APPLYING A VEHICLE-MILES OF TRAVEL CALCULATION METHODOLOGY TO A COUNTY-WIDE CALCULATION OF BICYCLE AND PEDESTRIAN MILES OF TRAVEL

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ABSTRACT

Vehicle miles of travel are widely used in transportation planning, policy and research. In spite of the growing recognition of the importance of non-motorized travel, comparable estimates of bicycle and pedestrian miles of travel (BPMT) are rarely calculated largely due to the difficulty and expense of manually collecting bicycle and pedestrian (BP) counts. This paper uses a set of BP counts at 29 locations in Chittenden County Vermont, including three sites with more than a full year of counts, to explore the barriers to calculating reliable estimates of BPMT. Adjustment factors for converting single-day BP volumes into annual average daily BP volumes are calculated using the methodology in the Traffic Monitoring Guide (1) as well as a variation on this method that uses cluster analysis of weather patterns rather than calendar months to determine the seasonal adjustment periods. Finally, these adjustment factors are applied to four sets of BP network link classification systems resulting in eight estimates of BPMT and these estimates are compared to results from the 2009 National Household Travel Survey. The estimates based on adjustment factors ranged from 73.8 million to 295.8 million BPMT per year, far higher than the estimate of 31.5 million BPMT which is reached when only the NHTS data is used. The wide range of estimates produced demonstrates the need for more widespread BP data collection and further refinement and validation of BP link classification systems.

INTRODUCTION

Estimates of vehicle-miles of travel (VMT) are used extensively in transportation planning, policy and research. These estimates are used for infrastructure planning, for funding-allocation decisions, as measures of accident exposure, access and economic activity, and to calculate vehicle emissions and energy use. Procedures for estimating annual VMT are well established and rely on automated counting methods to collect continuous count data at a relatively small number of sites (1-3). Based on these continuous counts, a series of adjustment factors are calculated to account for variations in traffic levels at different hours of the day, days of the week and months of the year. These adjustment factors are then applied to more numerous, less expensive, short-duration counts taken at roadways with similar traffic patterns, creating comprehensive estimates of the annual average daily traffic (AADT) on all road links within a given study area. Multiplying the AADT estimates for each road link type by the number of network miles of that link type and summing the results for all road types yields the total VMT on the network. While several variations on the factor calculation process exist, each of these factoring methods have been shown to produce fairly comparable results (2). Because of the many uses for VMT estimates and the well established methods for calculating them, estimates are regularly made at the federal, state and local levels.

In spite of the growing recognition of the importance of non-motorized travel, comparable estimates of bicycle and pedestrian miles of travel (BPMT) are rarely calculated. The Bureau of Transportation Statistics has identified the systematic, methodologically consistent collection of non-motorized travel data, including annual average daily bicycle and pedestrian volume (AADBPV) and total BPMT, as a priority for improving infrastructure and safety analysis (4). One of the primary obstacles to calculating BPMT values is the expense of collecting of bicycle and pedestrian (BP) counts (5, 6). Because pedestrian movement is less restricted than vehicle movement and because pedestrians may move in closely overlapping groups, the counting process is more difficult to automate then it is for vehicles (5). Newer pneumatic and infrared equipment works well in some settings but is not well suited to all outdoor environments (7). Consequently, BP counts remain more dependent on expensive manual data collection and continuous count data is scarce. In addition, BP counts have tended to focus on more highly traveled paths in more bike- and pedestrian-friendly towns leaving significant spatial gaps in BP datasets (8). These temporal and spatial shortcomings present two distinct challenges for BPMT calculations. First, in the absence of continuous count data, it is difficult to develop adjustment factors that accurately account for seasonal variations in non-motorized traffic. While researchers have developed extrapolation techniques based on short duration counts, these extrapolation measures generally focus on converting hourly counts to daily (9-11) or weekly BP volumes (9) and most do not provide annual BPMT estimates. Second, the lack of diversity in count locations makes it difficult to create factor-groupings that accurately reflect BP patterns, especially in lower pedestrian-volume regions. As a result, researchers often assume negligible or even no non-motorized traffic in outlying areas and the defensibility of region-wide estimates is compromised (12).

This paper presents and compares eight annual BPMT estimates for Chittenden County, Vermont calculated using seasonally specific, day-of-week adjustment factors. These estimates were calculated using two different adjustment factor methodologies and four different methods for categorizing BP network links. The adjustment factors were derived using the Traffic Monitoring Guide's (TMG) (1) standard AADT calculation methodology as well as a variation on this method that uses cluster analysis of weather patterns rather than calendar months to determine the seasonal aggregations periods. Comparing the BPMT results achieved using each of the factor methodologies makes it possible to assess the adequacy of monthly aggregation periods in capturing the effects of seasonality on BP volumes. Additionally, each count site and each link in the BP network was categorized according to four classification systems intended to group links in the BP network that experience similar BP traffic volumes. There is considerable uncertainty regarding the best methods for grouping network links so using four different classification systems helps illuminated the impact differing approaches may have on BPMT estimates. Finally, these count based BPMT estimates are compared to a survey based BPMT estimate calculated from the 2009 National Household Travel Survey (13).

Because pedestrians and cyclists are more exposed to the elements than motorists, they are likely to be more sensitive to seasonal changes than are motorists. Prior research has shown that weather can account for a significant proportion of the variability in BP counts (14). Calendar months, however, may not capture the true seasonal variability as it affects BP travel. In Vermont, for example, early November may be characterized by comparatively mild temperatures while late November is frequently below freezing and snowfall is not uncommon. Similarly dramatic changes in temperature and precipitation can be experienced between the beginning and end of March and at other intra-month periods. Alternately, the summer months in many parts of the US have relatively little weather variation. Consequently, this paper presents two sets of seasonally specific, day-of-week adjustment factors for converting single-day BP counts to AADBPV for Chittenden County, Vermont. These adjustment factors were derived from three sets of continuous, full-year BP counts collected by the Chittenden County Metropolitan Planning Organization (CCMPO) using infrared-sensitive lens counters. The first set of adjustment factors was calculated using a monthly aggregation period which is the standard approach for capturing seasonal variations in traffic volume. The second set of factors was calculated for six cluster-seasons determined by a cluster analysis of weather data and is intended to more accurately reflect the seasonal patterns in BP traffic. The monthly and cluster-seasonal based adjustment factors differ at a statistically significantly level for approximately 20% of the days of the year.

Count sites and links in the BP network were grouped according to four classification systems. One classification system considered all count sites as belonging to the same undifferentiated group. Three additional classification systems were intended to group links in the BP network that experience similar BP traffic volumes. The first of these classification systems is based on the functional class of the road, the second on clustered land-use parcels and the third on residential density. For each classification system, AADBPV values were calculated for each category within that classification system and multiplied by the cumulative length of all BP network links in that category. Applying both the cluster-seasonal and monthly adjustment factors to the counts sites without any classification and with each of the three classification systems resulted in eight BPMT estimates for the county. A ninth estimate, based on the NHTS, is provided for comparison purposes.

This paper is organized as follows. The Data section presents the data sources and data collection methods used in this study. The Adjustment Factors section describes the adjustment factor methodology from the TMG as well as the two aggregation methodologies used to create adjustment factors and the difference between the resulting sets of adjustment factors. The three classification systems used for estimating BPMT are described next along with the final BPMT estimates that are produced using each classification system. The final section of the paper provides the authors' conclusions and recommendations for future research.

DATA

Non-Motorized Travel Count Data

This study considered bicycle and pedestrian counts collected between 2007 and 2011 from sidewalks, shared-use paths, and road shoulders at 29 locations throughout the county using pyroelectric infrared sensors and a motion-sensitive, closed-circuit digital video camera. The pyroelectric sensors detect the infrared emitted by the human body allowing multiple people to be counted individually even if they are close together. Three of the 29 counts include more than a year's worth of data while the remaining sites have between one day and six weeks of data. Full-year counts are required to create seasonal adjustment factors using the methodology recommended in the TMG but are extremely rare for BP counts. Such extended duration counts would have been cost prohibitive to collect manually and thus the use of automated counting devices was pivotal to the creation of this dataset.

As shown in Figure 1, the final dataset consisted of 29 count locations throughout the county – three with full-year counts, 15 with multi-day counts, and 11 with single-day counts. The CCMPO has also collected partial-day BP counts at 21 other locations throughout the county. However, since time-of-day adjustments vary considerably from site to site (11), these partial-day counts were not used in this study.

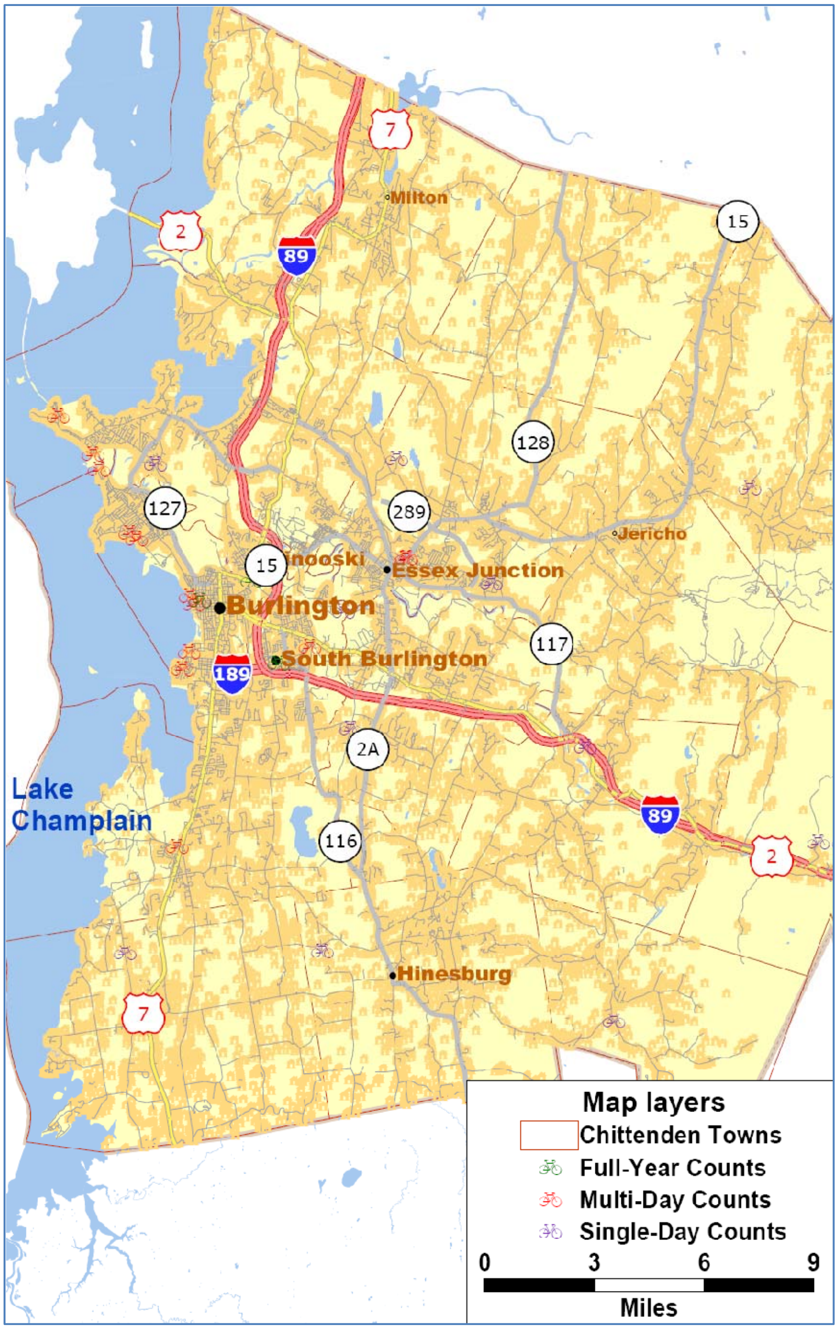

Figure 1 BP count locations in Chittenden County, Vermont.

Table 1 shows summary data for the three full-year count sites. Counts at SOBR06 were taken from September 2008 through August 2010, at BURL12 from August 2009 through October 2010 and at BURL02B from March 2009 through April 2011. While the TMG recommends using continuous count vehicle data only from the year for which VMT is being estimated (1), others suggest that pedestrian adjustment factors in areas with relatively little development can reasonably be applied for five to 10 years(6). On this basis, we assumed that count data from all years at the three sites could be used to calculate the adjustment factor without additional corrections.

Table 1 Summary Data from Full-year Count Sites

			Weekly Total Counts			
ID	**Surrounding Land-Use**	**Town**	**Avg.**	**Min.**	**Max.**	**Std. Dev.**
SOBR06	Public-Institutional	South Burlington	931	168	1,886	420
BURL12	Mixed-Use	Burlington	2,844	647	4,695	1,240
BURL02B	Mixed-Use	Burlington	5,321	2,597	6,928	986

Figure 2 shows daily BP volumes for each day of the year for each of the full-year count sites. The counts have been normalized so that the AADBPV at each site is equal to one. Counts at the same sites on the same day of the year, e.g. January1, 2009 and January 1, 2010 at SOBR06, were averaged together prior to data normalization. Ideally full-year continuous counts would be available for each path and roadway type in the county, this level of spatial coverage is not currently available so a single set of adjustment factors was created from these three sites and applied to all count sites regardless of link type. The yearly patterns for all three full-year sites are broadly similar, suggesting that a single set of adjustment factors may be adequate.

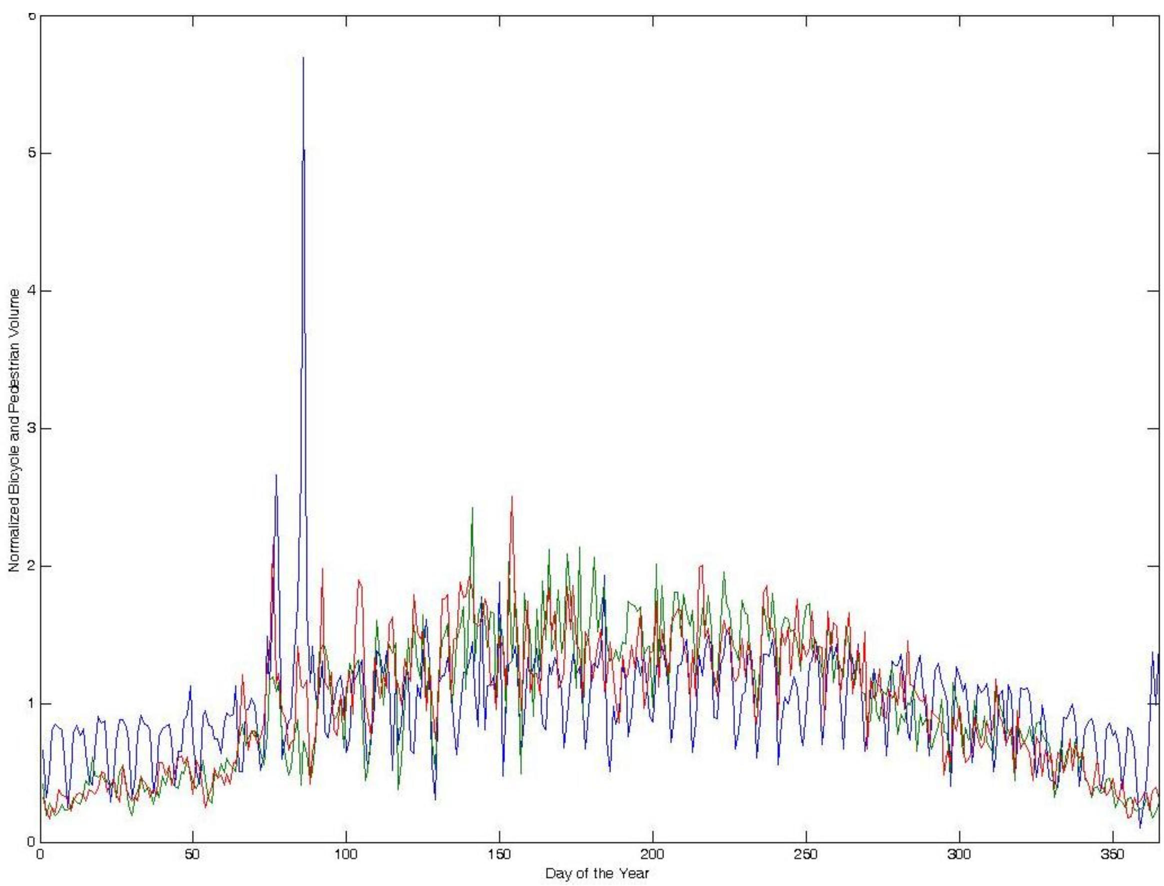

Figure 2 Bicycle and Pedestrian Volumes at Continuous Count Sites

Spatial Land-Use Data

In order to categorize the count locations within each of the three link classification systems, this study made use of parcel-level zoning data and residential density data for Chittenden County from the CCMPO and street class data from the US Census. A complete BP network was created by merging shared-use paths and the street network and subsequently removing limited-access highways and ramps where non-motorized travel is prohibited.

Within the parcel-level zoning database, parcels are categorized as agricultural (includes agriculture, forestry, fishing and hunting), commercial (includes general sales and services), public institutional (includes public administration and education), recreational (includes arts, entertainment, and recreation), residential (includes residence and accommodation), transportation (includes transportation, communication, information, and utilities) or other (includes all other land-uses). In Chittenden County, residential and agricultural land uses make up the highest proportion of the total area, both exceeding 30 percent. The next highest categories are public-institutional and recreational, together comprising 20 percent of the total area. Commercial land-use types were lower and mostly concentrated in the Burlington urban area.

The housing/dwelling units layer from the CCRPC was developed in 2005 from parcel records for Chittenden County. Each housing point in this dataset represents a housing structure in Chittenden County. For each housing structure, attributes indicating the type of structure are included, along with the number of dwelling units (DUs) represented at the point. The dataset is intended to identify the location and type of dwelling units for future land-use and transportation modeling efforts. One of the most complete sources of street mapping for the entire United States is the US Census Topologically Integrated Geographic Encoding and Referencing system (TIGER) line layer. The 2009 TIGER layer for Chittenden County was used in this research. The TIGER data includes the following Census Feature Class Codes:

- Above A49: Vehicular trails and minor streets
- A41, A43, A45, A49: Local, neighborhood, and rural roads
- A31, A33, A35, A39: Secondary and connecting roads
- A21, A23, A25, A29: Primary roads without limited access
- A11, A15, A17, A19: Primary highways with limited access

CREATING TEMPORAL ADJUSTMENT FACTORS

In order to estimate AADBPV from single-day counts using the methodology recommend in the TMG (1), a series of adjustment factors were developed based on data from the full-year count sites. For this study, adjustment factors were developed for each day of the week in each seasonal aggregation period (either a month or a cluster-season) by finding the ratio between the AADBPV and the average pedestrian volume for each day of the week in each aggregation period. Equation 1 shows the calculation for the period average day-of-week BP volume (PADoWBPV) for day-of-week *d* at a given site *s* in aggregation period *p*. In this equation, C_d is the BP count for a given day of the week (Sunday, Monday, Tuesday, etc.) and *nD* is the number of counts collected on that day of the week in that aggregation period, e.g. the four Mondays in January. Equation 2 shows the AADBPV for site *s*, using the AASHTO "average of averages" method recommended in the TMG. The equation averages the PADoWBPV for each of *nP* aggregation periods and then for each of the seven days of the week. Finally, Equation 3 shows the calculation of the adjustment factor (AF) for day-of-week *d* at a given site *s* in aggregation period *p*.

$$PADoWBPV_{psd} = \frac{1}{nD}\sum_{d=1}^{nD} C_d \tag{1}$$

$$AADBPV_s = \frac{1}{7}\sum_{i}^{7}\left[\frac{1}{nP}\sum_{p=1}^{nP}\left(PADoWBPV_{psd}\right)\right] \tag{2}$$

$$AF_{psd} = \frac{AADBPV_s}{PADoWBPV_{psd}} \tag{3}$$

Identification of Aggregation Periods

As discussed previously, monthly aggregation periods may not adequately capture seasonality. For this reasons, a k-means cluster analysis was used to identify cluster-season aggregation periods as characterized by clustered weather patterns.

Before performing the cluster analysis, the annual distributions of these weekly total counts were plotted and reviewed to identify any obvious patterns. This plot is in Figure 3. The solid lines on the chart were added to qualitatively identify temporal sequences which appeared to trend uniformly in the data. As expected, these divisions seem to coincide with significant climate changes throughout the year in Chittenden County.

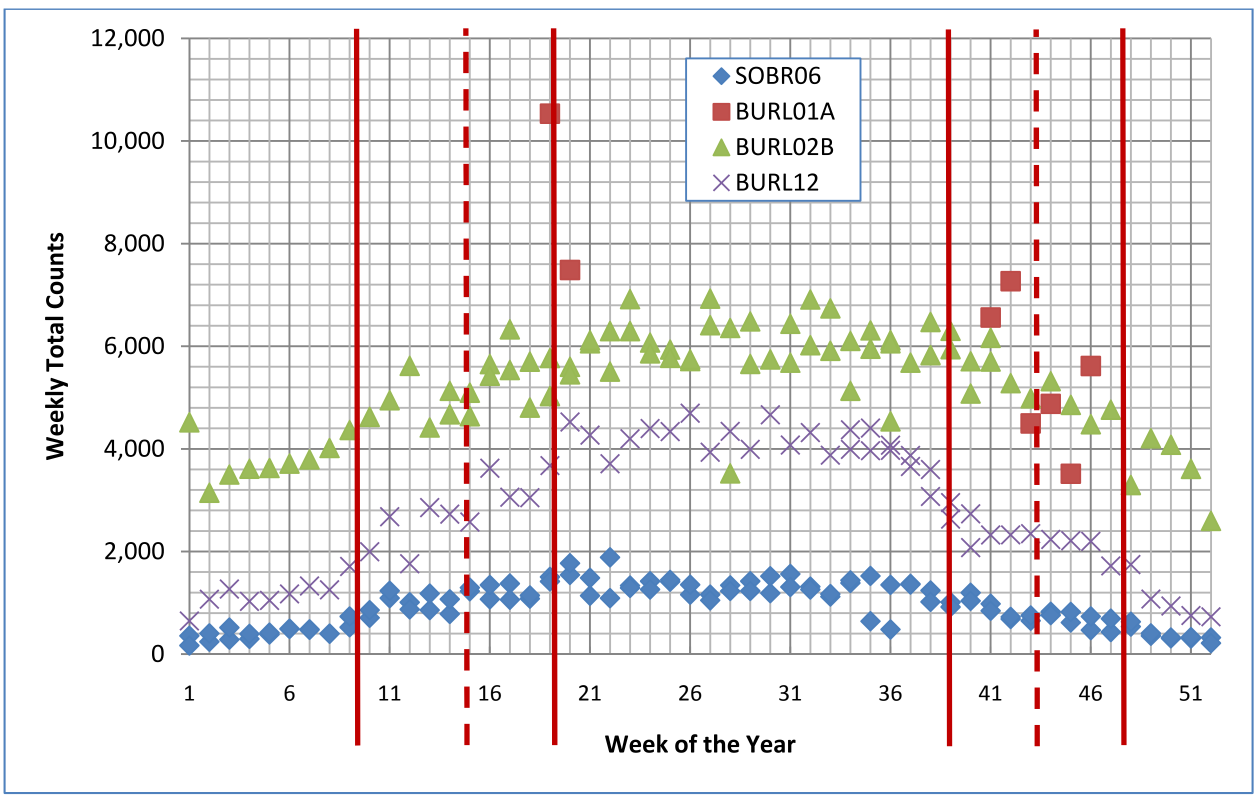

Figure 3 Weekly BP Totals at Full-Year Count Sites

Next, a clustering process was initiated to identify significant shifts in climate throughout the year, using weekly average weather data for Burlington, Vermont. Weekly averages for temperature, rainfall, snowfall, and wind speed for the weather station at Burlington International Airport were obtained (15). K-means clustering was used on the weekly averages, for four clusters, corresponding to the traditional four seasons of the year. The four-cluster analysis resulted in a total of six "breaks" in the year, where significant shifts took place, and the cluster assignment shifted accordingly. Therefore, the analysis was repeated using six clusters, once again resulting in six seasonal shifts which corresponded exactly with the breaks identified in the four-cluster analysis. These results suggest that there are actually six significant changes in climate throughout the average year in Burlington, Vermont. These cluster-seasons are shown in Table 2.

Table 2 Cluster-Seasons Found Using Cluster Analysis of Weather Data

	Week of the Year		
Cluster	**Start**	**End**	**Months Included**
1	48	12	Part of November, December January, February, and Most of March
2	13	17	Part of March and April
3	18	21	Most of May
4	22	39	Part of May, June, July, August, and September
5	40	43	Most of October
6	44	47	Part of October and Most of November

Each of the qualitative separations shown in Figure 3 coincides with a cluster transition in Table 2. The additional separations created by the six clusters in Table 2 are shown in Figure 3 as dashed lines.

Calculation and Comparison of Monthly and Cluster-Season Adjustment Factors

For each of the three full-year sites, adjustment factors were calculated for each day of the week and each aggregation period. This produced 84 adjustment factors using the monthly aggregation method (seven days of the week for each of 12 months) and 42 adjustment factors using the cluster-season aggregation method (seven days of the week for each of 6 seasons). The variance and standard deviation for each adjustment factor were calculated using a formula for the variance of the quotient of two variables given in of (16). In the absence of a good estimate for the covariance term between dividend and divisor, this term was omitted from the variance calculation (NIST, 2003). Calculating the variance associated with each adjustment factor made it possible to determine if monthly and cluster-seasonal aggregation differed significantly.

As an example, the adjustment factors for converting Tuesday counts to AADBPV derived from site BURL02B is shown for each aggregation period in Table 3. The overlap between the 12 monthly and six cluster-seasonal aggregation periods is such that there are 16 unique pairings of monthly and cluster-seasonal adjustment factors over the course of a year. The differences in the adjustment factors for each aggregation period for each of these 16 occurrences are shown in the last column of Table 3. For each of these 16 occurrences there is an adjustment factor for each day of the week creating a total of 336 pairs of monthly and seasonal adjustment factors. Of the 336 pairs of adjustment factors, 63 differ significantly at a significance level of 0.90 or higher. The majority of the statistically significant differences occur in Weeks 5-8, Week 44 or Week 48 – February, late October and late November respectively. A slightly greater number of significant differences occurred between Friday and Monday than from Tuesday to Thursday. In general, the standard deviations were larger for the cluster-season based factors than the monthly aggregated factors.

Table 3 Tuesday Adjustment Factors for BURL02B

Weeks of the Year	Month	Cluster-Season	Monthly Aggregation Adjustment Factor	Monthly Aggregation Standard Deviation	Cluster-Seasonal Aggregation Adjustment Factor	Cluster-Seasonal Aggregation Standard Deviation	Difference in Adjustment Factors	
1 – 4	January	1	1.20	0.11	1.11	0.33	0.09	
5 – 8	February		1.21	0.09			0.10	*
9 – 12	March		0.89	0.30			-0.22	
13	March	2	0.89	0.30	1.01	0.34	-0.12	
14 – 17	April		1.00	0.34			-0.01	
18 – 21	May	3	0.83	0.10	0.86	0.12	-0.03	
22	May	4	0.83	0.10	0.84	0.15	-0.01	
23 – 26	June		0.78	0.11			-0.05	
27 – 31	July		0.85	0.16			0.01	
32 – 35	August		0.81	0.17			-0.02	
36 – 39	September		0.78	0.07			-0.05	
40 – 43	October	5	0.77	0.09	0.81	0.11	-0.04	
44	October	6	0.77	0.09	0.99	0.13	-0.21	*
45 – 47	November		0.95	0.10			-0.03	
48	November	1	0.95	0.10	1.11	0.33	-0.15	*
49 – 52	December		1.04	0.35			-0.07	

* Difference is statistically significant at the .9 level.

Once the adjustment factors were calculated for each of the three full-year count sites, they were averaged across these sites to create the final adjustment factors for each aggregation period and day-of-week.

LINK AND COUNT SITE CLASSIFICATIONS SYSTEMS

Given a representative set of BP count locations with an equal number of counts at each location, the average of the AADBPVs from each count location would provide an unbiased estimate of the true AADBPV across the study area. Multiplying the average AADBPV value by the total miles in the BP network and by 365 days of the year would yield an unbiased estimate of the annual BPMT. However, if the number of counts is unequal across the count locations or if these locations are not representative, this process will produce a biased BPMT estimate.

Bias can be reduced if count locations are classified such that sites with similar BP volumes are grouped together and separate BPMT estimates are calculated for each portion of the BP network that falls into each category in the classification system. Because street type, residential density (6) and land-use (6, 9) have been identified by other researchers as drivers of variation in BP volumes, this study implements classification systems based on those characteristics as well. For this paper, BPMT values were calculated without any classification of the count sites and BP network links and with the three classification systems described below.

Classification Systems

Roadway Functional Class

The first classification system categorized count locations based on the Census Feature Class Code of the road link adjacent to the count location or as "recreational" for those count locations which are not near a roadway. This system included four categories. The recreational category consisted of all shared-use paths that do not run alongside any portion of the roadway network. Recreational paths make up a less the two percent of the BP network but have the highest AADBPV of any category in this system and therefore contribute disproportionately to the BPMT total. The number of counts taken in each of these four categories and the total the BP network miles that are in each category are shown in Table 4.

Table 4 BP Network Classification by Roadway Functional Class

Count Location Category	Number of Counts	BP Network Miles
Recreational	996	29.5
Local, neighborhood, and rural roads	827	61.7
Secondary and connecting roads	11	90.2
Primary roads without limited access	416	1393.2
Totals	2250	1595.3

Residential Density

The second classification system categorized links and count locations based on the residential density around the count location. Residential and commercial densities are two of the factor grouping methods recommended in (6). Residential densities were divided in the three categories. Residential densities were determined by the number of DUs in each of the 0.3-mile grid cells used to cluster land-uses described below. Low residential density links were defined as those links in grid cells with fewer than 100 dwelling units per square mile. Links in grid cells with between 100 and 500 dwelling units per square mile were defined as medium density while those with more than 500 dwelling units per square mile were defined as high density links. The number of counts taken in each of these categories and the total the BP network miles that are in each category are shown in Table 5.

Table 5 BP Network Classification by Residential Density

Link Category	Number of Counts	BP Network Miles
Low Residential Density	778	810.5
Medium Residential Density	129	374.6
High Residential Density	1343	410.2
Totals	2250	1595.3

Clustered Land-Use Parcels

For the final classification system, count locations were classified based on the surrounding land use and the BP infrastructure available at that location. This land use classification system was based on a k-means clustering analysis of 0.3-mile grid cells from a previous study (8). Parcels were clustered into five land-use categories – agricultural, mixed-use, public-institutional, recreational and residential – which would be expected to experience significantly different AADBPVs. Because of the high number of counts on shared-use paths and the relatively high BP volumes on these paths, count locations were further subdivided into shared-use path and non-shared use categories. The number of counts taken and the total the BP network miles that are in each category in this classification system are shown in Table 6.

Table 6 BP Network Classification by Cluster Land-Use

Link Category	Number of Counts	BP Network Miles
Agricultural with shared-use path	29	6.4
Agricultural without shared-use path	6	380.2
Mixed Use with shared-use path	1263	25.7
Mixed Use without shared-use path	17	331.0
Public-Institutional with shared-use path	742	136.8
Public-Institutional without shared-use path	9	166.9
Recreational with shared-use path	89	5.3
Recreational without shared-use path	1	57.9
Residential with shared-use path	90	698.4
Residential without shared-use path	4	8.9
Totals	2250	1595.3

BPMT CALCULATIONS

In order to arrive at BPMT estimates for each classification system, the adjustment factors were applied to all of the 2250 unique single-day counts across all sites resulting in 2250 estimates of the AADBPV. For each classification system, AADBPV estimates within each category were averaged, resulting in a single AADBPV for that link category. This AADBPV value was then multiplied by the total miles in that category and by 365 days of the year to yield the annual BPMT for that category. Summing the category-level BPMT estimates provided the total, county-wide BPMT for Chittenden County.

As a comparison to these estimates, the total BPMT in Chittenden County in the NHTS (13) was also calculated. This value is an annual estimate which incorporates the person-trip weights in the NHTS data, which are intended to correct for bias in the 502 randomly selected households in the survey. Table 7 shows the final BPMT values for Chittenden County with each of the three classification systems as well as the BPMT estimate for Chittenden County from the NHTS.

Table 7 BPMT Calculated for Three Different Classification Systems

	Total BPMT	
NHTS Estimate	31,300,000	
Study Estimates		
Classification System	Monthly Adjustment factors	Cluster-Seasonal Adjustment Factors
No classification System	288,000,000	295,800,000
Residential Density	252,800,000	260,500,000
Road Functional Class	89,900,000	93,700,000
Land Use & Infrastructure Type	73,900,000	76,500,000

DISCUSSION AND CONCLUSIONS

The primary conclusion of this study is that determining the seasonal aggregation periods via cluster analysis does not produce BPMT estimates that are practically different than those produced using the traditional monthly aggregation period. This conclusion is supported by the similarity of the results for each classification system across aggregation periods (monthly/cluster-seasonal). This result is somewhat surprising since it has been shown that bicycle and pedestrian volumes are dramatically affected by season, but these effects seem to be adequately captured by monthly aggregation.

These results also suggest several important secondary conclusions. First, the count data used in this study confirms that BP activity occurs at some level along almost every link in the roadway network and therefore that rigorous BP counting of rural roadways is essential to accurately computing BPMT estimates. Second, grouping BP network links which experience similar BP volumes is likely to increase the accuracy of BPMT estimates when the raw count sites are not representatively distributed. This is evident when comparing the extremely high unclassified BPMT estimates with the more moderate results when links are classified according to road functional class or land use. Finally, surveys of BP activity may underestimate actual activity levels. Researchers suspect that survey-based estimates like the NHTS may systematically underestimate BPMTs for two reasons. The first is that respondents may not include all non-motorized trips when a travel-diary is recorded; trips initiated independently by youth or those which are relatively frequent but very short are particularly likely to be omitted. The second potential source of underestimation is an inherent bias toward denser areas that a random household-based survey incurs. Rural locations are not as well represented in raw trip counts in the NHTS, so rural households with a higher tendency toward non-motorized travel may not be well represented. These potential shortcomings establish the importance of non-motorized traffic counts in more rural areas for an accurate estimate of county-wide BPMTs.

This study also demonstrates that a number of challenges remain in the calculation of reliable BPMT estimates. These challenges arise primarily from the continued scarcity and lack of locational diversity in BP count data. Even in areas with a fairly long history of BP counts as in Chittenden County, there may be insufficient data to create defensible BPMT estimates. This conclusion is demonstrated by the wide variety of estimates which resulted from the different classification systems used in this study.

Further research on this dataset will include creating separate adjustment factors for cyclists and pedestrians, and testing classification systems and aggregation periods that are based on daily, as opposed to seasonal, weather. Because cyclist and pedestrians are likely to respond to seasonal variations differently, using separate adjustment factors for each would be expected to improve the accuracy of both the AADBPV and BPMT estimates. It may also be true that BP activity is more affected by daily weather (e.g., if it is raining in the morning or if it is cloudy) than by weather trends across seasons.

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REFERENCES

1. FHWA, *Traffic Monitoring Guide*. Publication FHWA-PL-01-021. FHWA, U.S. Department of Transportation, 2001.
2. Cambridge Systematics, Inc., *Use of Data from Continuous Monitoring Sites, Volume II: Recommendations*. 1994.
3. Wright, T., Hu, P. S., Young, J., and Lu, A. *Variability in Traffic Monitoring Data*. Oak Ridge National Laboratory, U.S. Department of Energy, 1997.
4. BTS, *Bicycle and pedestrian data: sources, needs, & gaps*. Publication BTS00-02. Bureau of Transportation Statistics, US Dept. of Transportation, 2000.
5. Hocherman, I., A.S. Hakkert, and J. Bar-Ziv. Estimating the daily volume of crossing pedestrians from short-counts. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 1168, 1988.
6. Greene-Roesel, R., M.C. Diogenes, and D.R. Ragland, *Estimating Pedestrian Accident Exposure: Protocol Report*. 2007, Safe Transportation Research & Education Center, Institute of Transportation Studies, UC Berkeley.
7. Greene-Roesel, R., et al. *Effectiveness of a Commercially Available Automated Pedestrian Counting Device in Urban Environments: Comparison with Manual Counts*, in *TRB Annual Meeting*. 2008: Washington DC.
8. Zhang, C., et al., *Towards More Robust Spatial Sampling Strategies for Non-motorized Traffic*, in *The 89th Annual Transportation Research Board Conference*. 2010: Washington DC.
9. Schneider, R., L. Arnold, and D. Ragland, Methodology for Counting Pedestrians at Intersections. *Transportation Research Record: Journal of the Transportation Research Board*, 2009. **2140**(-1): p. 1-12.
10. Soot, S., Trends in downtown pedestrian traffic and methods of estimating daily volumes. *Transportation Research Record: Journal of the Transportation Research Board*, 1991(1325).
11. Davis, S.E., L.E. King, and H.D. Robertson, Predicting Pedestrian Crosswalk Volumes. *Transportation Research Record: Journal of the Transportation Research Board*, 1988(1168).
12. Hammond, J.L. and P.J. Elliott. *Quantifying Non-Motorized Demand: A New Way of Understanding Walking and Biking Activity*. in *Using National Household Travel Survey Data for Transportation Decision Making: A Workshop*. 2011.
13. FHWA, *The 2009 National Household Transportation Survey*, FHWA, U.S. Department of Transportation, 2009.
14. Aultman-Hall, L., D. Lane, and R.R. Lambert, Assessing Impact of Weather and Season on Pedestrian Traffic Volumes. *Transportation Research Record: Journal of the Transportation Research Board,* 2009. **2140**(-1): p. 35-43.

15. MelissaData. *Climate Averages by Zip Code*. 2010 (cited 2010; Available from: http://www.melissadata.com/Lookups/ZipWeather.asp?ZipCode=05401.
16. NRC, *Regulating Pesticides*. 1980, Washington D.C.: National Academy of Sciences.