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Regional Models of Bicycle and Pedestrian Travel in Chittenden County, Vermont

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A Report from the University of Vermont Transportation Research Center

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Disclaimer

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1 Introduction and Objectives

Encouraging travelers to walk and bicycle in lieu of motorized modes of travel benefits both the traveler and the community at large. The traveler benefits from health improvements that have been shown to accompany increases in physical activity that can in turn reduce health-care costs on a larger scale. The community benefits from the reduced congestion and emissions associated with automobile travel. Even so-called recreational walking and bicycling can provide the same benefits for the individual and if they replaced recreation that involved driving provide transportation system benefits as well. Bicycling and walking have also been associated with economic development, including but not limited to tourism. Maximizing these system benefits is critically important for the state and municipalities, especially when funding for transportation is scarce.

In order to make better funding decisions for non-motorized transportation infrastructure, it is first necessary to understand comprehensively the walking and bicycling behavior of a region's inhabitants. With this understanding, current walking and bicycling behavior can be estimated throughout the region, programs to increase levels of non-motorized travel can be pursued and the return on investment in non-motorized infrastructure can be assessed. A comprehensive understanding of non-motorized travel behavior requires an understanding of its relationship to the built environment. Many researchers have focused their attention on improving our understanding of the relationship between the built environment and non-motorized travel. However, few of these studies support this connection in a region with a spectrum of urban to rural communities, where the effects of spatial dependency and land-use impacts are poorly understood. Bicycling and walking are typically assumed to be urban modes of travel and moreover, existing research has focused on these modes in urban settings.

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 crash and incident exposure, access and economic activity, and to calculate vehicle emissions and energy use. The lack of comparable estimates of bicycle and pedestrian miles of travel (BPMT) creates a lack of information for policymakers to use for funding, planning and managing non-motorized travel. The Bureau of Transportation Statistics (BTS) has identified the systematic, methodologically consistent collection of non-motorized travel data, including estimation of annual average daily bicycle and pedestrian volume (AADBPV) and total bicycle and pedestrian miles of travel (BPMT), as a priority for improving infrastructure and safety analysis (BTS, 2000). The overall objective of this project is to advance these non-motorized travel data methods and procedures focusing on a study area in Chittenden County (Burlington) VT.

The first results of this study examined the hourly distributions of non-motorized traffic data along shared-use paths in Chittenden County, Vermont and investigated the probable linkage between daily totals, hourly distribution signatures, and surrounding land-use. The goal was to pursue more robust data collection and methods to generate county-wide shared-use path BPMT.

Subsequent analysis focused on estimating county-wide BPMT with the existing shared-use path counts as well as new count data on roads. We proceeded to fill data gaps using video data collection which is described in detail and to test a variety of link-classification methods and temporal-aggregation methods for calculating total BPMTs based on sources of data collected from throughout the study area.

The outcome of the project are 16 separate annualized BPMT estimates for Chittenden County, Vermont calculated using the Traffic Monitoring Guide standard AADT calculation methodology (FHWA, 2001). These BPMT estimates were calculated using eight different methods for categorizing network links, two different methods of categorizing days of the week, and two different methods of representing the seasons of the year. There is considerable uncertainty regarding the best methods for grouping network links so using eight different classification systems helps illuminate the impact that these groupings have on regional BPMT estimates. Finally, these count-based BPMT estimates are compared to a survey-based BPMT estimate calculated from the 2009 National Household Travel Survey (NHTS) (FHWA, 2009). The total BPMT in Chittenden County from the NHTS was calculated to be 31.3 million miles per year.

2 Background

A critical goal of studies related to New Urbanism and Smart Growth is to increase levels of non-motorized travel (walking and bicycling) in neighborhoods and communities (Katz, 2004). Encouragement of non-motorized travel is critical not only for its own sake, but to reinforce the use of transit systems, since most transit trips include a walking or bicycling trip at both ends. In addition to serving as an alternative to motorized traffic and its environmental, energy and social costs, non-motorized travel has also been at the center stage for promoting healthy living. In a recent cycling and walking study (Zahran et. al., 2008) utilizing nationwide county-based data, the authors pointed out the spatial distribution of cycling and walking commute trips is positively associated with population density, natural amenities, education, wealth and estimates of local civic concerns.

Other studies have focused on the association between land-use, including zoning and physical characteristics, and non-motorized travel. Rodriguez and Joo (2004) examined the connection between non-motorized mode choices and built-environment-based variables, while considering typical modal characteristics. Local topography and sidewalk availability have been demonstrated as important to the attractiveness of non-motorized modes. Guo et. al. (2007) assessed the effects of the built environment on motorized and non-motorized trip-making. They concluded that very few built-environment factors would successfully lead to substitution of motorized travel by non-motorized modes. However, they argued that increases in bikeway density and the connectivity of the street network would have the best potential for doing so. Cervero and Kockelman (1997) found that density, land-use diversity, and pedestrian-oriented design significantly encourage non-motorized travel, although the impacts appeared fairly marginal. Frank and Engelke (2001) showed that grid street networks can promote bicycling and walking activities by reducing trip distances, offering alternative pathways, and slowing motorized travel. Cervero and Duncan (2003) found that, although personal and household factors were most significant, land-use and street connectivity in San Francisco also had a moderate effect on promoting short non-motorized trips.

More studies use the connection between non-motorized travel and improved physical health to support their research. Frank et al. (2005) found that measures of land-use, residential density, and intersection density in Atlanta were positively associated with daily minutes of moderate physical activity. Aytur et al. (2007) found that North Carolina communities designed for “active transportation” had the strongest influence on non-motorized travel levels among lower-income individuals. Cervero et al. (2009) found that street density, connectivity, and proximity to cycling lanes are essential to physical activity while land-use mixtures not.

Other studies attempted to address the relationship between pedestrian travel and environmental variables. Liu and Griswold (2007) demonstrated that pedestrian volumes can be reasonably estimated by environmental factors given appropriate measurement and geographical scale. Aultman-Hall et al. (2009) investigated pedestrian counts in Vermont to identify the influential factors for volume variability, and their models indicate weather and season diminish aggregate walking levels by a moderate amount.

Fewer researchers have been able to use location-specific counts to yield progress in non-motorized travel estimation at a microscopic scale. Pulugurtha and Pepaka (2008) studied the pedestrian counts collected at 176 intersections in the City of Charlotte, North Carolina and developed models predicting pedestrian activity using factors ranging from demographic characteristics to land-use characteristics. Their study results showed that urban residential density has the most significant impact on pedestrian activity at intersections. Using pedestrian crossing volumes at intersections, Schneider et al. (2009) created a pilot model that shows that number of jobs, number of retail properties, total population, and presence of a regional transit station close to an intersection are significant factors. Pucher et al. (2011) reviewed trends in bicycling levels, safety, and policies in North America, using national aggregate and city-specific data. They found a high degree of spatial variation and socioeconomic inequality in bicycling rates. While it is generally accepted that non-motorized travel varies with location, land-use, time-of-day, and season, robust patterns have not been characterized. Moreover, the range of land-use and spatial characteristics is often overlooked or over-simplified when selecting locations for the non-motorized traffic counts. Instead, researchers and planners often default to collecting data in the most traveled locations. The relationships between temporal patterns and spatial patterns have not fully been studied and the full range of data to consider these relationships has not been collected.

In spite of the growing recognition of the importance of non-motorized travel, estimates of BPMT are rarely calculated. One of the primary obstacles to calculating BPMT values is the expense of collecting bicycle and pedestrian (BP) counts (Hocherman et. al., 1988; Greene-Roesel et. al., 2007). 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 (Hocherman et. al., 1988). Newer pneumatic and infrared equipment works well in some settings but is not well suited to all outdoor environments (Greene-Roesel et. al., 2008). Consequently, BP counts remain more dependent on expensive manual data collection and continuous count data is scarce. Continuous counts that are available tend to focus on more highly traveled paths in more bicycle- and pedestrian-friendly towns, biasing volumes high and leaving significant spatial gaps, as found in this study.

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 season and weather-related 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 (Schneider et. al., 2009; Soot, 1991; Davis et. al., 1988) or weekly BP volumes (Schneider et. al., 2009) and most do not provide annual BPMT estimates. Second, the lack of diversity in count locations makes it difficult to create link classifications that accurately reflect BP patterns over a whole region, especially in more rural 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 (Hammond and Elliott, 2011).

3 Study Area

The study area for this project is Chittenden County, Vermont, the planning region for the Chittenden County Regional Planning Commission (CCRPC) (see Figure 1). The CCRPC area includes a 62-square-mile urban area that contains Burlington, the largest city in Vermont. It is bounded to the west by Lake Champlain and to the east by public lands in the Green Mountains. Chittenden County has the largest population and employment in the state, with approximately 150,000 residents (of approximately 620,000 in Vermont) and more than 100,000 jobs. Like most regions in the country, the urban core has spread into neighboring municipalities and now includes a suburban development pattern around the outskirts of Burlington. Vermont ranks high for its prevalence of walking and bicycling as a mode of transportation for commuting (http://www.bikewalkalliance.org/news/350-people-are-healthier-in-states-where-more-people-bike-and-walk-to-work), with a 12% overall mode share (Conger at. al., 2013) and Chittenden County's rate of walking bicycling is amongst the highest in the state, at nearly 17% of its daily person-trips per household (FHWA, 2009).

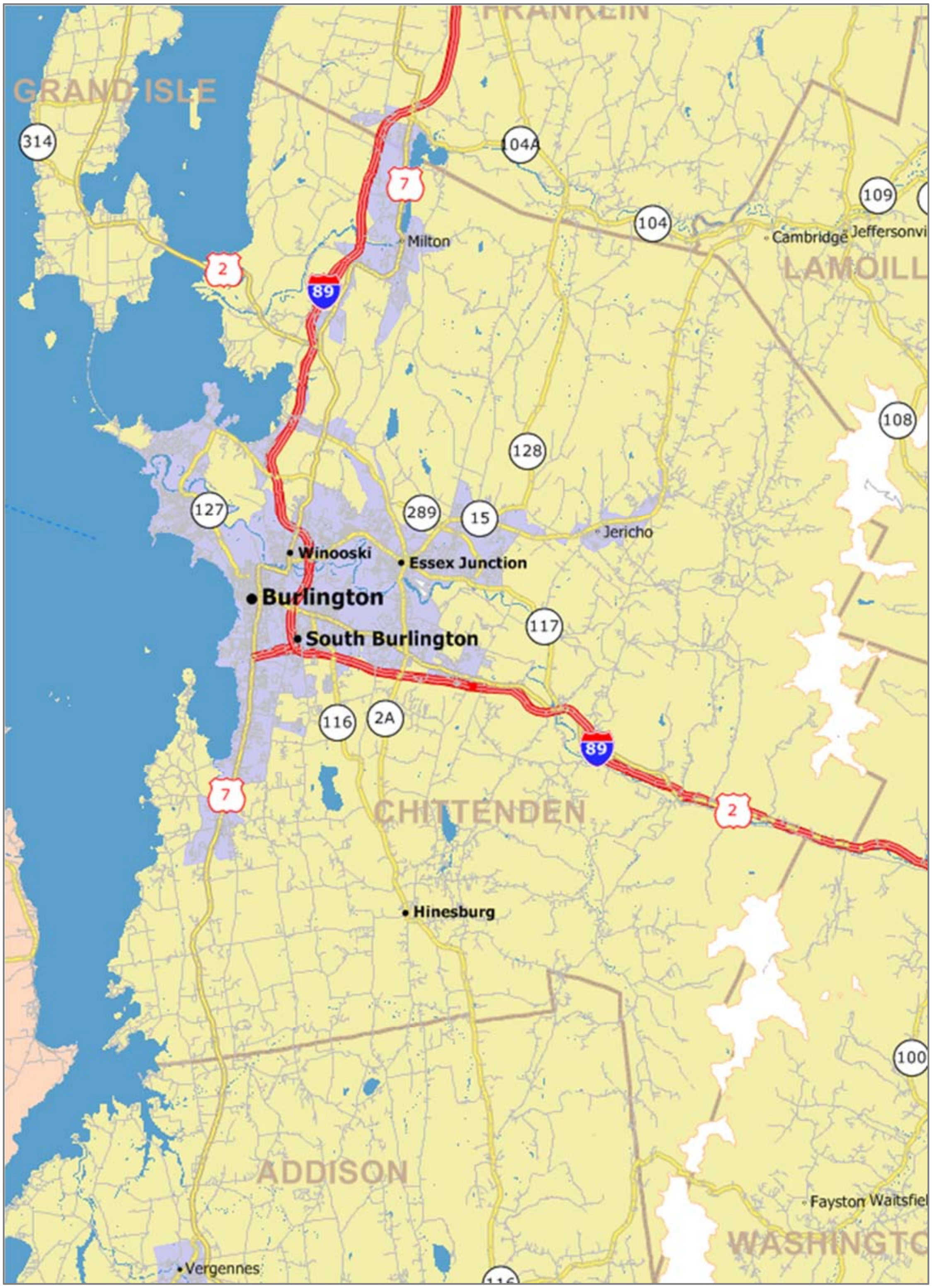

Figure 1 Project Study Area

4 Data

4.1 Link-Based Non-Motorized Traffic Counts

This project utilized bicycle and pedestrian counts collected between 2007 and 2013 from shared-use paths and road shoulders at a total of 62 locations throughout the County using pyroelectric infrared sensors (collected by CCRPC) and closed-circuit digital video camera (collected by the research team)(see Figure 2). Details of the video data collection procedures are described in Appendix A through C.

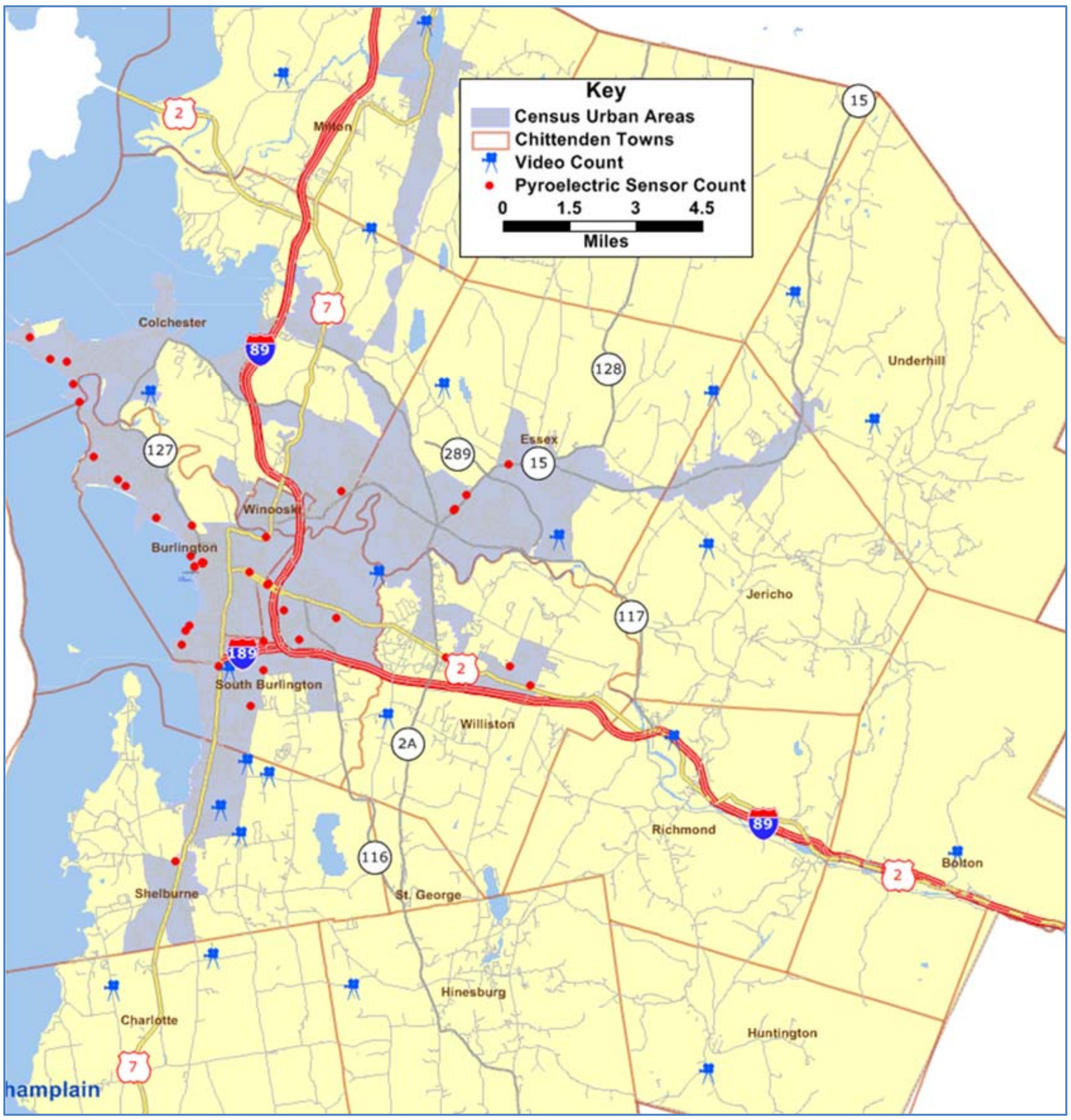

Figure 2 Link-Based Bicycle and Pedestrian Counts Used in this Study, 2007 – 2013

The pyroelectric sensors detect the infrared emitted by the human body allowing multiple people to be counted individually even if they are close together. An infrared sensor by EcoCounter was employed at all stations to collect combined pedestrian and bicycle count data. The device was capable of collecting bi-directional bicycle and pedestrian traffic, although only total counts (bicycle + pedestrian volume) were used in this study. The device's sensor detects the infrared radiation emitted by each person who passes by it, and the sensor's narrow profile further enables it to count two or more people following closely to one another (Bell, 2006). A previous study (Aultman-Hall et. al., 2009) utilizing counts collected by this type of counter indicated an accuracy level of 98% when compared to manual counts.

At the start of the project for the link-based hourly distribution analysis, infrared counts from 9 locations along paths in the Burlington area were used, because those were the only long-term counts available at the time. This existing count data (before 2009) was more plentiful (Figure 3) and was counted over multiple days and months (Table 1). Count stations were located on the shared-use paths with biases toward (1) locations with anecdotally higher non-motorized travel, and (2) locations with higher maintenance costs such as bridges. However, the relatively large dataset allowed travel on weekdays, Saturdays, and Sundays to be considered separately for shared-use paths. Table 1 lists the nine shared-use path count-stations used in the first part of this study, with the number of weekday, Saturday, and Sunday counts that were available at the time. In total, 265 days of non-motorized traffic volumes were used in analysis of hourly distributions on shared-use paths in section 6.1. All of these counts included at least 7 consecutive days.

The later digital video data was collected over periods of 1 to 3 days and manually reviewed at a desktop computer to count cyclists and pedestrians . The use of motion sensitivity and high-speed playback limited the amount of time needed to review the video data.

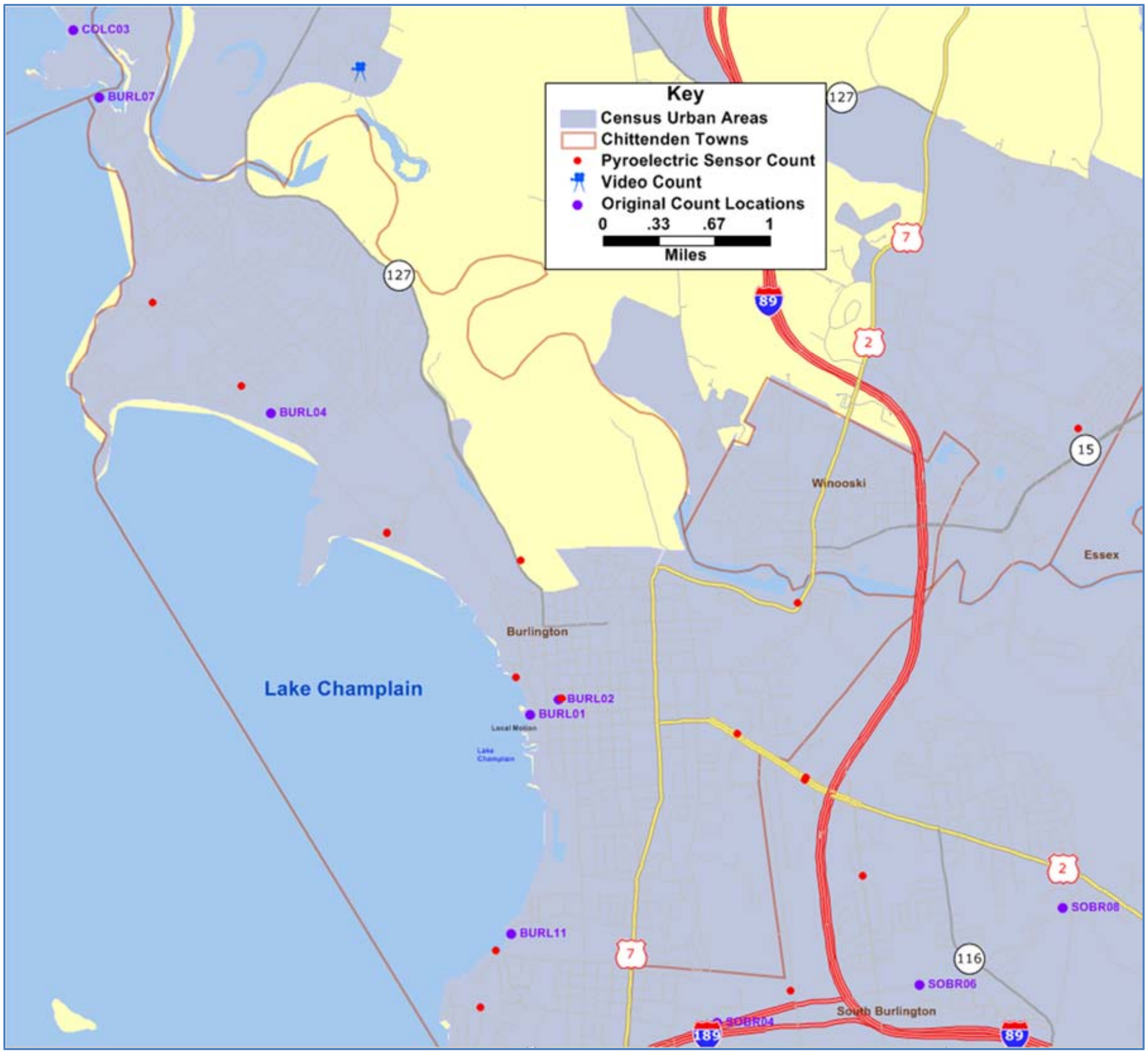

Figure 3 Count Locations Used in Burlington

Table 1 Shared-Use-Path Count Stations

Path Name	MPO ID	Count Duration	Weekdays	Saturday	Sunday	Holiday
Island Line	COLC 03	June 11 – August 18, 2008	36	7	7	1
	BURL 07	July 3 - July 31, 2007	20	4	4	1
	BURL 04	August 20 - September 23, 2008	24	5	5	1
	BURL 01	May 3 - May 20, 2007	12	3	3	0
	BURL 11	August 5 - September 1, 2008	19	4	4	1
UVM	SOBR 04	July 26 – August 3, 2008	5	2	2	0
Kennedy Drive	SOBR 06	Sep 2 – Sep 30, 2008; May 1 - May 26, 2009	38	8	8	1
	SOBR 08	July 12 - July 24, 2008	9	2	2	0
Downtown	BURL 02	April 26 - May 27, 2007	18	4	4	1

For the ultimate calculation of BPMT, count locations shown in Figure 2 were used. This included the original 9 shared-use path stations as well as additional infrared locations counted by the CCRPC during the first stage of the project. However, the team collected digital video data at 23 road shoulder locations selected based on the spatial distribution and representativeness of the infrared count locations. The supplemental set of count locations filled critical missing data gaps needed to calculate reliable BPMTs in the study region. Locations with full-year counts (N=14) were required to create seasonal adjustment factors using the methodology recommended by the FHWA (2001) for calculating BPMTs.

4.2 Land-Use Data

In order to assess the relationship between surrounding land use and non-motorized traffic volumes, several types of land use data were used. Parcel-level data is available from the CCRPC, and each parcel is associated with a Land-Based Classification Standard (LBCS) Activity Dimension provided by the American Planning Association:

- 1000 Residential activities
- 2000 Shopping, business, or trade activities
- 3000 Industrial, manufacturing, and waste-related activities
- 4000 Social, institutional, or infrastructure-related activities
- 5000 Travel or movement activities
- 6000 Mass assembly of people
- 7000 Leisure activities
- 8000 Natural resources-related activities
- 9000 No human activity or unclassifiable activity

The parcel activities were clustered into a smaller group of seven categories:

- Residential (includes residence and accommodation)
- Agricultural (includes agriculture, forestry, fishing and hunting)
- Recreational (includes arts, entertainment, and recreation)
- Commercial (includes general sales and services)
- Public institutional (includes public administration and education)
- Transportation (includes transportation, communication, information, and utilities)
- Others (includes all other land-uses)

The residential and agricultural clusters occupy the highest proportion of area in Chittenden County, both exceeding 30 percent. The next highest categories are public institutional and recreational, together comprising 20 percent of the total. Commercial land use types were concentrated in the Burlington urban area.

Household density and the presence of other destinations were deemed relevant measures of bicycle and pedestrian origins and destinations near count sites. Housing/dwelling unit information from the CCRPC was developed in 2005 from the residential 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 unit for land-use and transportation forecasting efforts. Residential density is used at the Census-block level from the 2010 US Census by dividing the number of households in each block by the area of the block.

Other destinations in the study area were taken from the Vermont E911 database and geographical information system (GIS), which consists of the location and functional classification of each habitable structure in the state. The Vermont E911 data includes residential locations (single-family, multi-family, seasonal, and mobile homes) and non-residential locations (commercial, industrial, educational, governmental, health-care and public gathering). Vermont is unique in that this E911 database is publicly available to support emergency-response personnel statewide via the Vermont Center for Geographic Information (VCGI).

4.3 The Non-Motorized Travel Network of Streets, Shared-Use Paths, and Sidewalks

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 2012 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

GIS layers showing the line locations of shared-use paths and sidewalks throughout Chittenden County were received from the CCRPC. Original locations of paths and sidewalks were provided to the CCRPC by the individual municipalities in Chittenden County.

Speed limits were used to develop the link attractiveness index for the BPMT procedure (section 6.3). Speed limits were taken from the CCRPC Regional Travel Model or estimated based on Census feature class for roadways not in the Model. Total roadway widths were taken from the Highway Performance Monitoring System (HPMS) for Vermont. The HPMS is a national-level highway information system that includes data on the extent, condition, performance, use and operating characteristics of the nation’s highways. The HPMS contains administrative and extent-of-system information on all public roads in each state.

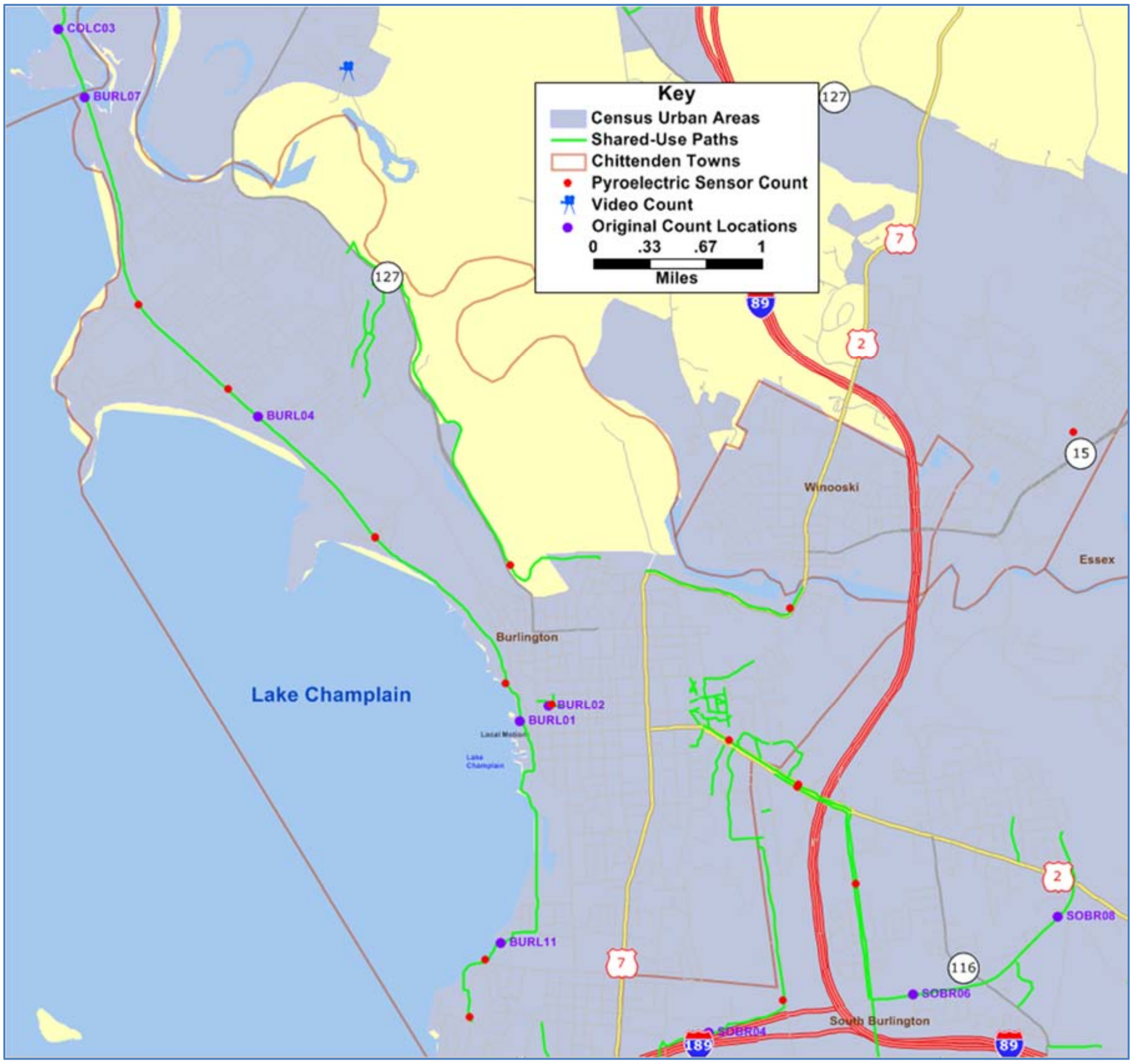

Figure 4 Shared-Use Paths in Chittenden County

The shared-use path network in the vicinity of the original 9 count locations is shown in Figure 4. The Island Line Trail runs through Burlington and to the north and south along the Lake Champlain shoreline. It traverses primarily residential and recreational land-use areas, including count locations BURL11, BURL01, BURL04, BURL07, and COLC03. The UVM Trail goes from Route 7, a major multilane arterial which serves as a critical link for north-south motorized traffic, along the eastern edge off the UVM campus parallel to I-89. This trail includes count location SOBR04 and is surrounded by tree-cover and farm areas on the UVM campus. The Kennedy Drive Trail runs parallel and adjacent to the entire length of the 4-lane arterial Kennedy Drive. It includes count location SOBR 06 and SOBR08 and is separated from the road by a 5-foot-wide green-strip. The fourth path is a short pedestrian and bicycle path that connects large downtown residential and hotel buildings to the Burlington's commercial center where BURL02 is located.

Critical to considering land use and its relationship to count volumes is the imposed lack of entry/exit points in some of the path corridors. The entry/exits to/from the paths were identified with the assistance of aerial photos and on-site visits. The majority of the access points along the paths are at their intersections with local roads. These “access points” along the shared use paths were critical to the accurate assessment of the land-uses associated with non-motorized travel, since access to land-use is controlled by these points. Note that path corridors like the Island Line Trail and the UVM Trail have fewer access points than paths in road corridors that parallel adjacent roadways such as the Kennedy Drive Trail.

The network of shared-use paths was merged with the network of all streets and roadways in Chittenden County in order to provide network for non-motorized travel. Highways and ramps where non-motorized travel is prohibited were removed from the merged network, as were streets that are accompanied by a shared-use path. Other line segments in the 2012 TIGER layer with feature class A50 and higher were also removed from the network. These segments consisted of access ramps, vehicular trails and minor streets where non-motorized travel is either prohibited or the streets are privately owned. In addition, streets with a sidewalk on at least one side of the road were flagged to indicate their increased attractiveness for non-motorized travelers.

Shared-use paths in the County were re-categorized for this study as road corridors paths and path corridors. Path corridors are those that are not adjoining and parallel to a roadway. Road corridor paths are those that run alongside a roadway, thereby providing an alternative to the traditional sidewalk. This new categorization recognizes potential differences in travel behavior on shared-use paths that run alongside a roadway and those that do not. Presumably, shared-use paths that run alongside a roadway are meant to replace the traditional sidewalk for pedestrians, but to also provide an alternative place for cyclists. However, cyclists may still have the option of travelling on the roadway. On a recreational shared-use path, both cyclists and pedestrians are travelling only on the path itself, and they are likely to encounter fewer motor vehicles. Therefore, making this distinction is critical to the calculation of BPMTs.

4.4 Weather Data

Weather information was used to categorize days of the week and to represent seasons of the year in the study area. For estimation of BPMT, the research team intended to test use of a day-of-week categorization that distinguished between days when it was raining or snowing and days when it was not. In order to make this distinction, precipitation data for every count-day to be used in the BPMT calculation was needed.

To obtain daily precipitation data, the team queried the Global Historical Climatology Network-Daily (GHCN-D) database. GHCN-Daily is a composite of climate records from numerous sources that were merged and then subjected to quality assurance reviews. The archive includes over 40 meteorological elements including temperature daily maximum/minimum temperature, temperature at observation time, precipitation, snowfall, snow depth, evaporation, wind movement, wind maximums, soil temperature, and cloudiness. Containing observations of one or more of the above elements at more than 40,000 stations that are distributed across all continents, the dataset is the world's largest collection of daily climatological data. The GHCN-D was accessed through the National Climatic Data Center's query tool for each of the land-based weather stations in Chittenden County, which are shown in Table 2.

Table 2 Land-Based Weather Stations in Chittenden County, Vermont

ID	Town	Start	End	Coverage
US1VTCH0020	Burlington	2012-01-17	2013-06-11	83%
US1VTCH0005	Burlington	2009-04-17	2013-06-11	74%
USW00014742	Burlington	1940-12-01	2013-06-10	100%
US1VTCH0003	Charlotte	2009-04-01	2013-06-11	71%
USC00432843	Essex Junction	1971-11-01	2013-06-11	68%
USR0000VESS	Essex Junction	1999-05-21	2013-06-11	88%
US1VTCH0015	Huntington	2010-08-22	2013-06-11	92%
US1VTCH0007	Huntington	2009-04-04	2012-12-30	16%
US1VTCH0012	Huntington	2009-08-12	2013-06-11	13%
US1VTCH0019	Jericho	2011-09-13	2013-06-11	95%
US1VTCH0013	Richmond	2009-01-21	2013-06-11	90%
US1VTCH0006	South Burlington	2009-05-02	2012-05-16	65%
US1VTCH0004	Underhill	2009-03-27	2013-06-11	100%
US1VTCH0011	Underhill	2009-06-18	2013-06-11	62%
US1VTCH0009	Underhill Center	2009-05-01	2012-12-12	38%

The precipitation data (in inches of rain or snow per day) was extracted for every link-based count-day in this study, at every monitoring station for which the count-day was available. In order to represent the seasons of the year, daily average values were used for the Burlington International Airport monitoring station for temperature (degrees F), rainfall (inches of rainfall per day), snowfall (inches of snowfall per day), and wind speed (mph).

The precipitation data (in inches of rainfall or snowfall per day) extracted for the third objective of this study was initially reduced to a binary variable identifying whether significant precipitation had occurred or not. A significant precipitation day was determined to be any day when more than 0.1 inches of precipitation (in rainfall equivalent) was measured. Next, each count-day was assigned a binary value (a rainy/snowy day or not), by first checking to see if the nearest weather station to the count location included data for the count-day. Note in Table 2 that only the weather station at Burlington International Airport covers the entire range of count-days in this study. If the nearest weather station included data for the count-day, the binary assignment for that weather station was assigned to the count-day at its location. If the nearest weather station to the count location did not have data for the count-day, then the binary assignment for the weather station at the Burlington International Airport (which includes every count-day in the data set) was assigned to the count-day at that location. This method ensured that the best possible rainfall information was used to assign each count-day a binary designation as a rainy day or not.

In order to represent the seasons of the year, daily average values were used for the Burlington International Airport monitoring station for temperature (degrees F), rainfall (inches of rainfall per day), snowfall (inches of snowfall per day), and wind speed (mph). The daily data was aggregated to the week for all 52 weeks of the average year in Burlington. A k-means cluster analysis was used with the weekly averages to identify clustered-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 5. The solid lines on the chart were added to qualitatively identify temporal sequences that appeared to trend with the data. As expected, these divisions seem to coincide with significant climate changes throughout the year in Chittenden County.

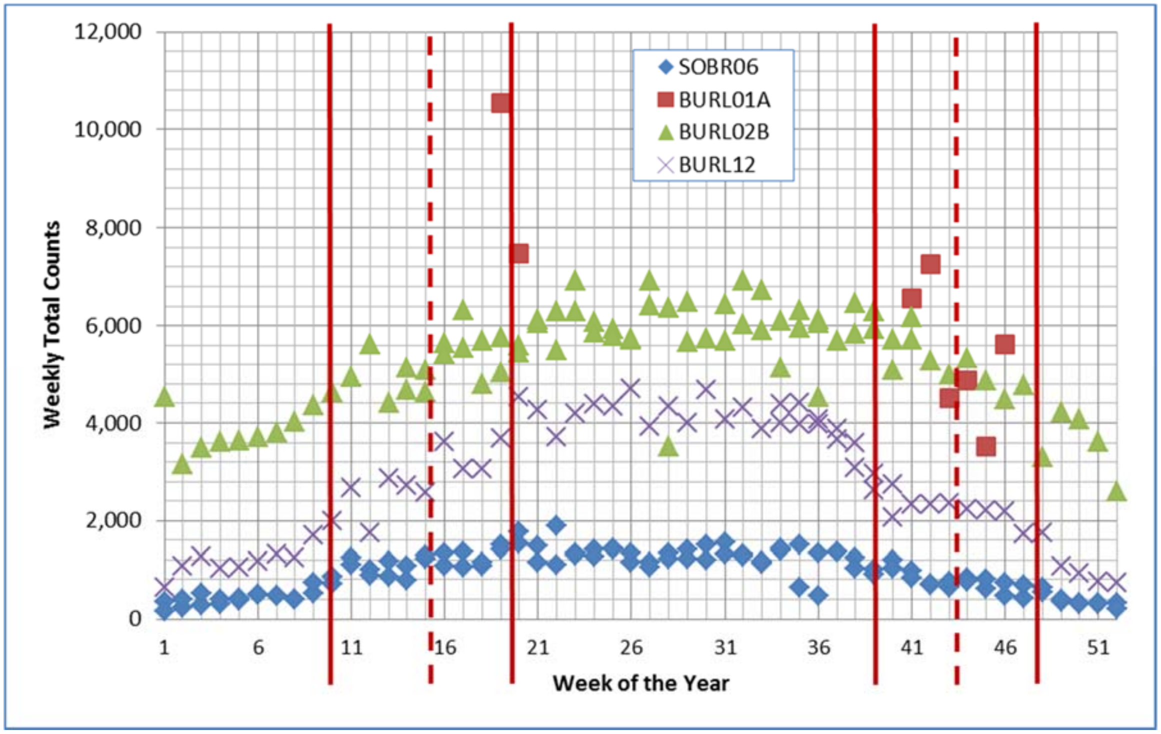

Figure 5 Patterns in Weekly Counts at Full-Year Count Sites

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 four of which corresponded with the breaks identified in the four-cluster analysis. These results suggest that there are actually six significant changes in climate throughout an average year in Burlington, Vermont. These cluster-seasons are summarized in Table 3.

Table 3 Cluster-Seasons Found for Burlington, Vermont

	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 5 coincided with a cluster transition found. Two additional separations created by the six clusters summarized in Table 3 are shown in Figure 5 as dashed lines. These clustered-seasons represent an alternative temporal period for calculating adjustment-factors to the traditional monthly period prescribed in the TMG (FHWA, 2001).

5 Data Preparation

5.1 Link-Based Non-Motorized Traffic Counts

Of primary interest in the first part of this study was not only the total daily volumes of non-motorized users on shared-use paths, but also the hourly distribution throughout the day. In a study assessing impact of weather and season on pedestrian volume conducted by Aultman-Hall et. al. (2009) utilizing year-round continuous hourly pedestrian counts at a sidewalk in downtown Montpelier, Vermont, the authors found consistency in some types of daily distributions. Aultman-Hall et. al. (2009) also found that during winter time the overall pedestrian volume reduced by 16%. To avoid any discrepancy caused by these seasonal impacts, this study includes only travel in milder-weather months of May through September. Holidays were removed from the data unless they occurred on weekends, in which case they were included as a weekend day. Ultimately, all link-based counts that exceeded 24 continuous hours were considered part of the data set. The CCRPC also collects partial-day link-based counts at other locations throughout the County. However, to avoid the need to make time-of-day adjustments, these partial-day counts were not used in this study. Figure 6 shows daily BP volumes for each day of the year for each of the full-year count sites before the removal of outliers. In the figure, 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 prior to normalization.

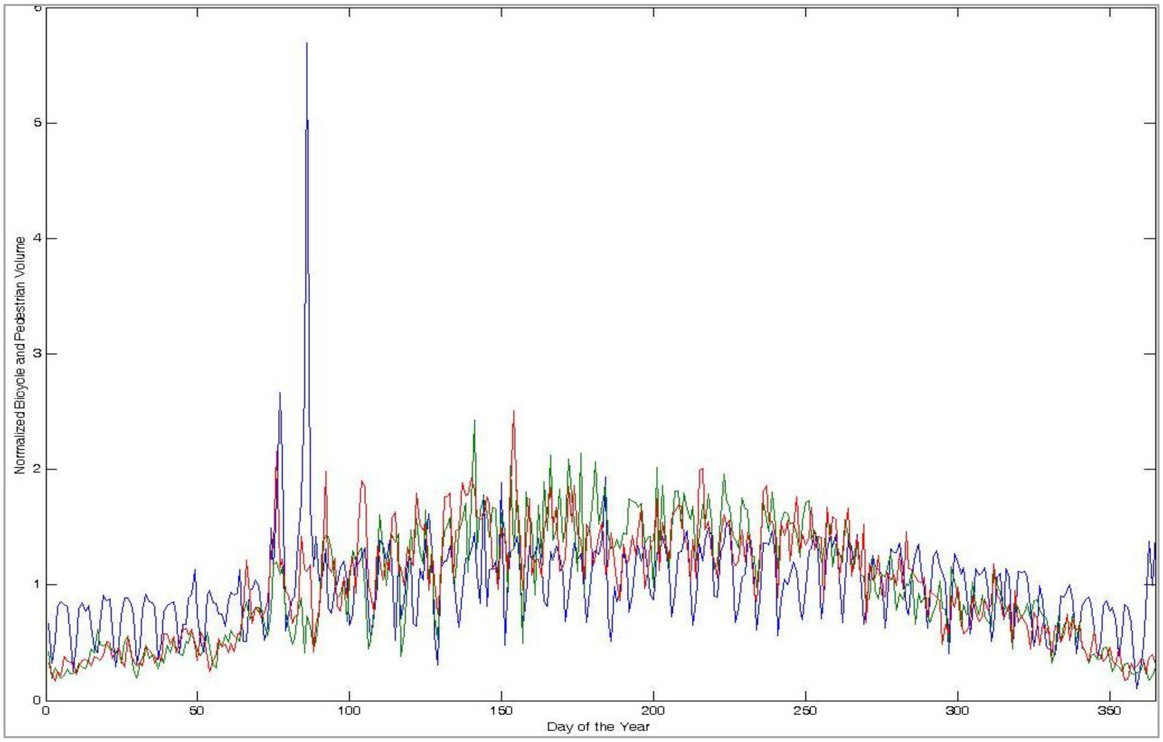

Figure 6 Normalized Daily BP Volumes for Full-Year Count Locations

Full-year counts are required to create seasonal adjustment factors using the methodology recommended in the TMG (FHWA, 2001). While the TMG recommends using count data only from the year for which total miles of travel are being calculated, that requirement is infeasible for BP counts. Others suggest that temporal adjustment factors in areas with relatively little development can be applied over multiple-year periods (Greene-Roesel et. al., 2007).

Ideally these full-year continuous counts would be available for each link type in the study area and for the entire year when the miles of travel are being calculated, these levels of spatial and temporal coverage are infeasible. So a single set of adjustment factors was created from the three sites available and applied to all count sites regardless of link type for all of the years used in the study. This aggregation is supported by the yearly patterns for all full-year sites shown in Figure 9. On this basis, we assumed that count data from all years (2007 to 2013) at the full-year sites could be used to calculate adjustment factors for the entire study area.

5.2 Link and Count Site Classification

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 this 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 (and inaccurate) 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 (FHWA, 2001). Because roadway type, residential density (Greene-Roesel et. al., 2007) and land-use (Schneider et. al., 2009; Greene-Roesel et. al., 2007) have been identified by other researchers as drivers of variation in BP volumes, this study used classification systems based on these characteristics. BPMT values were also calculated without any classification of the count sites to show the effect of the biases described above.

5.2.1 ROADWAY TYPE - 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 "path corridor" for those count locations that are not adjoining a roadway. This system included four categories:

- Path corridor
- Local, neighborhood, and rural roads
- Secondary and connecting roads
- Primary roads without limited access

The path corridor category consisted of all shared-use paths that do not run alongside any portion of the roadway network. Path corridors make up less than two percent of the BP network but have the highest AADBPV of any category in the system and therefore contribute disproportionately to the BPMT total. The number of counts taken in each of these four categories and the total BP network miles in each category are shown in Table 4.

Table 4 BP Network Classification by Roadway Functional Class

Category	No. of Count Locations	No. of Count-Days	BP Network Miles
Path Corridors	10	996	29.5
Local, neighborhood, and rural roads	15	827	61.7
Secondary and connecting roads	1	11	90.2
Primary roads without limited access	2	416	1393.2
Totals	**28**	**2,250**	**1595.3**

5.2.2 RESIDENTIAL DENSITY – DWELLING UNITS IN THE GRID CELL

The next classification system categorized links and count locations based on the residential density within the grid cell where it was situated. Residential and commercial densities are two of the factor grouping methods recommended in (Greene-Roesel et. al., 2007). 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 in each category are shown in Table 5.

Table 5 BP Network Classification by Residential Density

Category	No. of Count Locations	No. of Count-Days	BP Network Miles
Low Residential Density	12	778	810.5
Medium Residential Density	5	129	374.6
High Residential Density	11	1,343	410.2
Totals	**28**	**2,250**	**1595.3**

5.2.3 LAND-USE –LAND USE OF THE GRID CELL AND SHARED-USE PATH AVAILABILITY

For the first land-use-based classification system, count locations were categorized based on a combination of the clustered land-use category of the grid cell and whether BP infrastructure available at the location. Because of the high number of counts on shared-use paths and the relatively high BP volumes on these paths, count locations were subdivided into those with a shared-use path available and those without. The number of counts taken and the total BP network miles that are in each category in this classification system are shown in Table 6.

Table 6 BP Network Classification by Clustered Land-Use

Category	No. of Count Locations	No. of Count-Days	BP Network Miles
Agricultural with shared-use path	1	29	6.4
Agricultural without shared-use path	6	6	380.2
Mixed-use with shared-use path	7	1,263	25.7
Mixed-use without shared-use path	1	17	331.0
Public-institutional with shared-use path	2	742	136.8
Public-institutional without shared-use path	1	9	166.9
Shared-use path corridor	2	89	5.3

Category	No. of Count Locations	No. of Count-Days	BP Network Miles
Recreational without shared-use path	1	1	57.9
Residential with shared-use path	3	90	698.4
Residential without shared-use path	4	4	8.9
Totals	**28**	**2,250**	**1595.3**

5.2.4 LAND-USE - MODE OF PROXIMATE LAND-USE ACTIVITY CODE

Following the initial calculation of BPMTs (Dowds and Sullivan, 2011), a revised classification system based on land-use Activity code from the LBCS for parcels instead of grid cells was developed. For this system, the distribution of Activity codes of parcels within 2,500-feet of the count location were collected and the code that was most common (the mode) was assigned to the count location. This initial data set included only three Activity codes – 1000, 2000, and 8000. Therefore, the Activity codes that could be selected for each of the links in the BP network were limited to these three. The most common of these three codes within 2,500 feet was assigned to each network link. The number of counts and the total BP network-link miles for each category in this classification system are shown in Table 7.

Table 7 BP Network Classification by Land-Use Activity Code

Category	No. of Count Locations	No. of Count-Days	BP Network Miles
1000 –Residential activities	37	2,696	1554.8
2000 - Shopping, business, or trade activities	3	755	18.6
8000 - Natural resources-related activities	1	2	18.8
Totals	**41**	**3,453**	**1592.2**

Note that the number of count locations and count-days available in the data set had increased significantly by the time this second phase of BPMT counts was being developed. In addition, a more refined and updated version of the roadway network was used, and the BP network was measured at only 1,592 miles (as opposed to 1,595 miles previously). This discrepancy is not expected to affect the comparison classification systems in the results of the BPMT calculations.

5.2.5 LAND-USE – TOTAL DESTINATIONS

A land use classification method that took advantage of available destinations was developed. For each count location or link, the sum of the number of educational buildings within 1000 feet (from the E911 habitable structures layer), the number of all buildings within 2,500 feet (from the E911 habitable structures layer), and the number of intersections within 2,500 feet (from the topologically-corrected E911 roads layer) was taken as representative destinations. The distribution of these sums for the count locations was binned according to the Fisher-Jenks Algorithm version of the optimal method of irregular class creation. This method is sometimes called Natural Breaks. Bins for classification are determined so that each category is a cluster of values that minimizes within-group variance. Three bins, corresponding to locations with a low, medium, or high number of destinations available, were created. Bin intervals and the number of counts and network-link miles for each category in this classifications system are shown in Table 8.

Table 8 BP Network Classification by Total Destinations

Category	Bin Interval (No. of Destinations)		No. of Count Locations	No. of Count-Days	BP Network Miles
Low no. of destinations	0	500	31	787	1,253.4
Medium no. of destinations	501	1,700	8	1,911	296.4
High no. of destinations	1,701	6,315	2	755	42.4
Totals			**41**	**3,453**	**1592.2**

5.2.6 RESIDENTIAL DENSITY – HOUSEHOLDS IN THE CENSUS BLOCK

The determination of residential density used in the first phase of the classification for the Dowds and Sullivan (2011) paper was improved in the second phase by taking advantage of the 2010 Census data that had become available. Household densities at the Census block level were assigned to count locations for the block where the count was located. For network-links, the density was calculated as an average of all the Census block densities adjoining the link. Three bins encompassing the range of household densities among the count locations were determined using the Natural Breaks method and both count locations and network-links were assigned to these bins. Bin intervals and the number of counts and network-link miles for each category in this classifications system are shown in Table 9.

Table 9 BP Network Classification by Census-Based Residential Density

Category	Bin Interval (HHs per sq. mi.)		No. of Count Locations	No. of Count-Days	BP Network Miles
Low density	0	900	34	1,769	1,287.9
Medium density	901	2,000	4	915	176.1
High density	2,001	49,654	3	769	128.2
Totals			**41**	**3,453**	**1592.2**

5.2.7 ROADWAY TYPE - NON-MOTORIZED TRAVEL LINK-ATTRACTIVENESS INDEX

A new index, the link-attractiveness index (LAI) was developed to estimate the relative perceived safety and appeal of a roadway for walking and bicycling. The research team collecting video counts in more rural locations hypothesized that the experience of walking and bicycling was greatly affected by two factors, the total width of the roadway (shoulders plus lane widths) and the speeds of motorized vehicles on the roadway. Wider roads with wider shoulders were more appealing where no walking and bicycling infrastructure was available, and roadways where automobiles travelled faster were less appealing. In addition, team members felt that roadways where little or no shoulders or sidewalks were present were very unsafe. Based on these experiences, we proposed the LAI.

For count locations, the LAI was measured using the total roadway width (all lanes plus shoulders) and the speed limit. Speed limits were taken from the CCRPC Regional Travel Model or estimated based on road class. Total roadway widths were taken from the HPMS for Vermont. Total roadway width (in feet) was divided by the speed limit (in mph), then normalized so that the resulting values fell between 0 and 1. Shared-use paths in path corridor were given LAI of “1”.

For line segments, total roadway width was not available for every road. Therefore, the LAI was calculated as described previously for all roadways that had a total roadway width in the HPMS. For roadways adjoined by a shared-use path or a sidewalk, the roadway width was doubled before the LAI was calculated, to reflect the increased attractiveness of roadways with dedicated walking and bicycling infrastructure. LAIs for roadways without HPMS widths were calculated as an average of connected roadways that already had an LAI. This process was conducted iteratively until more than 80% of the line segments had an LAI. The remaining set of links without an LAI and not adjoining any links with an LAI were spot checked on aerial photographs, and all of the spot-checked links were found to have an LAI between 0.05 and 0.25, based on whether a sidewalk was present. Based on this information, the remaining links were given a LAI of 0.05 if they did not have a sidewalk and a LAI of 0.25 if they did.

Three bins encompassing the range of LAIs among the count locations were determined using the Natural Breaks method and both count locations and network-links were assigned to these bins. Bin intervals and the number of counts and network-link miles for each category in this classification system are shown in Table 10.

Table 10 BP Network Classification by Link-Attractiveness Index

Category	Bin Interval (HHs per sq. mi.)		No. of Count Locations	No. of Count-Days	BP Network Miles
Low LAI	0	0.30	15	30	1,478.2
Medium LAI	0.31	0.99	10	375	83.7
High LAI	1.00	1.00	16	3,048	30.3
Totals			**41**	**3,453**	**1592.2**

6 Methodology and Results

6.1 Land-Use as a Factor Impacting Traffic Volume along Shared-Use Paths Corridors

In this part of the study, the research team was interested in the land-use types around the nine shared-use path count-stations being considered, how the land-use types affected the daily pattern in hourly non-motorized traffic volumes, and whether the land-use type was distinct from the range of land-use combinations found in the whole County.

Many shared-use paths in Chittenden County do not have open access continuously along the trail. Therefore, users might be unaffected by the immediate surrounding land-use, but would instead be interested in the land-use at the access points. This assumption was made at all count stations except those in the Burlington downtown area, where access is more open. For example, a path used mainly for exercise or commuting which passes large agricultural lands is less related to that land-use type than shopping traffic in a downtown retail area. To account for these factors, at each non-motorized count location, the team identified the land-use at the nearest access points within a 1.5-km distance along the path from the count location. The probable connection between the hourly distribution at the count station and this land-use characteristic at the proximate access point was investigated. For each proximate access point, a 0.5-km square buffer was generated. The area for each land-use category in the buffer was assigned to the access point. Table 11 shows, for each count station, the total number of proximate access points, and the percentages of each land-use category represented in the buffer area.

Table 11 County-Wide Representation of Land-Use for Each Count Station Used in Shared-use Path Analysis

	Island Line					UVM	Kennedy Drive		Down town
Station no.	1	2	3	4	5	6	7	8	9
No. of access points	4	4	4	3	4	5	12	8	2
Land-Use									
Residential	40%	40%	41%	9%	15%	19%	37%	38%	11%
Commercial	0%	0%	0%	12%	8%	19%	7%	9%	34%
Recreational	12%	12%	20%	17%	23%	5%	6%	1%	7%
Public institutional	0%	0%	19%	2%	2%	5%	12%	5%	15%
Agricultural	13%	13%	4%	2%	3%	20%	19%	30%	1%
Transp.	8%	8%	10%	28%	16%	20%	5%	6%	25%
Other	27%	27%	6%	30%	33%	12%	18%	11%	7%

As suggested previously, stations 7 and 8 on the Kennedy Drive Trail, have more access points than the rest of stations. Five (1, 2, 3, 7 and 8) of the stations have relatively high surrounding residential land-use. Others include a more balanced mix of land uses.

Using the counts at each station, we developed average daily distributions of non-motorized traffic for Saturdays, Sundays, and an average weekday. For any of the distribution types (Saturday, Sunday, or weekday) at a particular count station, the hourly percentages were computed based on average hourly volumes for that day-type normalized over the duration of counts:

$$p_{ik} = \frac{(\sum_{n=1}^{N} h_{ikn})/N}{(\sum_{n=i}^{N} D_{in})/N} \tag{1}$$

Where p_{ik} stands for the average hourly percentage at hour k for day-of-week type i, h_{ikn} stands for hourly volume of hour k on day n for day-of-week type i, D_{in} stands for daily volume on day n for day-of-week type i, and N is the count duration.

The results of these calculations are illustrated in Figures 7a through 7i. To illustrate the strength of the distribution, the total daily counts are also provided.

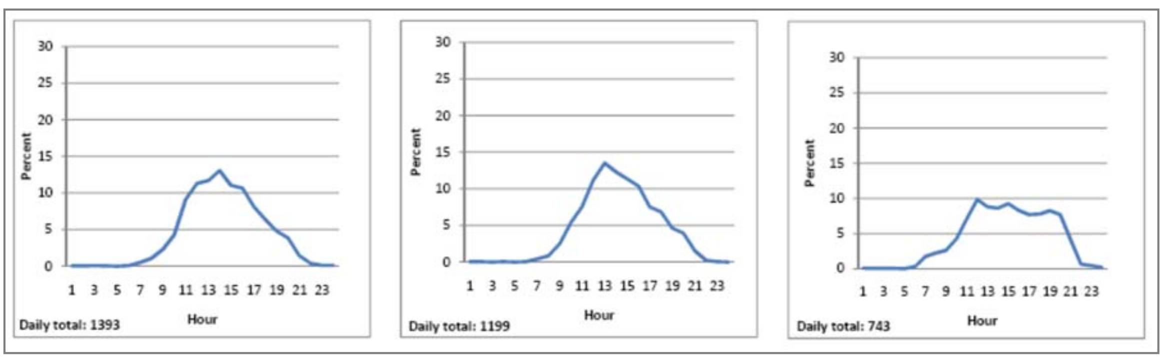

Figure 7a Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 1

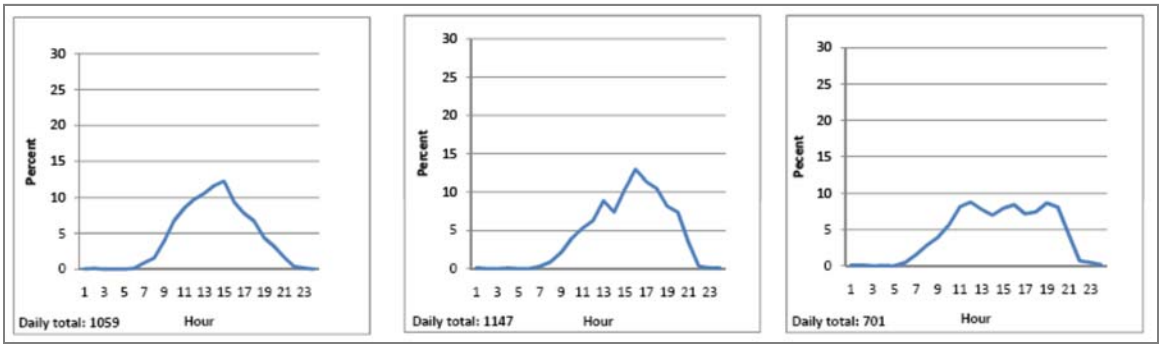

Figure 7b Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 2

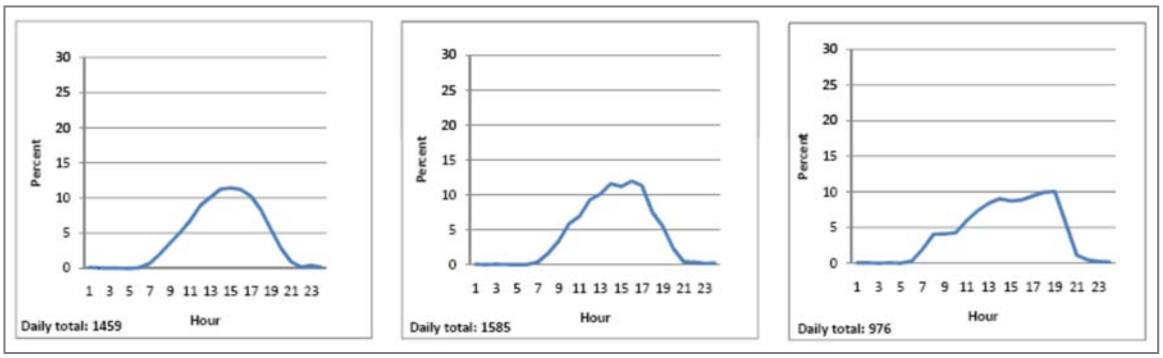

Figure 7c Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 3

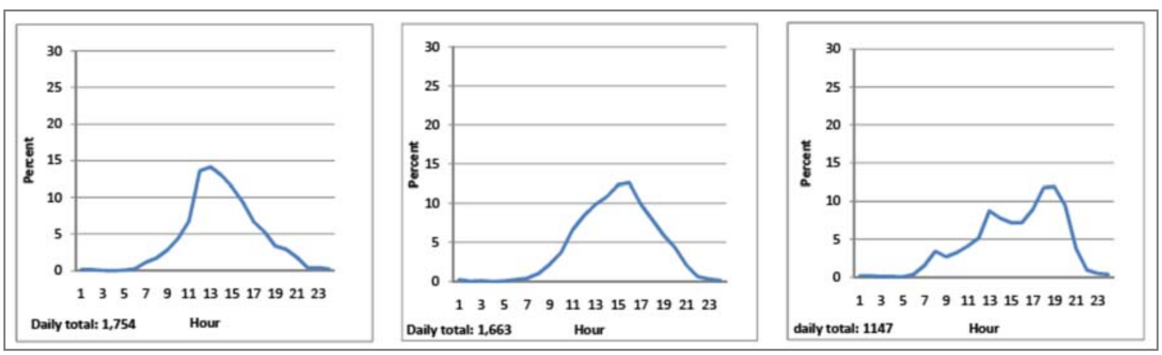

Figure 7d Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 4

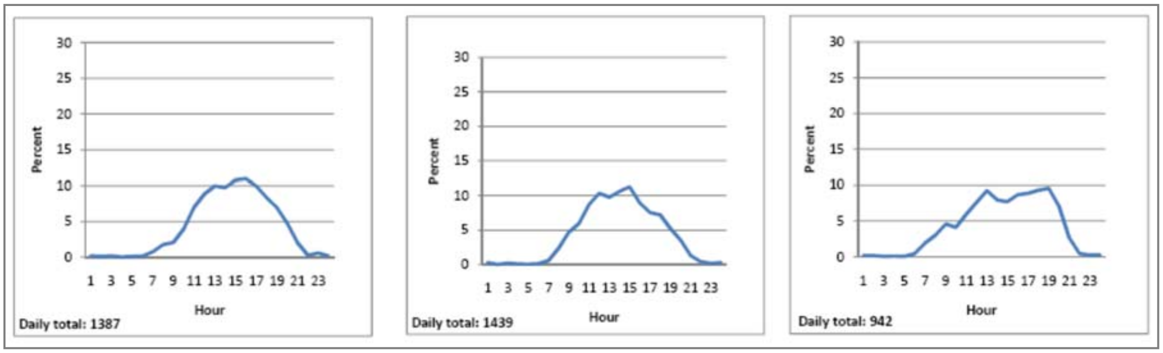

Figure 7e Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 5

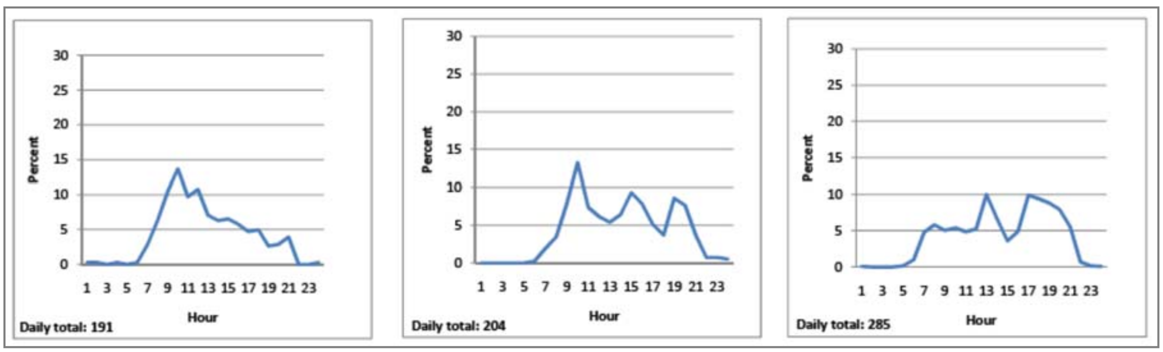

Figure 7f Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 6

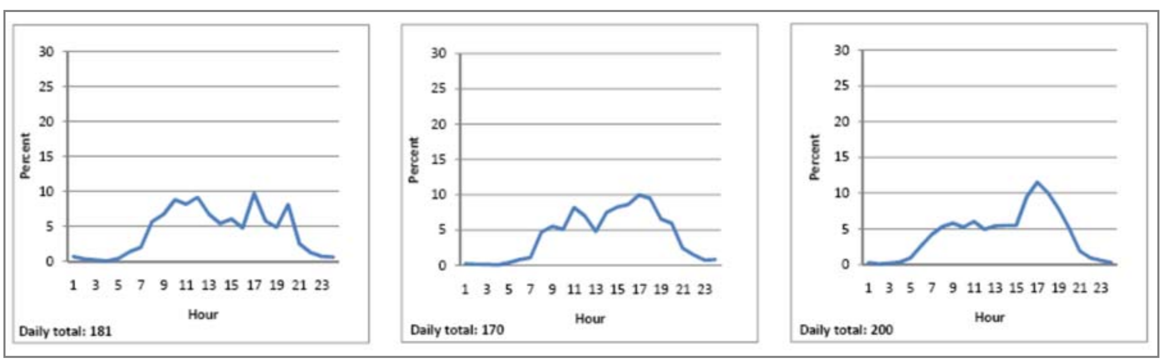

Figure 7g Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 7

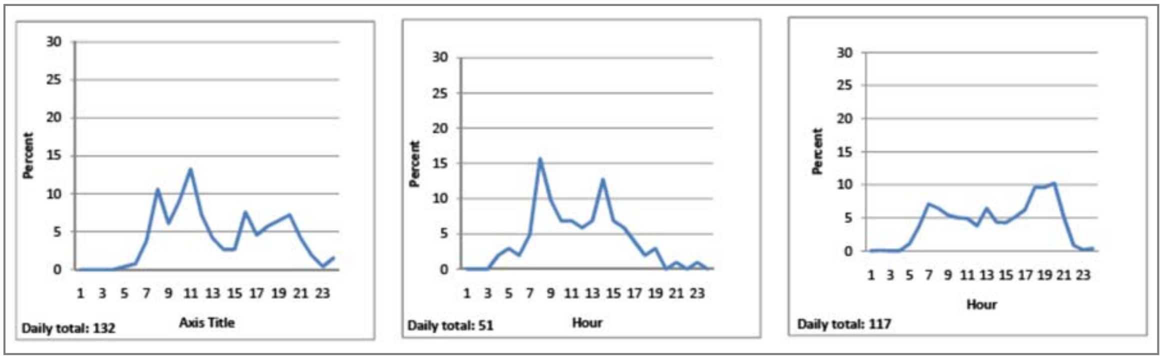

Figure 7h Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 8

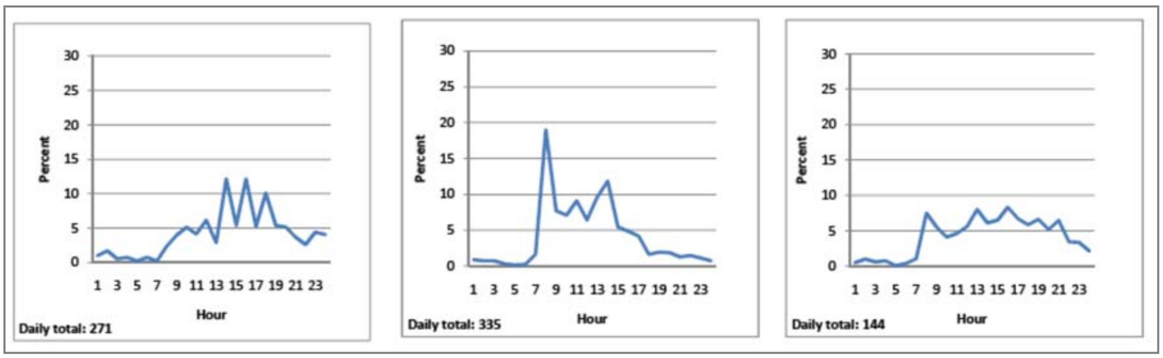

Figure 7i Daily Distribution of Non-Motorized Travel for a Saturday, a Sunday, and an Average Weekday at Station No. 9

While the nine sets of graphs show some differences in hourly non-motorized traffic patterns between weekdays and weekends, the differences are less than expected. In addition, a significant impact of accessible land-uses on non-motorized travel is not evident. Some evidence of distributional differences are evident when the number of access points is considered. The paths with fewer access points (stations 1 through 5) exhibit univariate distributions which are flattened on weekdays and more peaked on weekends. The paths with more access points (stations 6 though 8) have much more variable volume distributions throughout the day. However, the lack of a relationship between daily distributions and proximate land-uses may be an indication that a stronger and more robust measure of accessible land-use is needed.

A new framework was developed which allowed us to consider the overall land-use patterns in the entire County in relation to the land-uses around the shared-use path count locations. A grid system was created dividing the entire County into 0.5-km square polygons. The total length of links in the non-motorized travel street-path network was then computed for every each grid cell. Only the cells with non-zero length of links in the street-path network were carried forward. These grid cells covered 60% of the area of the county. A K-means clustering method was then adopted to categorize those non-zero cells into homogenous groups based on the land use categories within each.

K-means clustering method has been a popular data-mining tool in various fields after it was first introduced in 1967 (MacQueen, 1967). The non-zero cells each include a percentage of their cell area occupied by the different land-use categories in Table 2. The K-means cluster analysis was conducted to group cells by the relationship between their land-use category distributions. In the cluster analysis, the non-zero cells were partitioned into five clusters such that elements in the same cluster tends to be more similar than elements in different clusters. The aim of the K-means cluster algorithm is to classify a set of data points into K categories through the clusters defined a priori (MacQueen, 1967).

The main idea is to define K initial cluster-centroids and then to relate the rest of the cells to these centroids depending on their Euclidean separation. First, the method assigns each data point to the nearest cluster center according to the Euclidean distance:

$$C_j^{i+1} = \{c_1^{i+1}, c_2^{i+1}, \ldots, c_k^{i+1}\},$$
$$c_j^{i+1} = \{x \mid d(x, \mu_j^i) \le d(x, \mu_{j'}^i), 1 \le j, j' \le k \quad and \quad j \ne j'\}$$

Once all points have been assigned to a cluster, the cluster-centroids are recalculated based on their assigned data points:

$$\mu_j^i = \frac{1}{|c_j^i|} \sum_{x \in c_j^i} x \qquad (2)$$

Where C is the set of clusters c, $d(x, \mu^i{}_j)$ is the Euclidean distance between x and $\mu^i{}_j$, $|c^i{}_j|$ is the number of points in cluster j after the ith iteration, and $\mu^i{}_j$ is the centroid of cluster j after the ith iteration.

The iterations continue until the cluster-centroids do not move. Following this procedure, the set of non-zero cells were grouped into five clusters based on the distributions of their six land-use percentages. The five clusters were named according to the mix of land-use categories they contained – mixed-use, public institutional, residential, recreational, and agricultural. Table 12 contains a summary of the distribution of cluster-cells in the County, and the land-use mix that characterizes each cluster.

Table 12 Summary of the Distribution of Land-Use Clusters

	Cluster Name and Mix of Land-Uses by %				
Land-Use Category	Mixed	Pub. Inst.	Res.	Rec.	Agr.
Residential	23	9	75	17	17
Commercial	8	1	1	1	0
Recreation	4	2	2	63	1
Public institution	3	80	1	0	0
Transportation	16	3	5	5	4
Agriculture	16	3	16	9	75

Land-Use Category	Cluster Name and Mix of Land-Uses by % Mixed	Pub. Inst.	Res.	Rec.	Agr.
Others	30	2	2	6	2
No. of Grid Cells in Cluster	518	101	1451	140	1242
No. of Stations in Cluster	1	1	6	1	0

The bottom row of Table 12 shows the clusters for the 9 shared-use path count stations analyzed in this part. The iniquity in the cluster-representation indicated by this row may explain the similarity in the daily distribution patterns. Figure 8 illustrates the distribution of these cluster types in the vicinity of the shared-use paths.

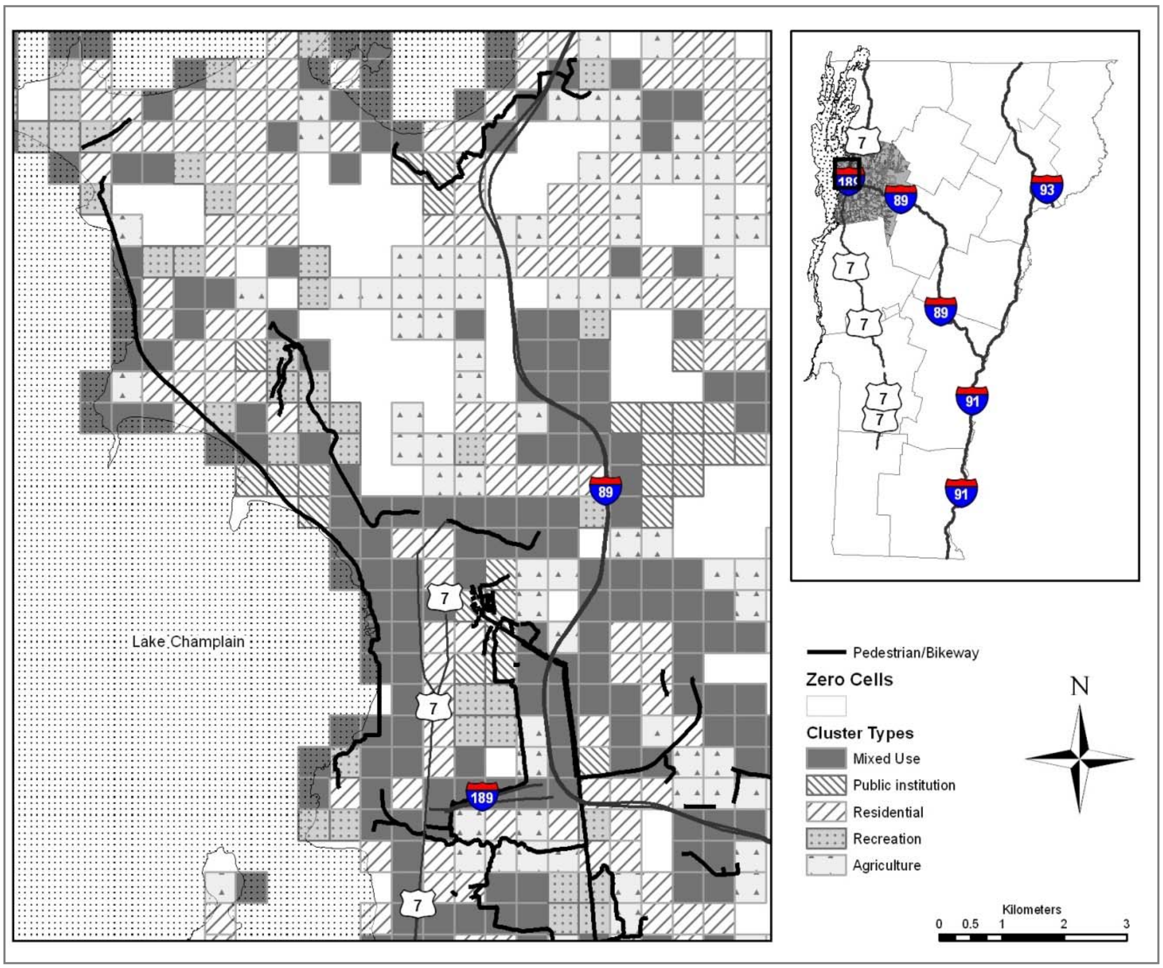

Figure 8 Grid-Cell Cluster Analysis Results near Shared-Use Paths

Mixed-use clusters possess a relatively high concentration in the urbanized area which is more developed and economically active than the rest of the County. The mixed-use cluster has the highest levels of commercial and transportation land-uses but also includes significant residential land-use. The public institutional cluster is represented by a high-level of public institution land-use, including school and government campuses. Similarly, residential, recreational and agricultural clusters, respectively, have their highest representative land-use categories as residential, recreational, and agricultural. Recalling that grids without any roads or trails have been excluded, one might expect there are additional agricultural and residential grids in the county with fewer institutional and recreational cluster. There are also a reasonable number of mixed-use areas.

For ease of classification, the network-mileage within each grid-cell was grouped as either low (< 0.30 mile), medium (> 0.30, < 0.50 mile) or high (> 0.50 mile). A description of the new land-use cluster classification and the level of network-mileage for each count station is provided in Table 13.

Table 13 Shared-Use-Path Count Station, Land-Use and Network Mileage Representation

Path Name	MPO ID	Stn #	Number of Access Points	Network Mileage	Land-Use Cluster
Island Line	COLC03	1	4	High	Recreational
	BURL07	2	4	Medium	Agricultural
	BURL04	3	4	High	Recreational
	BURL01	4	3	High	Mixed-Use
	BURL11	5	4	Low	Mixed-Use
UVM	SOBR04	6	5	High	Mixed-Use
Kennedy Drive	SOBR06	7	12	High	Public Inst.
	SOBR08	8	8	High	Mixed-Use
Downtown	BURL02	9	2	High	Mixed-Use

Still, the land-use cluster does not appear to have a relationship with the distribution of hourly non-motorized traffic shown in Figures 4a to 4i. The network-mileage represented by each count station is somewhat related to the hourly distributions, but not as much as the number of access points are. These results indicate that either (1) proximate land-use is not significantly relevant to the hourly distribution of non-motorized travel, or (2) the land-use cluster analysis is not an effective method of classifying proximate land-use. In fact, the hourly distribution may be most closely related to the total daily volume at each count station, indicating that an analysis which focuses on hourly distribution may need a minimum count volume for comparative statistical analyses.

6.2 Regional Calculation of Bicycle and Pedestrian Miles of Travel

The ultimate goal of the project was to create a robust data set of link-based non-motorized traffic counts that would yield a robust calculation of total annual bicycle and pedestrian miles of travel in the study area.

6.2.1 RECOMMENDATION OF SAMPLE LOCATIONS FOR NON-MOTORIZED TRAFFIC

In order to calculate reliable estimates of BPMT, the research team was no longer only concerned with the hourly distributions of the data. Instead, this section of the analysis began with an assessment of temporal and spatial gaps in the entire existing set of multi-day counts of non-motorized travel in the County. The grid-cell clusters developed during the analysis of shared-use path count locations (section 6.1) were used to initiate the calculation of BPMT. However, due to the limited effectiveness of the land-use clusters a quality check of the grid-cell method considering specific origins and destinations of bicycle and pedestrian travel (instead of land uses) was necessary to ensure robust results for this analysis.

To assess spatial gaps in the data, a cross-classification table was developed to group all of the non-zero grid-cells in the County by cluster-type and miles of walk-bicycle network in the cell, as shown in the first three columns in Table 14. The representation of the 14 samples already collected is shown in the next three columns, and the number of samples remaining to be collected in order to improve spatial representation is shown in the last three columns.

Table 14 Link-Based Count Locations Spatial-Gap Assessment

	Existing Classification			Classification of Existing Samples			Remaining Samples Needed to Match Existing Classification		
	Miles of Walk-Bicycle			Miles of Walk-Bicycle			Miles of Walk-Bicycle		
Cluster Type	low	med	high	low	med	high	Low	med	high
Residential	13%	14%	15%			1	3	3	3
Mixed-Use	4%	3%	8%	1		7**		1	
Agricultural	15%	14%	6%		1		4	2	1
Public-Institutional	1%	1%	2%			2*			
Recreational	2%	1%	1%			2	1		

*Includes a full-year sample.

In all, 18 new samples were proposed to improve spatial representation in the County. Grid-cells corresponding to each cluster-type / miles of network classification were selected at random from all of the grid-cells where samples do not already exist. The specific sample location within each selected grid-cell was positioned adjacent to the most central or primary street in the grid. A summary of the proposed new count locations is provided in Table 15.

Table 15 Proposed New Link-Based Count Locations

ID	Street Name	Town	Classification	Longitude	Latitude
TRC01	Colchester Point Road	Colchester	Mixed-Use / Medium	-73301543	44550665
TRC02	Crosswind Drive	Charlotte	Agricultural / Low	-73239999	44349154
TRC03	Bean Road	Colchester	Residential / High	-73241711	44532617
TRC04	Lion Heart Drive	Milton	Agricultural / Low	-73177904	44642337
TRC05	Schillhammer Road	Jericho	Residential / Low	-72989863	44480272
TRC06	Mount Pritchard Lane	St. George	Residential / Low	-73102245	44369522
TRC07	McClellan Farm Road	Underhill	Residential / Low	-72915401	44544568
TRC08	Poker Hill Road	Underhill	Residential / Medium	-72925235	44568883
TRC09	Sawmill Road	Essex	Residential / Medium	-72985519	44532629
TRC10	Middle Road	Colchester	Residential / Medium	-73140967	44585425
TRC11	Lake Road	Milton	Residential / High	-73116022	44652545
TRC12	Greenbriar Drive	Essex	Residential / High	-73055462	44485977
TRC13	South Brownell Road	Williston	Agricultural / Low	-73134139	44426231
TRC14	West Main Street	Richmond	Agricultural / Low	-73007732	44422804
TRC15	Main Road	Huntington	Agricultural / Medium	-72987698	44312290
TRC16	Bolton Valley Access Road	Bolton	Agricultural / Medium	-72874547	44383042
TRC17	Mountain View Blvd	South Burlington	Agricultural / High	-73148322	44481260
TRC18	McGee Road	Essex	Recreational / Low	-73108126	44534435

These randomly-selected new count locations are shown in Figure 9.

Figure 9 Proposed New Non-Motorized Travel Count Locations

To ensure adequate temporal representation, the full-year count set was also to be supplemented with new samples. Therefore, three of the 18 new locations were chosen for full-year counts. The remaining 15 locations were to be multi-day counts which include at least a full week, preferably two (to ensure that both weekend-days are represented). The three full-year counts were to be chosen from locations with the following classifications:

- Residential / Medium: TRC08, TRC09, or TRC10

- Residential / High: TRC03, TRC11, or TRC12
- Agricultural / Low: TRC02, TRC04, TRC13, or TRC14

These supplemental full-year counts would ensure that the four most common grid-cell classifications (Residential / Medium, Residential / High, Agricultural / Low, and Mixed-Use / High) in the County are represented by full-year counts, and that a defensible seasonal assessment of non-motorized travel is possible. Currently, only one of these four classifications (Mixed-Use / High) is represented seasonally.

The grid-cell method was validated by considering origins and destinations of bicycle and pedestrian travel. Appropriately-sized travel buffers were drawn around the existing multi-day count locations, and the expanded set of existing and proposed locations. Based on the findings of Jinyong et. al. (2009), walk and bicycle buffers of 0.62 miles and 2.50 miles, respectively, were used. Origins and destinations were collected from the E911 database. Using the E911 database, it is possible to aggregate the buildings within Chittenden County into a collection of eight land-use classes, as shown in the first column of Table 16.

Table 16 Aggregation of Land-Uses from Origins and Destinations for Existing Multi-Day Counts

	Existing Total in the County		Existing Multi-Day Counts Represent: Within Walking Buffer		Within Bicycling Buffer	
Land-Use Class	No.	% of total	No.	% of total	No.	% of total
Residential	50,005	92.22%	8,500	88.41%	24,540	89.87%
Commercial	3,223	5.94%	922	9.59%	2,171	7.95%
Farm	106	0.20%	1	0.01%	29	0.11%
Lodging	108	0.20%	16	0.17%	78	0.29%
Industrial	168	0.31%	16	0.17%	81	0.30%
Educational	270	0.50%	37	0.38%	199	0.73%
Health Care	60	0.11%	34	0.35%	50	0.18%
Recreation/Culture	282	0.52%	88	0.92%	157	0.57%

An assessment of the potential origins and destination represented by the existing multi-day counts was made by counting the number of buildings within the buffers that fall into each land-use class. These totals are shown in the last four columns of Table 16. This assessment was repeated with buffers around the expanded set of existing and new count locations. The results of this assessment are shown in Table 17.

Table 17 Aggregations of Land-Uses from Origins and Destinations for Existing and Proposed Multi-Day Counts

	Existing Total in the County		Existing and Proposed Multi-Day Counts Represent: Within Walking Buffer		Within Bicycling Buffer	
Land-Use Class	No.	% of total	No.	% of total	No.	% of total
Residential	50,005	92.22%	10,418	89.38%	42,622	91.51%
Commercial	3,223	5.94%	1,022	8.77%	3,043	6.53%
Farm	106	0.20%	9	0.08%	80	0.17%
Lodging	108	0.20%	27	0.23%	106	0.23%
Industrial	168	0.31%	17	0.15%	167	0.36%
Educational	270	0.50%	37	0.32%	259	0.56%
Health Care	60	0.11%	35	0.30%	60	0.13%
Recreation/Culture	282	0.52%	91	0.78%	239	0.51%

Comparing the percentages represented by each land-use class from Table 16 to Table 17, it is clear that a substantial improvement in the coverage of origin- and destination-classes will be achieved with the addition of the new proposed count locations. In particular, representation of walking and bicycling activity around residential buildings improved more than 1%. Commercial origins and destinations, which are over-represented in the existing counts, are brought down to a level of representation that is much closer to that of the rest of the County. Representation of buildings in other land-use classes is improved as well.

A final measure of the representation-error was calculated for this validation. By finding the average difference between the "% of total" columns for the Existing Total in the County, and each of the representations assessed, we can determine more precisely how the addition of the new count locations will fill spatial gaps in the data set. Overall, the average difference improved from 1.07% to 0.83% for walking, and from 0.61% to 0.19% for bicycling. These are substantial improvements, and will allow more defensible conclusions to be drawn about non-motorized travel trend in the County. Once these new samples are collected, the result will be a more robust, heterogeneous data set for non-motorized travel modeling and exposure estimation.

6.2.2 RECOMMENDED COUNT DATA COLLECTION PROCEDURE FOR RURAL SAMPLE LOCATIONS

The need for count data at rural sample locations was challenged by the lack of infrastructure at many of the locations selected - no sidewalks, narrow or absent shoulders, heavy, tall vegetation, and high vehicle speeds. Methods considered for collection of counts at these locations included the pyroelectric sensor, a pavement-loop counter, a video camera in a parked vehicle, and a video camera mounted on a power pole. Given the limited shoulder width at several of the proposed location, the video camera mounted on the power pole was determined to be most feasible method to provide consistency at all of the proposed locations.

A closed-circuit digital video camera was purchased for obtaining rural BP counts. The camera featured motion sensitive activation, color infrared LEDs for night vision, a weatherproof metal housing, and amounting bracket (see Figure 10).

Figure 10 Closed-Circuit Digital Video Camera Used for Video Counts

The following guidelines were used to optimize the positioning of the camera relative to the roadway being counted:

- Orient the camera orthogonally to the roadway travel direction.
- Avoid obstructions in the foreground of the image
- Attach the camera to a power pole or tree that is far enough from the road so that objects on both sides of the road appear to move at a similar speed.
- Avoid intersections in the image
- Avoid locations where sunlight or reflective surfaces are directed into the camera

Use of a video camera for data collection imposed a number of constraints on the data. In particular, due to the limited storage capacity and battery power of the camera system, full-week counts were not feasible. In lieu of full-week counts, 48-hour count periods were used but each location was counted for a 48-hour period including weekdays, and for a second 48-hour period including the weekend.

The video camera, however, was also not feasible for the collection of counts at sites selected for full-year counts, due to the limitations on battery life and equipment security. The use of the pyroelectric sensor seemed impossible without also picking up the motorized vehicles on the roadway, since a separated path for motorized and non-

Figure 11 Pyroelectric Sensor Functional Diagrams

motorized travelers is required between the sensor and the edge of the BP travel lane for these sensors to work effectively (see Figure 11).

The team considered allowing the sensor to pick up motorized travel in the background (on the roadway), while picking up non-motorized travel in the foreground (on the shoulder), then subtracting counts of motorized travel for a final count of non-motorized travel. However, the need for discrete, directional motorized traffic counts for the counting period was not feasible. Next, the team considered orienting the counters so that the sensor pointed at a 45-degree angle, from its mounted point down to the edge of the road shoulder. This method was tested extensively but found to inconsistently either miss non-motorized travelers who were inadvertently traveling in the roadway, or include motorized vehicles that drifted onto the shoulder and triggered the sensor. A rigorous comparison was made of the counts collected in this fashion, and companion counts collected using digital video. The counts collected from the sensor were found to be in error, and the errors did not follow a consistent pattern. Therefore, the collection of full-year counts at locations without non-motorized infrastructure was not possible.

A thorough description of the final set of locations where counts were collected is provided in Section 4.1.

6.2.3 CREATION OF ADJUSTMENT-FACTORS

In order to estimate AADBPV from single-day counts using the methodology recommend in the TMG (FHWA, 2001), a series of adjustment factors were developed based on data from the full-year count sites available. For Phase A, three full-year count sites were available. For Phase B, five full-year count sites were available, making the adjustment-factors generally more robust.

6.2.3.1 PHASE A

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 9 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 10 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 11 shows the calculation of the adjustment factor (AF) for day-of-week d at a given site s in aggregation period p.

$$PADoWBPV_{psd} = \frac{1}{nD}\sum_{d=1}^{nD} C_d \tag{9}$$

$$AADBPV_s = \frac{1}{7}\sum_{i}^{7}\left[\frac{1}{nP}\sum_{p=1}^{nP}\left(PADoWBPV_{psd}\right)\right] \qquad (10)$$

$$AF_{psd} = \frac{AADBPV_s}{PADoWBPV_{psd}} \qquad (11)$$

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 clustered-season aggregation period. The variance and standard deviation for each adjustment-factor for each method were calculated using a formula for the variance of the quotient of two variables which themselves have a given variance (NRC, 1980). In the absence of a good estimate for the covariance term between dividend and divisor, this term was omitted from the variance calculation. Calculating the variance associated with each adjustment-factor made it possible to determine if the precision of the monthly aggregation procedure differs throughout the year, and if the monthly aggregation period improves upon the seasonal aggregation period.

As an example, the adjustment factors for converting Tuesday counts to AADBPV derived from link-based count site BURL02B is shown for each aggregation period in Table 18.

Table 18 Tuesday Adjustment Factors for BURL02B

Weeks of the Year	Month	Cluster -Season	Monthly Aggregation Adj. Factor	σ	Clustered-Season Aggregation Adj. Factor	σ	Difference between Adj.Factors	
1 – 4	January	1	1.20	0.11	1.11	0.33	0.09	
5 – 8	February	1	1.21	0.09	1.11	0.33	0.10	*
9 – 12	March	1	0.89	0.30	1.11	0.33	-0.22	
13	March	2	0.89	0.30	1.01	0.34	-0.12	
14 – 17	April	2	1.00	0.34	1.01	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	4	0.78	0.11	0.84	0.15	-0.05	
27 – 31	July	4	0.85	0.16	0.84	0.15	0.01	
32 – 35	August	4	0.81	0.17	0.84	0.15	-0.02	
36 – 39	September	4	0.78	0.07	0.84	0.15	-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	6	0.95	0.10	0.99	0.13	-0.03	
48	November	1	0.95	0.10	1.11	0.33	-0.15	*
49 – 52	December	1	1.04	0.35	1.11	0.33	-0.07	

Notes:
σ – standard deviation of the adjustment factor
* - indicates that the difference is statistically significant at the 0.90 level.

The overlap between the 12 monthly and the six cluster-season 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 24. In general, the standard deviations were larger for the cluster-season-based factors than for the monthly factors. However, the differences were only statistically significant at the 0.90 confidence level for 3 of the 16 pairings. These findings can be weighed against the cost of representing each individual month of the year with continuous counts, particularly for the winter months, when collection of continuous counts can be particularly challenging. For cluster-season 1, an adjustment factor of 1.11 was calculated at BURL 02B. The average adjustment-factor for the monthly aggregation period was similar (1.06), and the average standard deviation improved over the cluster-season method (0.19 versus 0.33), but the improvement may not justify the expense of monthly representation for winter BP counts.

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

6.2.3.2 PHASE B

For Phase B, the research team decided to use the monthly aggregation period since all of the full-year count sites had complete data for the entire year, so gaining the improved accuracy of the monthly aggregation would not require any additional data collection. However, a new day-of-week distinction was made in an effort to reduce the data set by aggregating over the week, instead of over the seasonal. Since previous studies had shown a significant effect on BP volumes from daily precipitation as well as season, the team decided to test the effects of daily precipitation on the calculation of BPMTs. For this phase, the 5 weekdays were aggregated into 2, and the 2 weekend days were adjusted to 2 different types of weekend days. Using the binary rain variable as a new distinction, a total of four day-of-week types were created from the original seven:

- Weekday with precipitation
- Weekday without precipitation
- Weekend-day with precipitation
- Weekend-day without precipitation

This day-of-week aggregation was expected to better represent the effects of precipitation on daily BP volumes, enough to allow individual days of the week to be aggregated into two classes – the weekday and the weekend-day.

6.2.4 RESULTS

In order to arrive at BPMT estimates for each classification system, the adjustment factors were applied to all of the unique single-day counts across all sites resulting in 2,250 estimates of the AADBPV for Phase A and 3,453 estimate of AADBPV for Phase B. For each classification system, AADBPV estimates within each classification category were averaged, resulting in a single AADBPV for each 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 (FHWA, 2009) was also calculated, and revealed to be 31.3 million miles per year. 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 19 shows the final BPMT values for Chittenden County for each of the link-classification systems and for the different approaches to calculating temporal adjustment-factors.

Table 19 Annual BPMT Calculated for All Link-Classification and Temporal-Aggregation Systems

Phase	Spatial Link-Classification Type	Spatial Link-Classification System	Temporal Adjustment-Factor Approach: Using Monthly / Day-of-Week Adj. Factors (Both Phases) BPMT	σ	Using Cluster-Season / Day-of-Week (Phase A) or Monthly / Precipitation-Day (Phase B) Adj. Factors BPMT	σ
A	NA	None	288.0	NA	295.8	NA
A	Res. Density	Dwelling Units in the Grid Cell	252.8	NA	260.5	NA
A	Roadway Type	Functional Class	89.9	NA	93.7	NA
A	Land-Use	Land-Use of the Grid Cell and path Availability	73.9	NA	76.5	NA
B	Land-Use	Mode of Proximate Land-Use Activity Code	211.2	7.9	207.7	9.0
B	Land-Use	Total Destinations	149.4	5.8	146.2	5.8
B	Res. Density	HHs in the Census Block	268.3	9.9	264.2	11.4
B	Roadway Type	Link Attractiveness Index	46.1	9.5	47.6	10.5

Note: All values are in millions of miles.

Of particular note in the results is the variation between temporal adjustment-factor approaches and spatial link-classification systems. For all of the temporal adjustments, very little variation was seen when the spatial classification systems are held constant. The differences do not appear to be statistically significant, although this was not tested. However, the changes in link-classification systems produced dramatically different results, ranging from 46.1 million BPMTs to a 295.8 million BPMTs. The estimate resulting from the link-classification system which produced the lowest standard deviation is also the closest to the mean of all of the estimates, 173.2 million.

7 Conclusions

In the first part of this study, the research team focused on hourly distributions of non-motorized traffic data at nine locations along shared-use paths in Chittenden County, Vermont. Two methods, a direct spatial-buffer method and a k-means clustering method, were used to investigate the relationship between the land-use proximate to each count station and the hourly distributions of non-motorized traffic. The analysis failed to reveal significant variations in the hourly distributions relative to the land-use proximate to the count location, even when access points to shared-use paths were considered. The land-use clustering method implemented in this part proved useful later in the study.

In the second larger part of the study, the k-means clustering method was again used to assess the existing data (14 total locations) was assessed for temporal and spatial gaps. Significant spatial and temporal gaps were revealed and a plan for multi-day and year-long counts of non-motorized travel was prescribed to diversify count locations. The collection of additional samples was expected to create a more robust, heterogeneous data set for non-motorized travel modeling and exposure estimation. New proposed sample locations were selected to fill these gaps and a separate method was used to validate the new locations. The separate method took advantage of the E911 occupied-structures dataset to aggregate the total possible origins and destinations for non-motorized travel around the proposed multi-day count locations. The origin-destination method demonstrated that the clustering method was effective at classifying the count locations according to their proximate land-use. It also confirmed that the supplementation of the count dataset with the new count locations would improve its representation considerably.

An important finding in this part of the study was that BP activity occurs along almost every link in the public roadway network. Therefore, robust BP counting of rural roadways is essential to accurately compute regional BPMT estimates. More effective counting systems are needed for roadways without BP infrastructure – no sidewalks, no shoulders, no shared-use paths. More widespread counts will help focus the need for infrastructure in areas where current BP activity and help identify safety relationships. The classification system and grouping of BP network links for aggregation is critical to the estimation of BPMT when the count sites are not widely and representatively distributed. More effective classification systems will lead to better precision, as measured by the standard deviation. This improvement is evident when comparing the extremely high unclassified BPMT estimates with the more moderate results when links are classified systematically by roadway class, land use, or residential density.

Another finding in this study collaborates the assertion that travel surveys of BP activity may underestimate the actual miles of travel on the roadway network, putting funding allocations for non-motorized infrastructure at an inherent disadvantage. Researchers suspect that survey-based estimates of BPMT from sources 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, those which are relatively frequent but very short, and those which have not particular destination 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 accurate estimate of regional BPMTs.

These results also demonstrated that challenges remain in the calculation of reliable BPMT estimates. These challenges arise primarily from the continued scarcity and lack of spatial diversity in BP count data. Even in areas with a fairly long history of BP counts, like Chittenden County, there may be insufficient data to create defensible BPMT estimates. This conclusion is demonstrated by the wide variation in the estimates that resulted from the different classification systems used in this study. Temporal representation was not nearly as important as spatial.

The study results can facilitate better estimation of bicycling and walking volumes at intersections across Chittenden County, which is conducive to local transportation planning, facility design, safety improvement, and operational analysis. Given the count-type dependent variable that cannot be measured continuously in spatial area, it is worthwhile to perform similar investigation via other geospatial methods such as point pattern analysis (Upton and Fingleton, 1985). Kriging is another method by which a model surface can be estimated so that non-motorized traffic volumes can be estimated at unsampled locations.

Future research can also explore the effect of buffer areas on the level of spatial dependency in the data, and on the model results. This exploration could be accomplished by testing a larger range of buffer areas between the typical distance of a walking trip (1 km) and the typical size of one of the towns in our study area (10 km). Examining the changes in the model results with each buffer area will provide a dual indication of the effect of buffer area on spatial dependency and the effect of buffer area on the model results. These models can be critical in the consideration of the optimal scale at which to make funding decisions regarding non-motorized travel infrastructure.

Further should explore the benefits offered by creating separate adjustment factors for cyclists and pedestrians. Because bicyclists 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. Further research could also separate BP activity by travel purpose, particularly for rural activity, where BP activity seems to be dominantly recreational, with no specific destination. The characteristics of these trips and the effects of the built environment on them will likely be different from those that are more affected by the proximity of land-uses and destinations.

8 References

Aultman-Hall, Lisa, Damon Lane, and Rebecca R. Lambert. 2009. "Assessing Impact of Weather and Season on Pedestrian Traffic Volumes." Transportation Research Record: Journal of the Transportation Research Board 2140: 35–43.

Aytur, Semra A, Daniel A Rodriguez, Kelly R Evenson, Diane J Catellier, and Wayne D Rosamond. 2007. "Promoting Active Community Environments through Land Use and Transportation Planning." American Journal of Health Promotion: AJHP 21 (4 Suppl) (April): 397–407.

Bell A., 2006. Technology Innovations: Infrared Bicyclist & Pedestrian Counter. Bike/Ped Professional: Journal of the Association of Pedestrian and Bicycle Professionals. A publication of the Association of Pedestrian and Bicycle Professionals, Hamilton Square, NJ, Summer 2006, pp 4-5.

BTS, 2000. "Bicycle and Pedestrian Data: Sources, Needs, and Gaps." A publication of the Bureau of Transportation Statistics of the U.S. Department of Transportation. Prepared for BTS by William Schwartz and Christopher Porter, Cambridge Systematics, Inc.

Cervero, Robert, and Kara Kockelman. 1997. "Travel Demand and the 3Ds: Density, Diversity, and Design." Transportation Research Part D: Transport and Environment 2 (3) (September): 199–219.

Cervero, Robert, and Michael Duncan. 2003. "Walking, Bicycling, and Urban Landscapes: Evidence From the San Francisco Bay Area." American Journal of Public Health 93 (9) (September): 1478–1483.

Cervero, Robert, Olga L. Sarmiento, Enrique Jacoby, Luis Fernando Gomez, and Andrea Neiman. 2009. "Influences of Built Environments on Walking and Cycling: Lessons from Bogotá." International Journal of Sustainable Transportation 3 (4): 203–226.

Conger, Matt, James L. Sullivan, and Glenn McRae, 2013. The Vermont Transportation Energy Profile. Prepared by the UVM Transportation Research Center for the Vermont Agency of Transportation Policy & Planning Section, August 2013.

Davis, S. E., L. Ellis King, and H. D. Robertson. 1988. "Predicting Pedestrian Crosswalk Volumes." Transportation Research Record 1168: 25-30.

Dowds and Sullivan, 2011. "Applying a Vehicle-miles of Travel Calculation Methodology to a County-Wide Calculation of Bicycle and Pedestrian Miles of Travel." Prepared for the 91st Annual Meeting of the Transportation Research Board, Washington, D.C., January 22-26, 2012.

Elliott, Preston J., and Jeffrey L. Hammond. 2010. "Quantifying Non-Motorized Demand—A New Way of Understanding Walking and Biking Demand." In Green Streets and Highways 2010, pp. 107–115. A publication of the American Society of Civil Engineers.

FHWA, 2001. "Traffic Monitoring Guide." Publication FHWA-PL-01-021. Federal Highway Administration of the U.S. Department of Transportation.

FHWA, 2009. "The 2009 National Household Transportation Survey." Federal Highway Administration of the U.S. Department of Transportation.

Frank, Lawrence D., and Peter O. Engelke. 2001. "The Built Environment and Human Activity Patterns: Exploring the Impacts of Urban Form on Public Health." Journal of Planning Literature 16 (2) (November 1): 202–218.

Frank, Lawrence D, Thomas L Schmid, James F Sallis, James Chapman, and Brian E Saelens. 2005. "Linking Objectively Measured Physical Activity with Objectively Measured Urban Form: Findings from SMARTRAQ." American Journal of Preventive Medicine 28 (2 Suppl 2) (February): 117–125.

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.

Greene-Roesel, Ryan, Mara Chagas Diogenes, David R. Ragland, and Luis Antonio Lindau. 2008. "Effectiveness of a Commercially Available Automated Pedestrian Counting Device in Urban Environments: Comparison with Manual Counts." Prepared for the 87th Annual Meeting of the Transportation Research Board, Washington, D.C., January, 2008.

Greene-Roesel, Ryan, Mara Chagas Diogenes, and David R. Ragland. 2010. "Estimating Pedestrian Accident Exposure." PATH Research Report (May).

Guo, J. Y., Bhat, C., and Copperman R. B., 2007. Effect of the built environment on motorized and non-motorized trip making. Transportation Research Record: Journal of the Transportation Research Board, No. 2010, Transportation Research Board of the National Academies, Washington, D.C., 2007, pp. 1–11.

Hammond, J.L. and P.J. Elliott, 2011. 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.

Hocherman, I., A. S. Hakkert, and J. Bar-Ziv. 1988. "Estimating the daily volume of crossing pedestrians from short-counts." Transportation Research Record: Journal of the Transportation Research Board, No. 1168, Transportation Research Board of the National Academies, Washington, D.C., 1988, pp. 31-38.

Jinyong, Jiang, Yun Meiping, and Yang Xiaoguang. 2009. "Statistical Analysis on Non-motorized Transportation Mode Choice Considering Trip Distance and Car Availability." In International Conference on New Trends in Information and Service Science, 2009. NISS '09, pp. 181–186.

Katz, Peter, 1993. The New Urbanism: Toward an Architecture of Community. 1st ed. McGraw-Hill Professional.

Liu, XiaoHang, and Julia Griswold. 2007. "A Method for Estimating Pedestrian Volume for Street Intersections in San Francisco." Prepared for the 86th Annual Meeting of the Transportation Research Board, Washington, D.C., January, 2007.

Lu, George X., James Sullivan, and Austin Troy. 2012. "Impact of Ambient Built-Environment Attributes on Sustainable Travel Modes: A Spatial Analysis in Chittenden County, Vermont." Prepared for the 91st Annual Meeting of the Transportation Research Board, Washington, D.C., January 22-26, 2012.

Macqueen, JB. 1967. "Some Methods of Classification and Analysis of Multivariate Observations." In the Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability, Berkeley, California. University of California Press, 1967, pp 281-297.

NRC, Regulating Pesticides. 1980, Washington D.C.: National Academy of Sciences.

Owens, Peter M., Linda Titus-Ernstoff, Lucinda Gibson, Michael L. Beach, Sandy Beauregard, and Madeline A. Dalton. 2010. "Smart Density: a More Accurate Method of Measuring Rural Residential Density for Health-related Research." International Journal of Health Geographics 9 (1) (December 1): 1–8.

Pucher, John, Ralph Buehler, Mark Seinen, 2011. Bicycling renaissance in North America? An update and re-appraisal of cycling trends and policies. Transportation Research Part A: Policy and Practice, Volume 45, Issue 6, July 2011, pp. 451–475.

Pulugurtha, Srinivas S., and Sudha R. Repaka. 2008. "Assessment of Models to Measure Pedestrian Activity at Signalized Intersections." Transportation Research Record: Journal of the Transportation Research Board 2073: 39–48.

Rodrıguez, Daniel A., and Joonwon Joo. 2004. "The Relationship Between Non-motorized Mode Choice and the Local Physical Environment." Transportation Research Part D: Transport and Environment 9 (2) (March): 151–173.

Schneider, Robert, Lindsay Arnold, and David Ragland. 2009. "Methodology for Counting Pedestrians at Intersections." Transportation Research Record: Journal of the Transportation Research Board 2140: 1–12.

Schneider, Robert, Lindsay Arnold, and David Ragland. 2009. "Pilot Model for Estimating Pedestrian Intersection Crossing Volumes." Transportation Research Record: Journal of the Transportation Research Board 2140: 13–26.

Soot, S. 1991. "Trends in downtown pedestrian traffic and methods of estimating daily volumes." Transportation Research Record No. 1325: 75-82.

Tobler, W. R. 1970. "A Computer Movie Simulating Urban Growth in the Detroit Region." Economic Geography 46 (June 1): 234–240.

Troy, Austin, and Morgan Grove. 2008. "Property Values, Parks, and Crime: A Hedonic Analysis in Baltimore, MD." Landscape and Urban Planning 87 (3): 233–245.

Upton, Graham, and Bernard Fingleton. 1985. Spatial Data Analysis by Example. Vol.1: Point Pattern and Quantitative Data. Wiley Series in Probability and Statistics, John Wiley & Sons Inc,

VTrans, 2010. Continuous Traffic Counter Grouping Study and Regression Analysis, Based on 2009 Traffic Data. Prepared by the Vermont Agency of Transportation, Planning, Outreach & Community Affairs: Traffic Research Unit.

Zahran, Sammy, Samuel D. Brody, Praveen Maghelal, Andrew Prelog, and Michael Lacy. 2008. "Cycling and Walking: Explaining the Spatial Distribution of Healthy Modes of Transportation in the United States." Transportation Research Part D: Transport and Environment 13 (7) (October).

Zhang, Chen, Lance Jennings, Lisa Aultman-Hall, and Daryl Benoit. 2010. "Toward More Robust Spatial Sampling Strategies for Non-motorized Traffic." Prepared for the 89th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2010.