates are computed. An explanation of the method that can correct for short-duration anomalies and discontinuities is given in the section 3.3.2.

The impact of weekends and holidays

Weekends and holidays tend to be associated with highly variable cycling demand. The day-to-day or week-to-week fluctuations can be difficult to model. One option, in treating weekends and holidays, is to simply remove those days of count data from the data sample used to estimate AADB. However, removing all days with greater variability in cycling demand can produce misleading estimates since weekends and holidays represent almost a third of all days. Removing the weekends and holidays from the AADB estimate of a utilitarian facility will have the effect of exaggerating the AADB estimate. On the other hand, removing those days from the AADB estimate of a recreational facility will have the effect of supressing the AADB estimate. Another approach is to treat weekends and holidays separately, both for the short-duration count as well as for the reference count. An explanation of the method that can account for some of the estimation errors associated with bicycle count data taken during weekends and holidays is given in the section 3.3.2.

3.3.2 Methods for improving AADB estimation accuracy

In this research, we explore two novel approaches for extrapolating AADB that build from the DFM developed by Nosal (*4*) and that have the potential to achieve more consistently accurate estimates than previously reported methods. The methods explored are referred to as DFM with filtering, and DFM with separate treatment of weekdays and weekends.

Disaggregated factor method with filtering:

As mentioned previously, the DFM is susceptible to producing an AADB estimate with a large error in cases where either the reference count or short-duration count are not accurate. The sensitivity to error is highest in the case where the reference experienced a significant undercount during the same period as the short-duration count was taken. One possible solution to reduce error in the AADB estimation is to analyse the distribution of daily AADB estimates and remove the outliers. In order to remove erroneous AADB estimates, a sufficient amount of data must be collected in the short-duration count. In this study, we explore the performance of a filtering algorithm using a 14-day short-duration count. The algorithm is iterative: it begins filtering the highest AADB daily value, then it filters the lowest value. The process continues to alternate between high and low values until both a high and a low iteration have failed to remove the AADB value in question. The process is illustrated in the flowchart below (**Figure 2**).

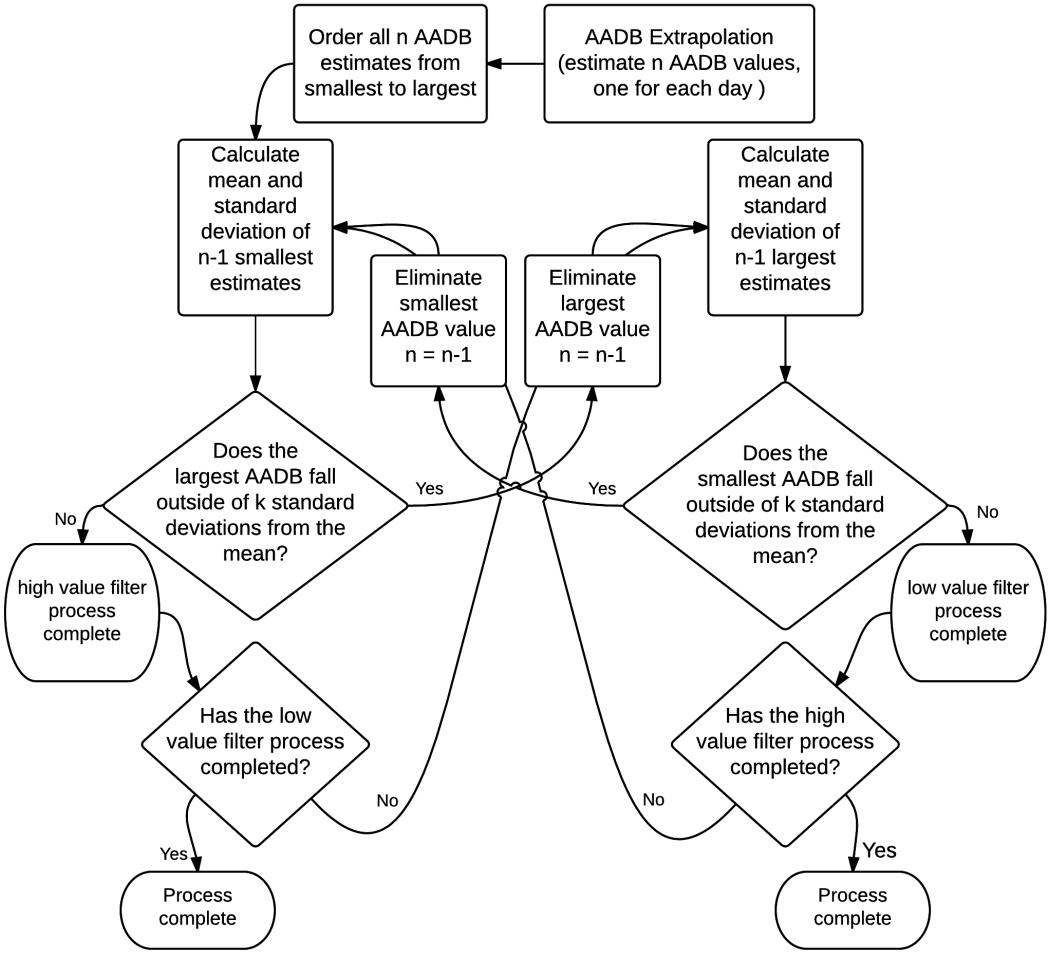

FIGURE 2: Algorithm for DFM with filtering.

The parameter k (seen in **Figure 2**) is defined as the number of standard deviations from the mean AADB that make up the threshold for keeping a daily AADB. If a daily AADB falls outside of k standard deviations from the mean, that daily AADB is considered an outlier and removed from the data. In the limited testing that was done on the process, the optimum k value was found to be $3 + 0.25i$ where i is the iteration number.

Disaggregated factor method with separate treatment of weekdays and weekends

As mentioned previously, the DFM is susceptible to introducing error to the AADB estimate when weekend and holiday data is used to extrapolate the AADB. Most cycling facilities have a different average demand on weekdays compared to weekends and holidays. Using a single $AADB_y$ value from the reference count **(Eq. 5)** can produce misleading results. For example, when extrapolating AADB on a utilitarian facility, using a single $AADB_y$ value tends to exaggerate weekend and holiday AADB estimates and underrepresent weekday AADB estimates. The opposite is true for recreational facilities where the highest bicycle demand tends to be on weekends and holidays. One possible solution to reduce error in the AADB estimation is to treat the daily weekday and weekend/holiday AADB estimates separately. This modification to the DFM

involves computing separate reference $AADB_y$ values for weekdays and weekend/holidays **(Eq. 6)**: $AAWB_y$ is the Average Annual Workday Bicyclists for year y, and $AAWHB_y$ is the Average Annual Weekend and Holiday Bicyclists for year y. Each of these values are then separately used to calculate the daily factors of the reference counting sites: Disaggregate Factor for Working Days on days j of year y ($DFWD_{y,j}$), and Disaggregate Factor for Weekends and Holidays on day j of year y ($DFWH_{y,j}$). Two additional factors are introduced to account for short-term counting periods with a weekday to weekend/holiday ratio that differs from the typical 5:2. The $\widehat{AADB}_{i,y,j}$ formula becomes:

$$\widehat{AADB}_{i,y,j} = \frac{1}{n+m}\left(\frac{5}{n} * \sum_j SDB_{i,y,j} * \frac{1}{DFWD_{y,j}} + \frac{2}{m} * \sum_j SDB_{i,y,j} * \frac{1}{DFWH_{y,j}}\right), \text{ where}$$

(Eq. 6)

$\widehat{AADB}_{i,y,j}$ is the estimated AADB for short-term site *i* and year *y*, based on the short-term count taken on day *j,* which ranges from the first to last day of the short-term count,

n and *m* are respectively the number of weekdays and weekend/holidays in the short-term count period,

$SDB_{i,y,j}$ is the observed Short-term Daily Bicyclists for short-term site *i* and year *y*, based on the short-term count taken on day *j,*

$DFWD_{y,j}$ the Disaggregate Factor for Working Days on day j of year y of the long term count site, is $DWB_{y,j}/AAWB_y$, where $DWB_{y,j}$ is the Daily Workday Bicyclists of day j and $AAWB_y$ is the Average Annual Workday Bicyclists for year y,

$DFWH_{y,j}$ the Disaggregate Factor for Weekends and Holidays on day j of year y of the long term count site, is $DWHB_{y,j}/AAWHB_y$, where $DWHB_{y,j}$ is the Daily Weekend and Holiday Bicyclists of day j and $AAWHB_y$ is the Average Annual Weekend and Holiday Bicyclists for year y.

4. DATA

The continuous bicycle count dataset used in this analysis was obtained from inductive loop bicycle counters manufactured by Eco-Counter and owned by the Cities of Montréal, Ottawa, Arlington and by Vélo Québec. 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; 9; 12; 13*).

The data used to test the methods developed in this study came from 22 long-term bicycle counters: six located in Ottawa, five in Arlington, eight in Montréal and three in Québec outside of Montréal. Using data from three long-term reference sites, the validation method was tested. Using data from all long-term reference sites, the clustering technique was tested. One of the long-term counting sites was used to simulate a short-duration bicycle counting site and data from two long-term reference sites were used to test the two AADB extrapolation methods developed in this study against a previously reported method. The accuracy of the extrapolation performed by the three methods was evaluated using the average absolute error between the estimated and observed AADB values. More in-depth information on the data used to test each method is given in section 5.

5. RESULTS AND DISCUSSION

The results and discussion are given for each of the methods developed in this study and described in section 3.

5.1 Validating reference count data

The validation technique tested in this study effectively disentangled the erroneous AADB estimates from the rest. **Figure 3** (top) displays the distribution of values derived by taking the quotient of daily factors from two long-term counting sites (De Maisonneuve at Peel and Côte-Saint-Catherine) in Montréal during the cycling season of 2013. Data spans 240 days, from April 1 to Nov 26. Of the 240 days, four days fall outside of three standard deviations of the mean ratio. All four outliers were found to be due to erroneous counts: In one case, the counter located at De Maisonneuve at Peel significantly undercounted from 6:00AM to 3:00PM on Nov 6th, 2013 – the low counts were likely due to a utility vehicle parked in the cycling facility. Since the anomalous period was shorter than one day and the anomalous hourly counts were non-zero, the anomalous data would have been difficult to detect without the use of this method.

This method could also be developed for use in the second process, matching counting locations, i.e. to determine if two counting locations are of a similar type (utilitarian, recreational, mixed-utilitarian, or mixed recreational). Two similar counting locations would produce quotients of daily factors with a low variance, while different counting locations, with differing temporal patterns, would produce quotients that varied tremendously. **Figure 3** (bottom) displays the distribution of values derived by taking the

quotient of daily factors from two pairs of long-term counting sites. On the left, the distribution from two utilitarian counting sites in Montreal during the cycling season of 2013 (De Maisonneuve at Peel and Côte-Saint-Catherine). On the right, the distribution from one utilitarian and one recreational counting site in Montréal during the cycling season of 2013 (De Maisonneuve at Peel and Pier Dupuis). Further work is required to develop and test variance thresholds that would effectively separate good and bad matches.

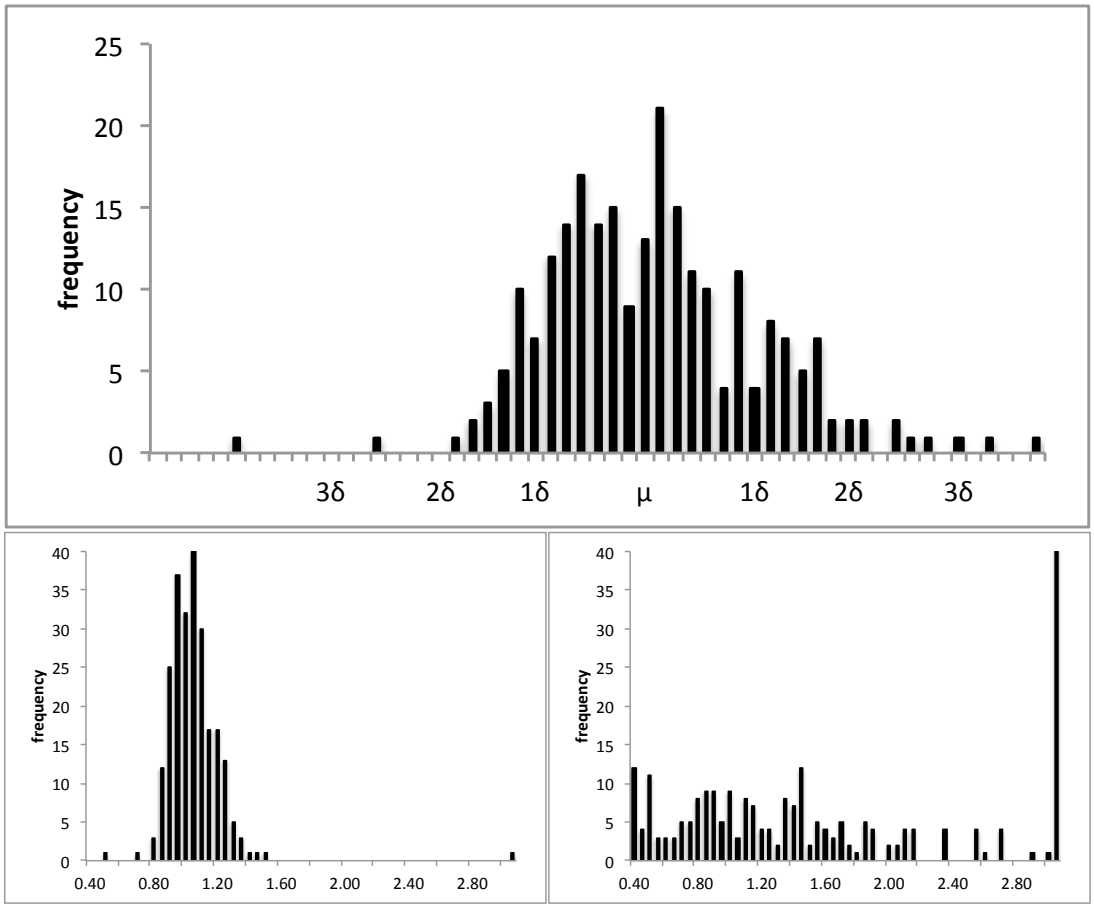

FIGURE 3: Top, the distribution of the quotient of the daily factors of two reference counting sites in Montréal (De Maisonneuve at Peel and Côte-Saint-Catherine). Bottom left, the distribution of the quotient of the daily factors from two utilitarian counting sites in Montreal during the cycling season of 2013 (De Maisonneuve at Peel and Côte-Saint-Catherine). Bottom right, the distribution from one utilitarian and one recreational counting site in Montreal during the cycling season of 2013 (De Maisonneuve at Peel and Pier Dupuis).

5.2 Matching short-duration counts to appropriate reference

The first stage of the proposed matching process requires clustering of all long-term counting locations used in a particular study. In this study, clustering was performed on 22 long-term test sites using data during the cycling season (April 1 – Nov 30) from 2011 to 2014. Not all locations had data spanning the entire cycling season for all four years, all complete years of cycling data were used. The data from each counting location was divided into separate cycling seasons, meaning that each site could be represented by as

many as four data points in the clustering analysis. A total of 77 cycling seasons of data were used as points in the analysis.

Using k-means with Euclidean distance as a dissimilarity measure and three indices defined in **Eq. 2-4**. The three-dimensional plot of the 77 cycling seasons is seen in **Figure 4**.

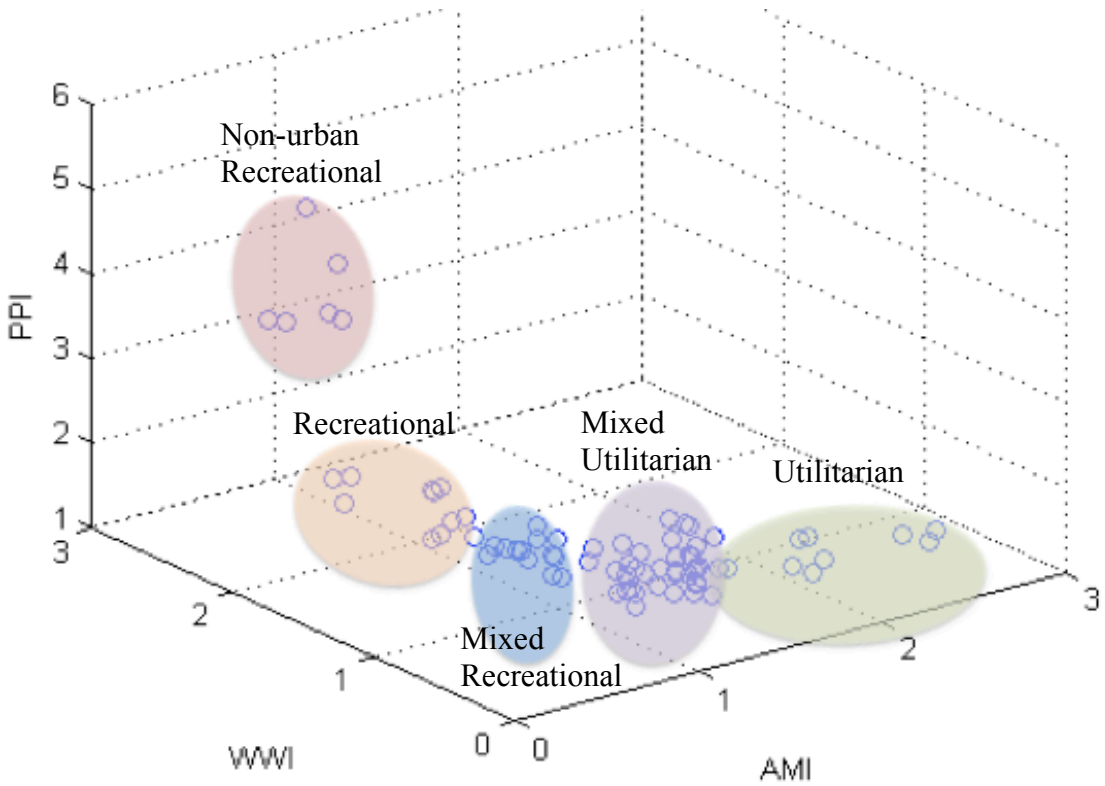

FIGURE 4: Cluster analysis of 22 long-term reference counters using five clusters and three indicators - AMI, WWI and PPI.

The cluster analysis was performed using three, four and five clusters. The ratio of within-cluster-variance to between-cluster-variance was lowest for the five cluster analysis. The new additional index used in this study, the peak period index (PPI), defined in **Eq. 4**, helped to isolate a fifth temporal profile that had not been previously reported: the non-urban recreational group. This group is characterized as having very high peak season cycling demand compared to shoulder season demand, as seen in **Figure 4.**

5.3 Extrapolating AADB from a short-duration count

Two modified disaggregated extrapolation techniques were tested in this study against the standard DFM. Both modified techniques produced AADB values that, on average, deviated less from the measured AADB value. All results in the extrapolation step were obtained from a well-matched long-term and short-duration counting site. In this study, the accuracy of an AADB extrapolation is defined in **(Eq. 7)**.

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

$\left|Error_{i,y,j}\right|$ is the absolute error for short-term site *i,* based on the AADB estimated on day(s) *j* in year *y,*

$\widehat{AADB}_{i,y,j}$ is 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 cycling year,

$\widehat{AADB}_{i,y}$ is the observed AADB for site i and cycling season y. The cycling season runs from April 1 until Nov 30.

The data used to test both modified DFMs and the standard DFM came from two long-term bicycle counters located in Montréal during the 2013 cycling season. One of these counters, located at Rachel and Papineau, was used as the "short-duration" counter, meaning that the data was broken up into consecutive one week (or two week) intervals starting from April 28 until October 27. The reference counter is located at De Maisonneuve at Peel. The measured AADB of the reference and "short-duration" counter, used to calculate the daily AADB estimates and the error of those estimates respectively, was the average bicycle demand between April 1 and Nov 30 (considered the cycling season in Montreal for the purposes of this study).

Disaggregated factor method with filtering:

The filtering technique significantly improved the accuracy of the AADB estimates using the DFM. As seen in **Figure 5,** the filtering technique removed anomalous daily AADB estimates in three of the two-week, short-duration periods. In each of these periods, a significant improvement in accuracy of the AADB estimate was achieved. As seen in **Table 1**, the average absolute error, across all 13 AADB estimates, decreased from 5.6% to 4.2% when the filtering technique was applied. Furthermore, the errors became more uniform across all of the short-duration periods when applying the filtering technique; the maximum absolute error of any two-week period was 8.9% compared to 13.7%.

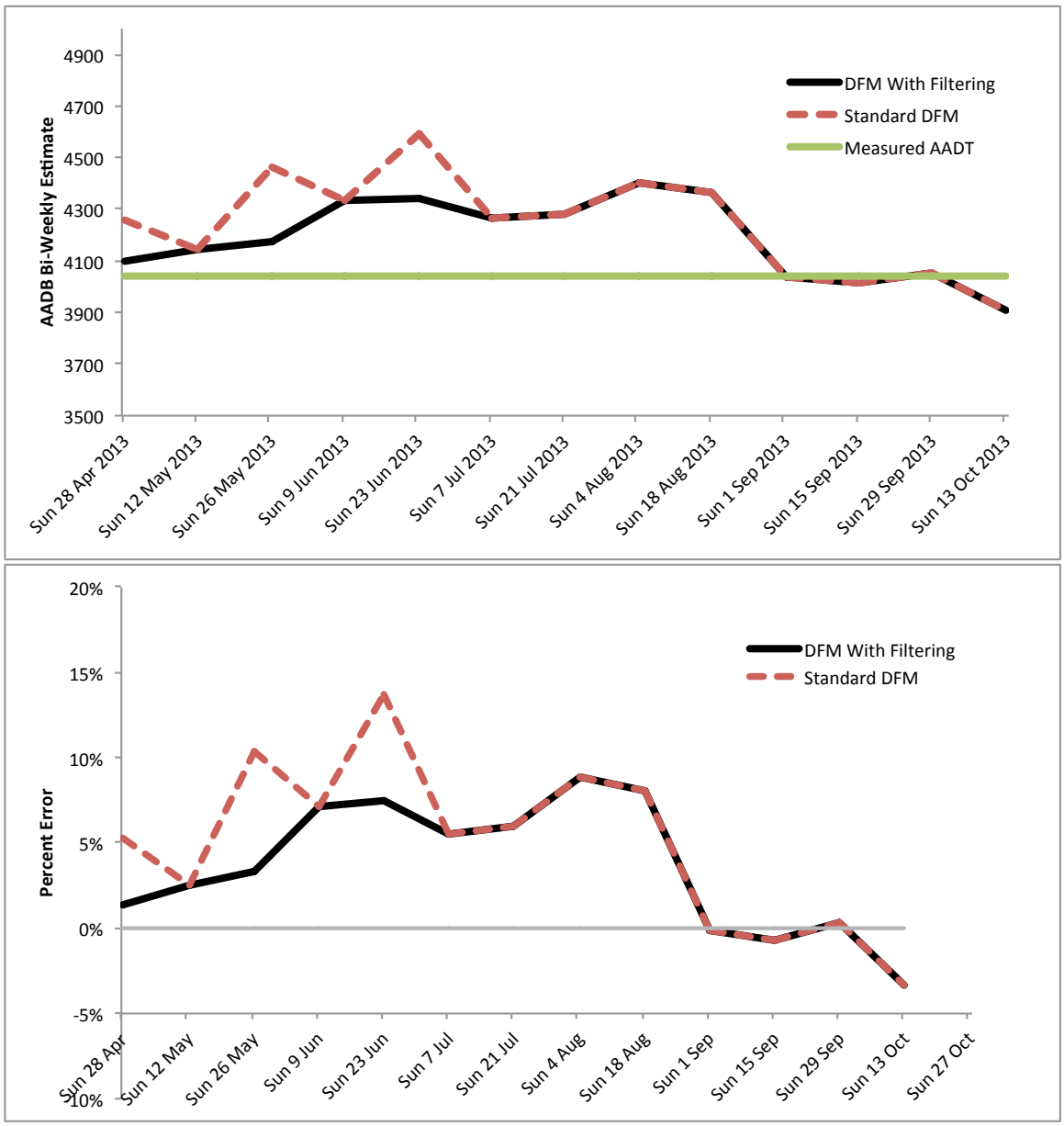

FIGURE 5: Comparison of Standard DFM, and the DFM with Filtering. Top, AADB estimates by two-week short-duration count; bottom, percent error of AADB estimates against measured AADB.

Disaggregated factor method with separate treatment of weekdays and weekends

The modification of the DFM to separate treatment of weekdays and weekends improved the accuracy of the AADB estimates on average. As seen in **Figure 6**, the technique improved the accuracy of all overestimated AADB values, however, it also decreased the accuracy of all underestimated AADB values. Overall, there was an improvement in the accuracy of the AADB estimates. As seen in **Table 1**, the average absolute error, across all 27 AADB estimates, decreased from 6.0% to 4.9% and the maximum absolute error of all short-duration periods decreased from 18.4% to 13.2% when the modification to the DFM was applied.

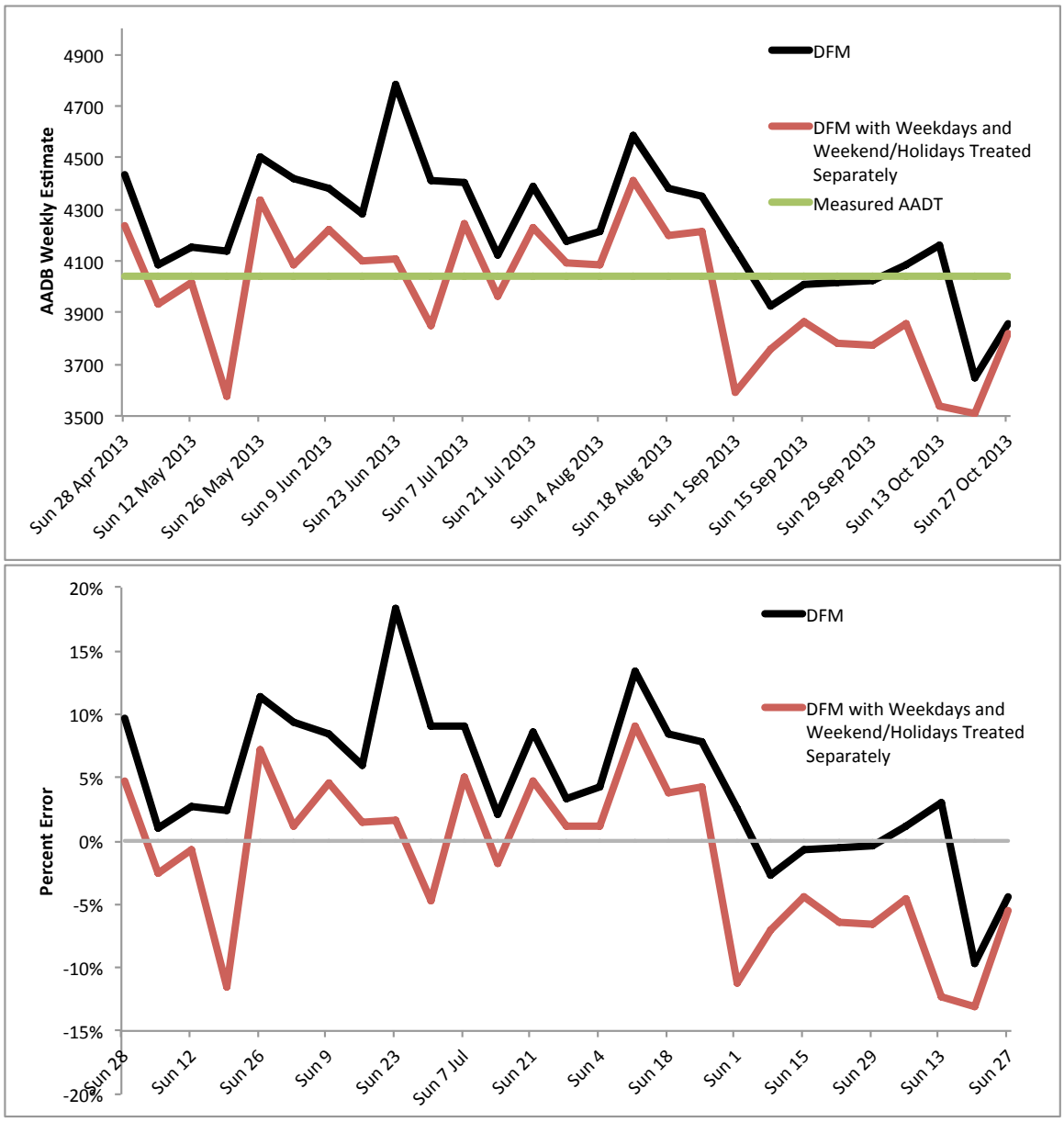

FIGURE 6: Comparison of Standard DFM, and the DFM with Weekdays and Weekend/holidays Treated Separately. Top, AADB estimates by one-week short-duration count; bottom, percent error of AADB estimates against measured AADB.

TABLE 1: Comparison of Standard DFM, the DFM with Weekdays and Weekend/holidays Treated Separately, and the Standard DFM with Filtering

Type of DFM	Standard	Weekdays and Weekend/Holidays Treated Separately	Standard	With Filtering
Length of short-duration count	7 days	7 days	14 days	14 days
Average Absolute Error for all short-duration counts	6.0%	4.9%	5.6%	4.2%
Maximum Absolute Error for a single short-duration count	18.4%	13.2%	13.7%	8.9%
Standard Deviation of Errors	4.5%	3.5%	4.1%	3.1%

6. CONCLUSIONS

AADB estimation from short-duration counts is non-trivial, laborious and can result in inaccurate measures when using traditional factoring methods. This study proposes a methodology that reduces estimation errors and facilitates automation of the AADB estimation. The methodology can be broken down into three steps: validating, matching, and extrapolating count data:

- For the validating step, the proposed method validates and identifies anomalous data in the long-term counting site and would be straightforward to automate. As tested in this study, the validation process identified four anomalous daily counts at two long-term counting sites over a single cycling season. This process could be automated to identify anomalies across multiple counting sites across many cycling seasons. The validation method was also explored to function as a matching process although more investigation is required.

- For matching, a method is proposed for clustering of counting sites, useful in matching short-duration and long-term counters. The clustering analysis proposed used three indicators rather than two as previously reported. The new indicator, PPI, improves the analysis by adding a metric for seasonal variation. Five distinct clusters emerged: utilitarian, mixed-utilitarian, mixed-recreational, recreational, and non-urban-recreational.

- For the extrapolation step, two modifications are proposed to existing methods in order to improve the robustness and accuracy of AADB extrapolation compared to previously reported methods. The first extrapolation method, the DFM with filtering, improved the AADB estimation accuracy, but perhaps of greater

importance, is that the variance of the absolute error and the maximum absolute error of any two-week period decreased significantly. The second method, the DFM with separate treatment of weekdays and weekends had similar results. The average AADB estimate error, the variance of the absolute error and the maximum absolute error of any one-week period were all reduced. It is worth noting that in both extrapolation modifications, the average AADB estimate error decreased as a result of a dramatic error reduction for the highest-error short-duration periods. The two modifications were designed to account for the factors (discussed in section 3.3.1) that degrade AADB estimation accuracy. The DFM with filtering method accounts for short-duration anomalies and discontinuities, while the DFM with separate treatment of weekdays and weekends accounts for the count variation attributed to weekends and holidays. Both of these methods make AADB estimation more robust, an important quality for a fully-automated extrapolation process.

Future work will include testing the validation, matching and extrapolation methods developed in this study with larger datasets, i.e. additional long-term counting sites from various regions across North America over multiple years. Improved methods that more reliably match short-duration counting sites with long-term reference sites will be developed. The clustering analysis will be further tested, improved and automated. Secondly, the validation process developed in this study will be expanded to function as a matching process. Developing robust methods that match short-duration and reference sites with similar traffic patterns will ensure greater accuracy of AADB extrapolation.

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