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Understanding the Use of Non-Motorized Transportation Facilities

Final Report

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16. Abstract (Limit: 250 words)

Traffic counts and models for describing use of non-motorized facilities such as sidewalks, bike lanes, and trails are generally unavailable. Because transportation officials lack the data and tools needed to estimate use of facilities, their ability to make evidence-based choices among investment alternatives is limited. This report describes and assesses manual and automated methods of counting non-motorized traffic; summarizes counts of cyclists and pedestrians in Minneapolis, Minnesota; develops scaling factors to describe temporal patterns in non-motorized traffic volumes; validates models for estimating traffic using ordinary least squares and negative binomial regressions; and estimates bicycle and pedestrian traffic volumes for every street in Minneapolis. Research shows that automated counters are sufficiently accurate for most purposes. Automated counter error rates vary as a function of type of technology and traffic mode and volume. Across all locations, mean pedestrian traffic (51/hour) exceeded mean bicycle traffic (38/hour) by 35 percent. One-hour counts were highly correlated with 12-hour "daily" counts. Significant correlates of non-motorized traffic vary by mode and include weather (temperature, precipitation), neighborhood socio-demographics (household income, education), built environment characteristics (land use mix), and street (or bicycle facility) type. When controlling for these factors, bicycle traffic, but not pedestrian traffic, increased over time and was higher on streets with bicycle facilities than without (and highest on off-street facilities). These new models can be used to estimate non-motorized traffic where counts are unavailable and to estimate changes associated with infrastructure improvements.

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Executive Summary

Background and Research Objective: The general aim of the research described in this report is to increase understanding of the use of non-motorized transportation facilities in Minneapolis. Planners and transportation officials currently lack the data and tools necessary to make evidence-based choices about investment alternatives in non-motorized infrastructure. This research builds a foundation for this type of work by comparing automated counting technologies, validating various data sources, and developing first-generation models that will aid in the development of tools for practitioners.

Data and Methods: Technology for measuring non-motorized traffic has evolved and advanced but generally is not widely deployed. There are two distinct methods used to monitor non-motorized traffic: (1) short (1- or 2-hour) manual counts, and (2) continuous measurements using automated instruments. In Minneapolis both of these types of data are currently being collected. The City of Minneapolis Department of Public Works, Transit for Livable Communities, and University of Minnesota each run programs that collect both short, manual counts (on-street and urban trails) and continuous measurement (mostly urban trails). In general, the research presented here occurred in mainly four steps:

- collection and validation of existing counts of bicycle and pedestrian traffic in Minneapolis;
- acquisition and deployment of infrared counters for measuring mixed-mode trail traffic, including development of protocols for collection and validation of data;
- analyses of counts by mode and facility type;
- development of regression models for determining correlates of non-motorized traffic and estimating daily bicycle, pedestrian, and mixed-mode trail traffic.

Results and Key Findings: This research has resulted in several key findings about the use of non-motorized infrastructure and the relationships of neighborhood characteristics to non-motorized traffic volumes. More data and research is needed to confirm and extend our findings; however, the following conclusions represent a significant contribution to the understanding of non-motorized traffic volumes and patterns.

- Bicycles and pedestrians have been counted in a variety of ways since 2007 in Minneapolis. The most common type of count is the short (2-hour) peak-hour manual count. These counts are supplemented by a smaller number of continuous counts by various technologies.
- All traffic counts regardless of approach or technology used, including manual counts, include errors and therefore are estimates. In this report we describe correction equations for the various types of technology and discuss implications of error in manual counts.
- Bicycle and pedestrian traffic volumes vary significantly by location, infrastructure type, day of week (i.e., weekday vs. weekend), and month of year or season.

- Each type of non-motorized traffic (i.e., bicycle, pedestrian, and mixed-mode traffic) follows similar but distinct daily temporal patterns. These temporal patterns appear to be sufficiently stable to permit development of scaling factors that reflect the relationships between hourly and daily counts, weekday and weekend counts, and monthly counts.
- Analyses of both bicycle and pedestrian flows taken with manual counts indicate that peak hour traffic volumes correlate strongly with 12-hour traffic volumes.
- While more data would be helpful for non-motorized traffic modeling, we are able to demonstrate that with limited data first-generation models can effectively relate traffic volumes to certain neighborhood and infrastructure characteristics.

Conclusions and policy implications: We have demonstrated that with limited data there are a series of analyses and models that can be developed to aid planners in planning for non-motorized travel and for undertaking tasks such as allocating funding for non-motorized investments. Increasing the amount of available data would greatly improve the analyses and models presented here.

Chapter 1
Introduction

Although the federal, state, and local governments are investing hundreds of millions of dollars in non-motorized transportation facilities, traffic counts and other basic information about use of these facilities generally are unavailable for purposes of planning and management. Because officials lack both the data and tools needed to estimate use of facilities, their ability to make evidence-based choices among investment alternatives and to optimize management of infrastructure and transportation systems is limited. Officials need both information about volumes and patterns of traffic on non-motorized transportation infrastructure and new tools for estimating use for facilities where data are unavailable.

The general aim of the research described in this report is to increase understanding of the use of non-motorized transportation facilities. Using the City of Minneapolis as a study site, this report describes:

- The collection, validation, and analyses, of counts of bicycles and pedestrians on different types of non-motorized infrastructure using different methods, including manual field observations, magnetic loop detectors, and infrared counters;
- Standardized measures and scaling factors for describing patterns in bicycle and pedestrian traffic, including scaling factors for adjusting hourly counts to daily counts, weekend/weekday traffic ratios, and monthly adjustment factors; and
- The specification and estimation of models for identifying correlates of daily non-motorized traffic volumes and for estimating bicycle and pedestrian traffic where counts have not been taken.

This report also discusses the implications of this research for the planning and management of transportation systems.

Chapter 2 is a brief literature review that summarizes previous research related to use of non-motorized infrastructure. Chapter 3 presents methods used in the research. Chapters 4 and 5, respectively, describe traffic counts on different types of facilities and patterns in non-motorized traffic, including counts and patterns for bicycles, pedestrians, and mixed-mode trail traffic. Chapter 6 presents models that can be used to estimate daily bicycle, pedestrian, and mixed-mode traffic on different types of facilities. Chapter 7 discusses the results, identifies opportunities for additional research, and presents recommendations for operations and management of infrastructure for bicycles and pedestrians.

Chapter 2
Use of Non-Motorized Transportation Facilities: A Selected Review

Systematic research on use of facilities for non-motorized transportation has been conducted since at least the 1970s, and understanding of patterns of use and factors that affect use of these facilities has increased. However, transportation planners and managers still lack the data and tools they need to support analytic, evidence-based decisions for many, if not most practical applications such as optimizing the efficiency of investments in new facilities or in operations and maintenance of existing facilities. This chapter summarizes research that reflects the general understanding of use of non-motorized facilities, including information about bicycle and pedestrian traffic counts and volumes, temporal patterns in traffic, and models for estimating traffic volumes.

2.1 Measuring Use of Non-Motorized Traffic Facilities

Technology for measuring traffic has evolved and advanced, but generally is not widely deployed. There are two distinct methods used to monitor non-motorized traffic: (1) short (1- or 2-hour) manual counts and (2) continuous measurements using automated instruments. These methods are described briefly below. We also point readers to excellent reviews of these technologies for further details.[1-5]

Manual Counts: Manual count campaigns typically occur annually for short time periods (i.e., 1- or 2-hours). An advantage of manual counts is that a large number of locations can be observed albeit for relatively short time periods. These data enable researchers to investigate spatial patterns and variability of non-motorized traffic within an urban area. They also allows for comparison of different types of facilities and their relationship to neighborhood design, location, etc. A key limitation of manual counts is the lack of information about long-term temporal variation. Since these counts are typically for short periods it is difficult to infer differences in daily or seasonal patterns between locations or facility types.

Bicycle Loop Detectors: Inductive loop detectors are commonly used to count vehicles as well as for traffic signal control. Loop detectors work using the properties of induction to generate an electric current when a metal object passes over the unit. Loop detectors can be used to identify bicycles instead of vehicles by slightly altering the placement and design of each unit. For example, the City of Minneapolis currently uses loop detectors on the Midtown Greenway to estimate bicycle use. DPW's loop detectors provide counts in 15 minute increments and only need to be visited approximately once every three months to download data. However, since each loop detector's placement and installation may vary slightly correction factors are typically not uniform over each unit. Additionally, it is not possible to count pedestrians or non-metal bicycles using loop detection.

Infrared Counters: There are two types of infrared counters: active infrared and passive infrared. Active infrared counters emit a pulse signal across an area of interest to a receiver. Each time this beam is broken a count event is registered. Passive infrared detect heat signatures of a passerby to register a count event. Since active infrared requires both a transmitter and a receiver they are typically used on urban trail systems while passive infrared can be deployed in other areas (e.g., sidewalks). Infrared counters provide continuous measurements of non-motorized traffic (both pedestrian and cyclists) and error rates are typically uniform across different units and locations. However, memory capacity is typically small and it is necessary to download data more frequently than for other instruments (i.e., loop detectors). Since the infrared units are typically exposed above ground they are also slightly more prone to vandalism.

Video and Computer Imaging: Use of video streams and computer imaging are increasingly replacing the use of loop detectors for continuous measurement of vehicles. Improvements in the software associated with this process has allowed for distinction between modes (i.e., vehicles, bicycle, pedestrians). However, equipment and labor costs associated with data processing are typically much larger than for other instruments.

2.2 Patterns in Non-Motorized Traffic

Similar to automobile traffic there seem to be discernible temporal and spatial patterns in non-motorized travel behavior. However, these patterns seem to differ between modes (e.g., auto vs. cycling vs. walking). Temporal patterns vary on three time scales: (1) Hourly (i.e., within a day), (2) weekday vs. weekend (i.e., between days), and (3) seasonally (i.e., by month). For example, traffic patterns are different on weekends vs. weekdays; however, patterns among all weekdays (or all weekend days) are fairly consistent. Furthermore, volumes vary seasonally which is heavily dependent on weather.

There may also be regional differences in patterns of non-motorized traffic. Jones[6] illustrated that the patterns of trail use documented in Indianapolis vary from those in other regions of the nation and concluded that "unlike vehicle use patterns, there appear to be significant regional differences in seasonal patterns" and that, for non-motorized facilities, analysts may need to "accept variation as part of the normal estimating process." A review by Pucher et al.[7] highlights this point for bicycle infrastructure interventions stating that there is "considerable variation in estimated impacts, both by type of intervention and by study design, location, and timing". In Minnesota, MnDOT maintains monitoring stations at about 32,000 locations for automobiles but currently has no program to monitor bicycles and pedestrians. Given the temporal and spatial variability in non-motorized traffic demonstrated in these exploratory studies and the level of investment in non-motorized infrastructure it would be beneficial to collect data that could maximize the effectiveness of infrastructure investment.

2.3 Models for Estimating Non-Motorized Traffic

Researchers have worked on methods of estimating non-motorized traffic volumes for at least forty years. Two early examples from the 1970s are: (1) use of aerial photography to count pedestrians and develop regression models to estimate pedestrian traffic as a function of built environment variables[8] and (2) estimating pedestrian traffic per hour for blocks in Milwaukee, Wisconsin as a function of land use and other variables.[9] More than 20 years after these exploratory studies, Hunter and Huang[10] completed a comprehensive review of reports on the use of bicycle lanes and off-street trails and found wide variation in the level of detail and quality.

Although the scope of studies remains insufficient, researchers have added new insights in several key areas thought to impact non-motorized travel: Built environment characteristics,[11-13] infrastructure design characteristics,[14,15] neighborhood socio-economics,[16] and weather.[17] Furthermore, researchers have made incremental steps towards developing traditional traffic models (e.g., gravity models) for non-motorized travel by developing impedance functions for cycling and walking,[18] modeling mode share near bicycle facilities,[19] and building route-choice models.[20] For example, researchers explained more than eighty percent of observed variation in traffic at 30 locations on five multiuse trails in Indianapolis, Indiana by modeling daily counts as a function of weather, day of week (and month of year), neighborhood socio-demographics, neighborhood form, and trail characteristics.[14,21,22] They also demonstrated tradeoffs in quality of traffic forecasts associated with differences in the areal units used to calculate covariates (e.g., census tracts vs. network-defined “pedestrian access zones”).[21]

Chapter 3
Approach and Methods Used in Research

3.1 Measurements of Non-Motorized Traffic in Minneapolis

In addition to the preceding literature review, the general approach to this research included:

- collection and validation of existing counts of bicycle and pedestrian traffic in Minneapolis;
- acquisition and deployment of infrared counters for measuring mixed-mode trail traffic, including development of protocols for collection and validation of data;
- analyses of counts by mode and facility type;
- development of regression models for determining correlates of non-motorized traffic and estimating daily bicycle, pedestrian, and mixed-mode trail traffic.

The collection and analyses of traffic counts were undertaken in collaboration with professional staff in the Bicycle Program in the Traffic and Parking Services Division of the City of Minneapolis Department of Public Works (DPW); a nonprofit organization, Transit for Livable Communities (TLC); the Minneapolis Parks and Recreation Board (MPRB); and students in capstone and workshop courses at the Humphrey School of Public Affairs. The count locations are shown in Figure 3.1.

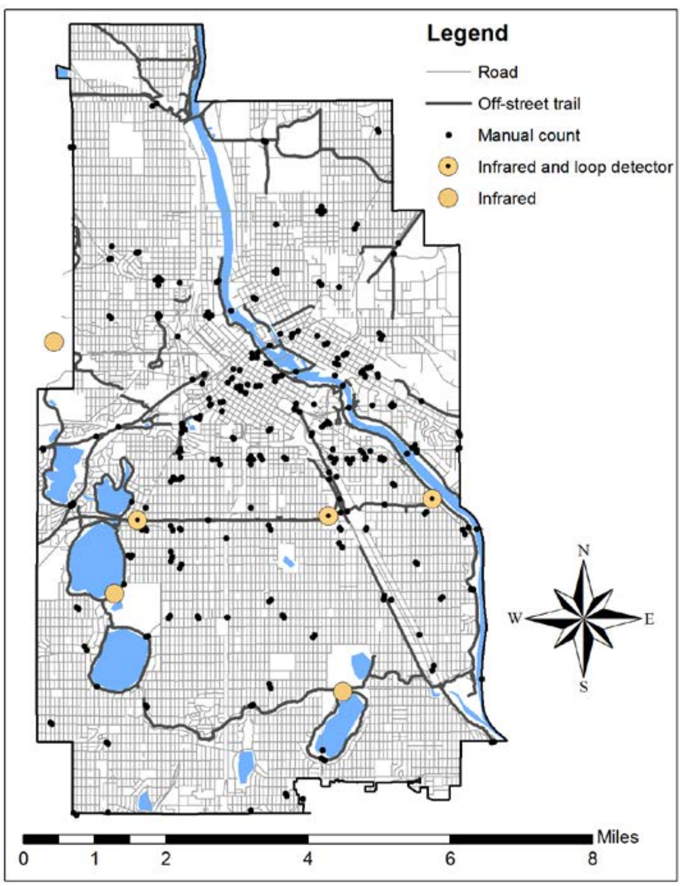

Figure 3.1. Locations of manual and continuous counts of non-motorized traffic.

3.1.1 Field Observations of Bicycle and Pedestrian Traffic

The DPW and TLC have cooperated in manual field counts of bicycle and pedestrian traffic at more than 240 locations in the City of Minneapolis since 2007. Counts are taken by employees and volunteers annually in September or October and occasionally at different times throughout the year. DPW and TLC use a non-random, purposive sampling approach: locations are selected because their characteristics are of special interest. For example, locations may be included in the sample because they are believed to have high volumes, have been the locations of accidents, or are the locations for proposed infrastructure improvements. Most counts are two-hour, peak hour counts, although some 12-hour counts have been taken. Because the location and timing of observations are not random, the results cannot be generalized more broadly to the rest of the city or to locations outside the city. Protocols for the DPW and TLC counts, which generally are consistent with those used by the National Bicycle and Pedestrian Documentation Project[23], are described in reports by DPW[24] and TLC.[25]

DPW and TLC have reported annual results and trends in volumes at locations over time[24,25], but due to staffing and other limitations, the organizations have not maintained an integrated, multi-year dataset or analyzed the data to identify systematic variation of traffic volumes in relation to facility type or location characteristics.

DPW and TLC provided copies of hundreds of spreadsheets containing the results of counts at different locations to the research team, and students in a capstone class developed an integrated dataset for all bicycle and pedestrian counts taken by DPW and TLC between 2007 and 2009. This data set included 458 counts of bicycle traffic and 458 counts of pedestrian traffic at 240 different locations.[26]

Using geographic information systems (GIS), researchers next identified characteristics of the sample locations including street functional classification, presence of a bus line, presence of a bicycle facility, and various land use and socio-demographic characteristics. The team then stratified the sample by street functional classification and other characteristics to determine whether traffic appeared to vary systematically with particular characteristics.

To illustrate the potential for error in manual field observations, a student team in a workshop class collaborating with this project conducted field counts of traffic at 2 locations and calculated inter-observer differences in hourly traffic volumes. The mean difference in hourly traffic counts taken by observers simultaneously at the same location was 1.4%.[27] Although no error rates are reported for the DPW/TLC counts, this error rate is believed to be an approximation of the magnitude of uncertainty that may be associated with all the manual field counts described in this report.

3.1.2 Magnetic Loop Detector Counts of Greenway Bicycle Traffic

The DPW maintains magnetic loop detectors to count bicycles at three locations on the Midtown Greenway, a 5.5 mile, multi-use urban trail on an historic rail line that that runs east-west across Minneapolis. The detectors, which are embedded in the asphalt trail, count changes in the electromagnetic field over a coil of wire that occurs when a bicycle with metal rims travels over the wire. Each change, or disturbance, is recorded as an event or a single use. The detectors are designed to provide both a count of total use and counts of bicycles riding in each direction. The detectors provide continuous 24-hour counts for the entire year (see Table 3.1 for a summary of available data).

Table 3.1. Deployment of magnetic loop detectors in Minneapolis.

Location	Days deployed	Usable days	Percentage
Hennepin	1,402	852	61%
Cedar	1,402	1,218	87%
West River Parkway	1,402	1,243	89%
Total	4,206	3,313	79%

Following installation, the DPW developed procedures for collecting and analyzing data obtained from the loop detectors but did not validate or calibrate the counts. Estimates of bicycle traffic potentially may be inaccurate because of detector malfunction or because of travel behavior of cyclists. For example, total counts of bicycle traffic may be low because bicyclists may ride on gravel shoulders adjacent to the trail and not be detected. Directional counts may be inaccurate because cyclists may ride in oncoming lanes.

Because pedestrians also use the trail, the bicycle counts are an underestimate of total trail traffic. Because of resource shortages and conflicting priorities, DPW has not produced estimates of total traffic on the trail.

Bicycle traffic volumes from the detectors are available for the trail near its intersections with Hennepin Avenue, Cedar Avenue, and the West River Parkway (Figure 3.1; Table 3.1). The DPW has maintained these detectors since at least 2007 and published reports that summarize daily and monthly bicycle volumes except when counters have malfunctioned.[24] The magnitude of error or uncertainty in these counts has not been estimated or reported by DPW.

The DPW provided copies of spreadsheets with bicycle counts to the research team which re-analyzed them. As part of the re-analysis, researchers conducted field observations to validate counts and, if needed, procedures for calibration.[27] The general approach to validation involved counting bicyclists on the trail at the location of each detector and then comparing hourly totals from the detector with the hourly observation totals. These investigations included 84 hours of manual field counts at the Hennepin location, 8 at the Cedar location, and 50 hours at the West River Parkway location.

The estimates of bicycle traffic at each location made with field observations varied from the estimates from the detectors at each location and were inconsistent. The counts from the detector at the Hennepin location were consistently high, overestimating hourly bicycle traffic volumes by an average of 27 percent, while the counts at the West River Parkway location were consistently low, underestimating hourly traffic by an average of 7 percent (counts at the Cedar location overestimated by 5%).[27,28] At each of the three locations, the magnitude of difference between the field directional counts and the detector directional counts was much greater than the difference for the total counts. The reasons for the differences in detector performance, including factors that contribute to higher or lower counts, are unknown. The magnitude of error associated with the directional counts is sufficiently high that use of the directional estimates is not advised.

Figure 3.2 presents scatter plots and ordinary least squares (OLS) regression lines for the observed and detector hourly counts at each location. Table 3.2 includes calibration equations estimated using OLS regression that can be used to adjust hourly counts from the detectors to account for the observed, systematic error associated in the detector counts. Calibration of hourly counts using equations estimated with OLS can result in estimates of negative traffic on days with low traffic volumes. For practical applications, estimates of negative traffic can be changed to zero. Alternatively, new correction equations can be estimated using different functional programs that constrain values to be at least zero or minimize the number of estimates with values below zero.

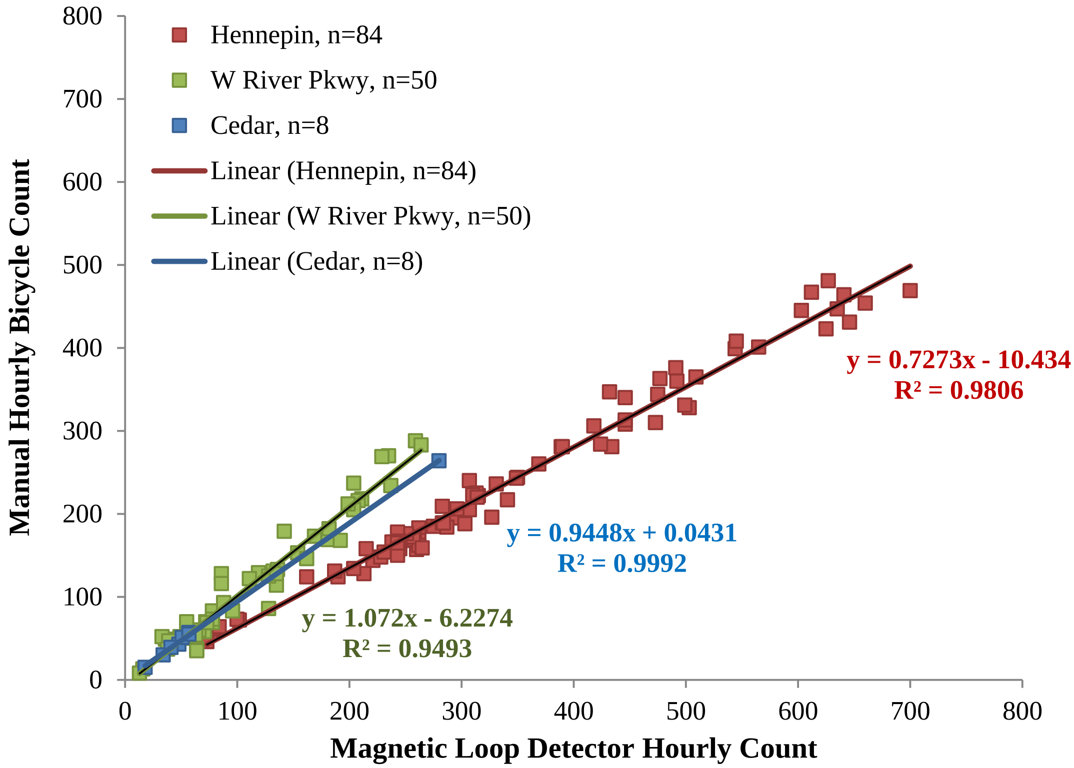

Figure 3.2. Scatter plot of manual counts vs. magnetic loop detector counts.

Table 3.2. Calibration equations for DPW magnetic loop detectors.

Location	**Hours**	**Mean hourly manual count**	**Mean hourly loop detector count**	**Correction equation**	**R-square**	**Mean % Error**
Hennepin	84	212	266	y=0.727x-10.43	0.981	45.0%
Cedar	8	73	69	y=0.945x-0.04	0.999	7.5%
W. River Pkwy	50	119	121	y=1.072x-6.23	0.949	15.2%

A challenge in interpretation and use of the counts from the magnetic loop detectors is the inconsistency in error, especially the fact that the same type of counters with the same settings are producing estimates of traffic volumes that are both higher and lower than observed volumes. Although the calibration equations can be applied to all historic counts at individual locations to account for error known to exist now, it is unknown how long the errors have persisted or whether the magnitude and direction of error have changed over time. While use of calibration equations to adjust historic counts seems essential given the magnitude of observed errors, the time period for which these calibration equations actually is appropriate is unknown. Periodic validation and calibration is essential for maintaining the most accurate estimates of traffic volumes from the magnetic loop detectors. The research team used the calibration equations in this report to update all DPW traffic counts.[28]

3.1.3 Infrared Counts of Mixed-Mode Trail Traffic

The research team obtained and deployed eight battery-operated Trailmaster ™ active infrared monitors at the six locations determined in consultation with DPW and MPRB (Figure 3.1). These locations include the three locations on the Midtown Greenway with magnetic loop detectors, adjacent locations on the separate bicycle and pedestrian trails around Lakes Calhoun and Nokomis, and a location on a multiuse trail in Wirth Park. Table 3.3 lists the infrared monitor locations, the dates of installation and operation, and the percent of total possible days for which counts are available. Missing counts may be due to monitor malfunction, loss of power, vandalism, or human error in data retrieval.

Table 3.3. Deployment of active infrared trail counters in Minneapolis.

Location	Days deployed	Usable days	Percentage
Midtown Greenway: Hennepin	558	519	93%
Midtown Greenway: Cedar	542	466	86%
Midtown Greenway: W River Parkway	416	379	91%
Lake Calhoun	386	344	89%
Lake Nokomis	386	351	91%
Theodore Wirth Parkway	385	354	92%
Total	2,673	2,413	90%

The Trailmaster ™ monitors consist of a transmitter and a receiver installed on opposite sides of the trail on posts approximately 48 inches high. The transmitter emits a stream of pulses across the trail to the receiver. The receiver records the time when the beam is interrupted by a trail user (i.e., when a predetermined number of pulses are not received). Each time stamp is an “event” or a single use. The monitors can hold 8,000 to 16,000 events, depending on the model. The monitors cannot distinguish between traffic modes (i.e., between bicyclists and pedestrians), and the counts are measures of all or mixed-mode traffic. The monitors also cannot distinguish direction of travel.

Trailmaster ™ monitors systematically undercount trail traffic because they record only a single event when users pass simultaneously. This type of measurement error can occur, for example, when users traveling in opposite directions pass at the same time or when bicyclists or pedestrians travel by two or more abreast. Other potential sources of error include missed observations from users passing so quickly they do not break the beam long enough to record an events, extra counts when users move back and forth across the beam multiple times, extreme weather events such as heavy, wet snowfalls that interrupt the beam, and purposeful blocking of the beam by users.

To obtain estimates of traffic volumes, the Trailmaster ™ data are downloaded in with a data collector, exported to an Excel © spreadsheet, and totaled by hour, adjusted to correct for the systematic undercount, and then aggregated by day.

To validate the traffic counts from the monitors and develop calibration equations, the team conducted field observations at the Hennepin, Cedar, and West River Parkway locations. Figure 3.3 present scatterplots and ordinary least squares (OLS) regression lines for the observed and monitor hourly counts at the three locations. The direction and magnitude of the monitor errors are consistent across locations, indicating that a single calibration equation can be used for all monitors. Table 3.4 includes calibration equations for each location plus a general equation estimated from pooled data from all locations.

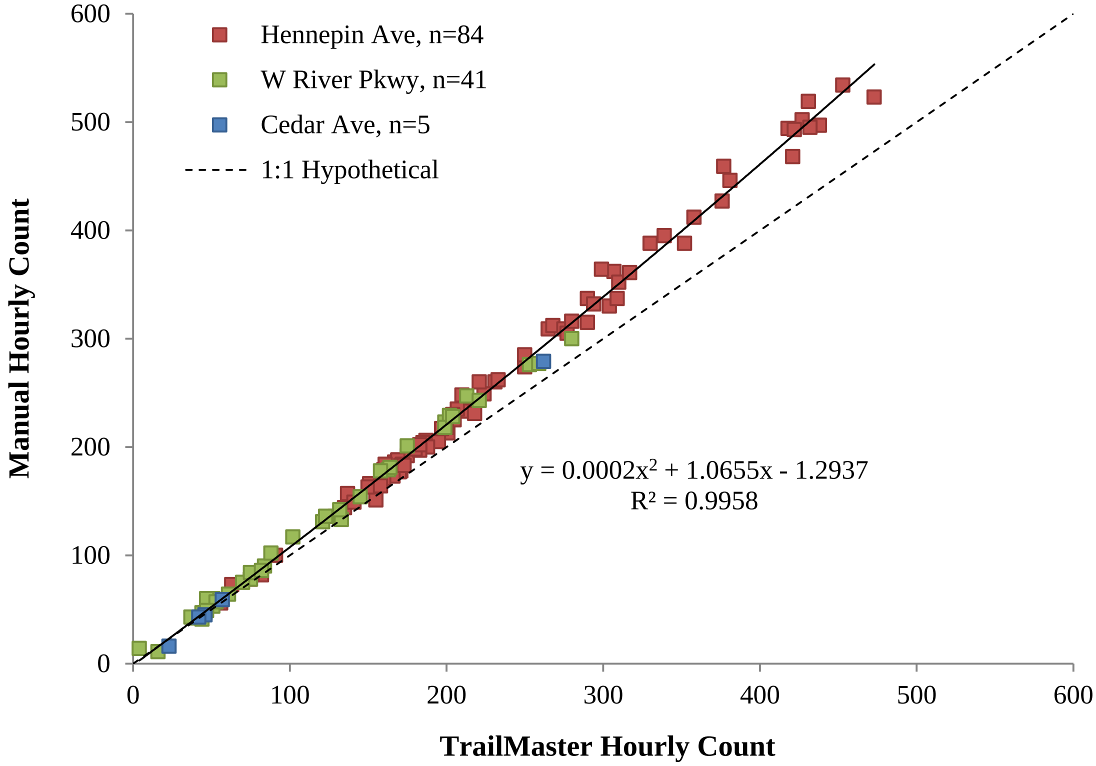

Figure 3.3. Scatter plot of manual counts vs. TrailMaster ™ infrared counts.

Table 3.4. Calibration equations for Trailmaster ™ active infrared monitors.

Location	Hours	Mean hourly manual count	Mean hourly TMI count	Correction equation	R-square	Mean % Error
Hennepin	84	235	264	y=1.1939x-16.703	0.9941	9.8%
Cedar	5	86	88	y=1.0857x-4.9726	0.9994	11.0%
W. River Pkwy	41	114	125	y=1.0995x-0.3899	0.9953	11.6%
Composite	130	191	213	y=0.0002x^2+1.0655x-1.2937	0.9958	10.2%

The calibration equations in Table 3.4 are for hourly mixed-mode trail traffic (i.e., cyclists and pedestrians combined). Different equations have not been estimated for the monitors installed along Lakes Calhoun and Nokomis where there are separate trails for bicyclists and pedestrians. It is likely that the rate of error in the counts provided by the Trailmaster ™ infrared monitors is a function of mode (i.e., the error rates likely are different for bicyclists and pedestrians). Additional field research is underway to develop calibration equations for these locations.

3.2 Temporal and Spatial Patterns in Non-Motorized Traffic

A principal objective of this research is to develop standardized measures and scaling factors that transportation planners and managers can use to describe patterns in bicycle and pedestrian traffic. Measures of hourly, peak hour, daily, and monthly traffic all are commonly used by analysts. In addition, estimates of traffic by facility type and other spatial factors often are useful.

3.2.1 Variations in Hourly Traffic

Variations in hourly traffic are described by:

- corrected hourly and daily counts, including peak-hour counts;
- corrected hourly counts as a percentage of daily traffic, where daily traffic is measured as 12-hour volumes or 24-hour volumes, for manual and automated counts, respectively;
- hourly scaling factors, computed as the value one divided by the proportion of daily traffic that occurs, on average, within the hour.

The hourly scaling factors are used to estimate daily traffic volumes from hourly volumes for modeling and other purposes.

3.2.2 Variations in Daily Traffic

Variations in daily traffic are described using the ratio of mean weekend daily traffic to mean weekday daily traffic. The weekend-weekday traffic ratios are computed for different months of the year. For any given location, a weekend-weekday ratio greater than one indicates that recreational rather than utilitarian trips likely accounts for most traffic. Weekend-weekday ratios can be used to estimate traffic volumes when observations for a particular day may be missing or when approximations of aggregate traffic volumes are needed.

3.2.3 Monthly and Seasonal Variations in Traffic

Monthly traffic counts are useful for illustrating the seasonal variation in non-motorized traffic associated with weather and other factors. Where the data record is sufficient, variations in monthly traffic for each location are described by:

- estimates of total and mean daily traffic;
- the percentage of total annual traffic;
- monthly scaling factors, computed as the value one divided by the average percentage of total annual traffic within the month.

3.2.4 Spatial Patterns in Non-Motorized Traffic

Transportation engineers classify streets by function and design volumes. Functional classifications used in the City of Minneapolis include principal arterial, A-minor arterial, B-minor arterial, collector, and local streets. Some of these streets include facilities such as painted bike lanes and others do not. In addition, there are off-street or separate facilities for pedestrians and cyclists, including sidewalks and trails like the Midtown Greenway. Other spatial characteristics, such as whether bus lines operate on a street, also may be associated with volumes of non-motorized transportation. To illustrate spatial patterns in volumes of non-motorized traffic, counts are stratified by street functional class, by the presence of a bus line, and by the presence of bicycle facilities on the street.

3.3 Models of Non-Motorized Traffic

A principal objective of this research is to specify and estimate models that can be used to determine correlates of non-motorized traffic and to estimate traffic where at locations where counts have not been taken. Separate models are developed for bicycle traffic, pedestrian traffic, and mixed-mode trail traffic.

In each of the models, daily traffic counts are the dependent variable. The general approach to modeling involves regressing the daily traffic counts on a vector of independent variables, including daily weather (e.g., temperature, precipitation, humidity); infrastructure type, including street classification and presence of bicycle facilities); presence of a bus line; dimensions of urban form (e.g., land use mix and population density); and neighborhood socio-demographics (e.g., household income, race, education attainment). GIS is used to identify these characteristics for each sample location. Regression models are estimated using both OLS and negative binomial regression. A brief description of the models for each mode is given below. See Chapter 6 for a full discussion of the model inputs and results.

3.3.1 Models of Pedestrian Traffic

Models of pedestrian traffic are developed from the DPW/TLC field observations using a two-step process:

1. all counts are converted to 12-hour daily counts using scaling factors, and
2. the estimated 12-hour daily pedestrian counts are regressed on the independent variables.

Counts from 240 locations taken between 2007 and 2009 are included the dataset used to estimate the model.

3.3.2 Models of Bicycle Traffic

Models of bicycle traffic also are developed from the DPW/TLC field observations using a two-step process:

1. all counts are converted to 12-hour daily counts using scaling factors, and
2. the estimated 12-hour daily bicycle counts are regressed on the independent variables.

Counts from 240 locations taken between 2007 and 2009 are included the dataset used to estimate the model.

3.3.3 Models of Multi-Mode Trail Traffic

Models of mixed-mode trail traffic are developed from the Trailmaster ™ 24-hour traffic counts. Only days with a full 24-hour count are included in the dataset used to estimate the models; days with partial counts were censored from the dataset. This process included mainly three steps:

1. all counts are corrected (on an hourly basis) using the correction equations described above.
2. all hourly counts are then aggregated to daily, 24-hour counts.
3. the aggregated daily counts are regressed on the independent variables.

Data from all eight locations where Trailmaster ™ monitors have been installed are included in the models; the number of daily counts available for each site varies.

Chapter 4
Traffic Volumes on Non-Motorized Infrastructure in Minneapolis

This chapter presents basic descriptive statistics by mode for each of the datasets described in Chapter 3. All values are adjusted as described previously and were joined to independent variables using a geographic information system (GIS).

4.1 Bicycle Volumes

4.1.1 Manual Counts by Bicycle Facility Type

The count locations by street functional class and bicycle infrastructure type are shown in Table 4.1. The sample includes observations from each type of street both with and without bicycle facilities, except for principal arterials, where no bicycle facilities exist and bicycle and pedestrian traffic is prohibited or discouraged. In general, the number of samples from each type of street is comparable, and the numbers of observations are sufficient for analysis.

One-third of all count locations occurred on A-minor roads of which two-thirds did not have any bicycle infrastructure. Fifteen percent of count locations were on B-minor streets, 18 percent were on local roads, and 20 percent were on major collectors. There were 29 trail locations that did not have a corresponding road. These included off-street bicycle paths as well as pedestrian and bicycle bridges.

Table 4.1. Count location breakout by bicycle infrastructure.

Bike Lane	Count Locations	Principal Arterial	A-Minor	B-Minor	Local	Collector	Trail
None	164	3	66	20	36	39	0
On-Street Bike Lane	39	0	11	16	5	7	0
Off-Street	33	0	2	0	0	2	29
Shared lane	4	0	0	0	3	1	0
Total	240	3	79	36	44	49	29

Estimated 12-hour bicycle counts by bicycle facility type are given in Table 4.2. The estimated 12-hour counts are based on the 2-hour field observations by DPW and TLC. Each count was scaled to a 12-hour count based on scaling factors described in Chapter 5. These data show that bicycle traffic volumes are highest on off-street trails followed by on-street bike lanes and shared lanes. The differences of mean bicycle traffic volumes between streets with bicycle facilities and streets without bicycle facilities are all statistically significant. Table 4.3 shows estimated 12-hour bicycle counts by street type stratified by the presence of a bicycle facility. Bicycle traffic volumes were higher for streets with bicycle facilities regardless of street type, however, the effect was most pronounced for minor arterials.

Table 4.2. 12-hour estimated bicycle counts (6:30am – 6:30pm).

Twelve Hour Estimated Counts	Off-Street	On-Street Bike Lane	Shared Lane	None	All
Count	100	81	5	272	458
Maximum	6,701	3,138	964	3,394	6,701
Mean	837*	566*	450*	362	502
Median	770	301	395	220	269
Minimum	20	41	71	0	0
Average Hourly	70	47	38	30	42

*Statistically significant from no bike infrastructure mean (p<0.05)

Table 4.3. Summary of bicycle counts by street functional class.

Roadway Functional Class	Bike Lane	Number of Counts	Maximum	Mean	Median	Minimum	Average Hourly
Principal Arterial	On-Street	N/A	N/A	N/A	N/A	N/A	N/A
	None	6	248	178	213	12	15
A-Minor	On-Street	17	1,909	776*	810	212	65
	None	145	3,393	430	246	0	36
B-Minor	On-Street	48	3,138	605*	277	53	50
	None	27	578	178	142	47	15
Collector	On-Street	16	1,412	422	238	41	35
	None	42	1,701	374	232	24	31
Local	On-Street	11	964	387	395	71	32
	None	52	1,029	277	196	13	23
Total	On-Street	92	3,138	579*	349	41	48
	None	272	3,394	362	220	0	30

*Statistically significant difference from no bike infrastructure (p< 0.05)

4.1.2 Magnetic Loop Detector Trail Counts

The three loop detectors located on the Midtown Greenway have various levels of systematic error (see Chapter 3). Below (Figure 4.1) we show average daily counts (by month) at each location after adjusting historic data according to our correction equations. It is important to note that this method may be inaccurate since we are unsure when the loop detectors started under-(over-)counting or if this error is changing over time. Further research could verify that this correction factor is stable. It would be beneficial to have field staff verify correction equations on an annual (or bi-annual) basis.

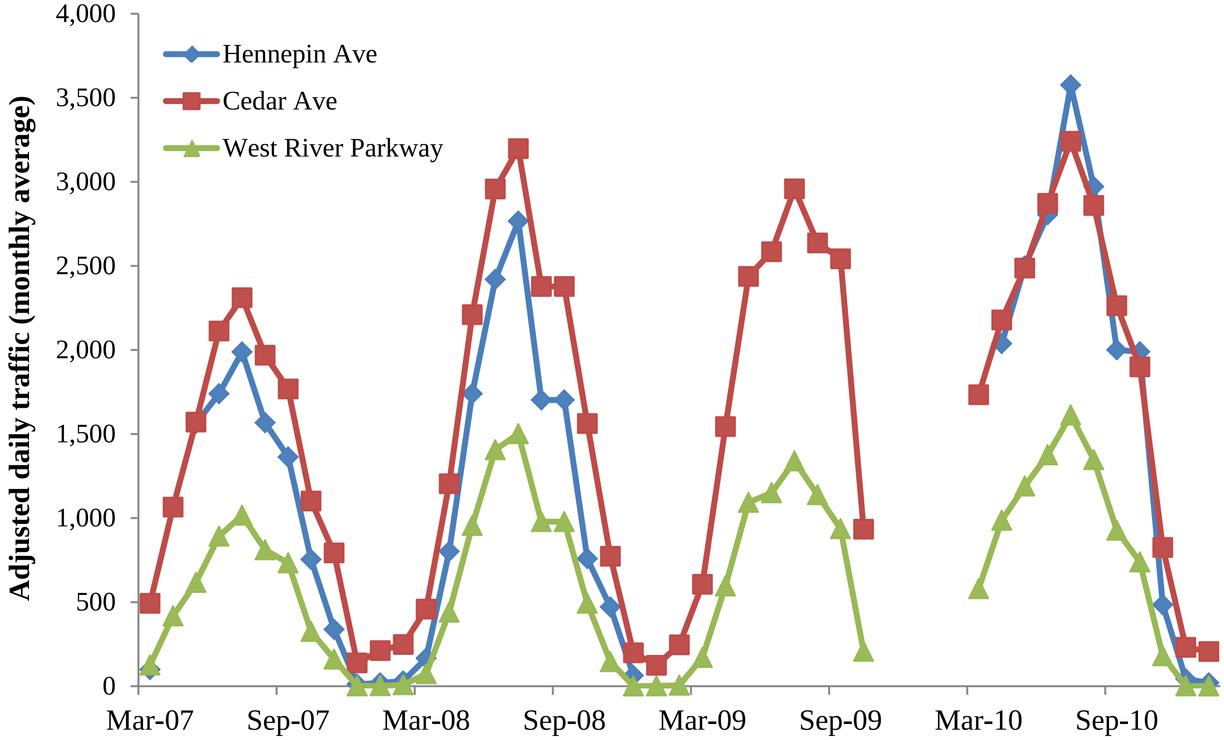

Figure 4.1. Adjusted average (monthly) daily traffic for each loop detector location.

4.2 Pedestrian Volumes

Pedestrian and bicycle counts were conducted at the same locations. Thus, the descriptive statistics for the counting locations in Table 4.1 for cyclists are the same for pedestrians. Table 4.4 shows estimated 12-hour pedestrian counts for each street type. Pedestrian counts were largest on minor arterial streets followed by collector and local streets. This trend is expected since retail and transit corridors are more likely to be located along minor arterial and collector streets.

Table 4.4. Summary of estimated 12-hour pedestrian counts by functional class.

Twelve Hour Actual and Estimated Counts	Principal Arterial	A-Minor	B-Minor	Collector	Local	Total
Count	6	160	72	58	63	359
Maximum	150	18,153	6,230	13,424	1,476	18,153
Mean	87	1,005	939	1,447	355	934
Median	86	674	315	461	230	443
Minimum	36	0	43	4	0	0
Average Hourly	7	84	78	121	30	78

Table 4.5 shows pedestrian counts stratified by the presence of a bus route. Table 4.6 shows pedestrian counts stratified by both presence of a bus line and street functional class. Pedestrian manual counts show higher levels at locations with a bus line. Fifty-eight percent of pedestrian counts occurred on streets with at least one bus line. The average 12-hour pedestrian count for locations with a bus line is almost twice that of locations without a bus line. Off-street trails display the lowest pedestrian counts at 440. Their physical distance from other destinations could account for this low use from pedestrians. The difference between the average of count locations on a bus line and the average of count locations not on a bus line is statistically significant.

Table 4.5. Summary pedestrian counts by presence of a bus line.

Twelve Hour (6:30am – 6:30pm)	On Bus Route	None	Trail
Count	265	94	94
Maximum	18,153	8,492	14,779
Mean	1,071*	547	440
Median	552	230	114
Minimum	0	0	0
Average Hourly	89	46	37

*****Statistically significant from no bus route mean ($p<0.05$)

Table4.6. Summary pedestrian counts by functional class and presence of a bus line.

Roadway Functional Class	Bus Line	Count	Maximum	Mean	Median	Minimum	Average Hourly
Principal Arterial	Yes	5	110	74	75	36	6
	No	1	150	150	150	150	13
A-Minor	Yes	147	18,153	1,071*	703	0	89
	No	13	1,122	272	186	13	23
B-Minor	Yes	60	6,230	1,055*	315	43	88
	No	12	800	359	325	61	30
Collector	Yes	38	13,424	1,512	397	4	126
	No	20	8,492	1,325	497	35	110
Local	Yes	15	1,003	359	367	44	30
	None	48	1,476	353	224	0	29
Total	Yes	265	18,153	1,071*	552	0	89
	None	94	8,492	547	230	0	46

*Statistically significant from “No” mean for same functional class ($p<0.05$)

4.3 Mixed-Mode Trail Volumes

The mixed-mode counts are shown in Figure 4.2 and are adjusted according to the correction equations described in Chapter 3. Trail volumes vary seasonally as well as between locations. Lake Calhoun and two locations along the Midtown Greenway (Hennepin Ave and Cedar Ave) consistently have the largest traffic volumes. Figure 4.2 shows the 30-day moving average of adjusted daily counts for three count locations on the Chain of Lakes park system (solid lines), as well as for three Midtown-Greenway locations (dashed lines). The 30-day moving average is the average of the previous 30 days of adjusted counts (i.e., each data point is the average of approximately one month of data).

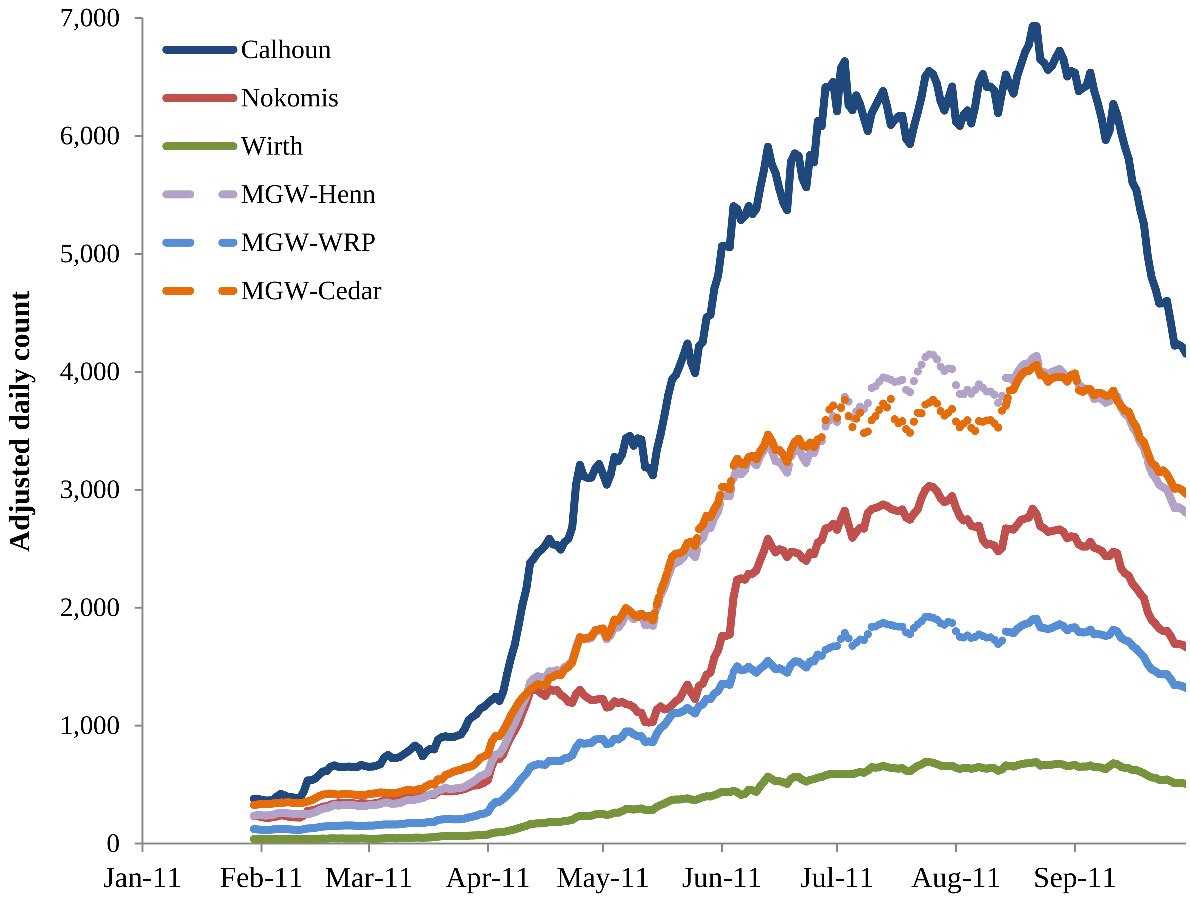

Figure 4.2. 30-day moving average of daily multi-mode counts on off-street trails from active infrared counters.

Chapter 5
Temporal and Spatial Patterns in Non-Motorized Traffic in Minneapolis

Hourly patterns in pedestrian and bicycle counts were analyzed for counts that were 12 hours or more per day in length for the combined TLC and City of Minneapolis dataset (n = 43). To make a comparison each count was normalized to a common unit. We chose the 12-hour count (6:30-18:30) as the basis for normalization (this time interval was chosen because it was the longest period of time for which a significant amount of manual count data was available across location types). The result is a curve that shows each 30-minute count period as a percentage of the total 12-hour count.

The normalized curves were averaged by time of day (each 30-minute period) to create a representative daily curve. This process was repeated for (1) bicycle loop detector Midtown-Greenway data, (2) bicycle manual count data, and (3) pedestrian manual count data. Figure 5.1 shows these curves plotted together to compare hourly patterns (see Appendix A).

Our analysis suggests that hourly patterns for bicycles track well between the two data sets. The Midtown Greenway has a slightly larger afternoon peak (than the manual bicycle counts across multiple locations) which may be due to elevated recreational uses during that period of the day. Pedestrian hourly patterns do not track well with either of the bicycle count patterns. Pedestrian traffic seems to increase consistently throughout the day with three distinct peaks: morning, noon-hour, and afternoon.

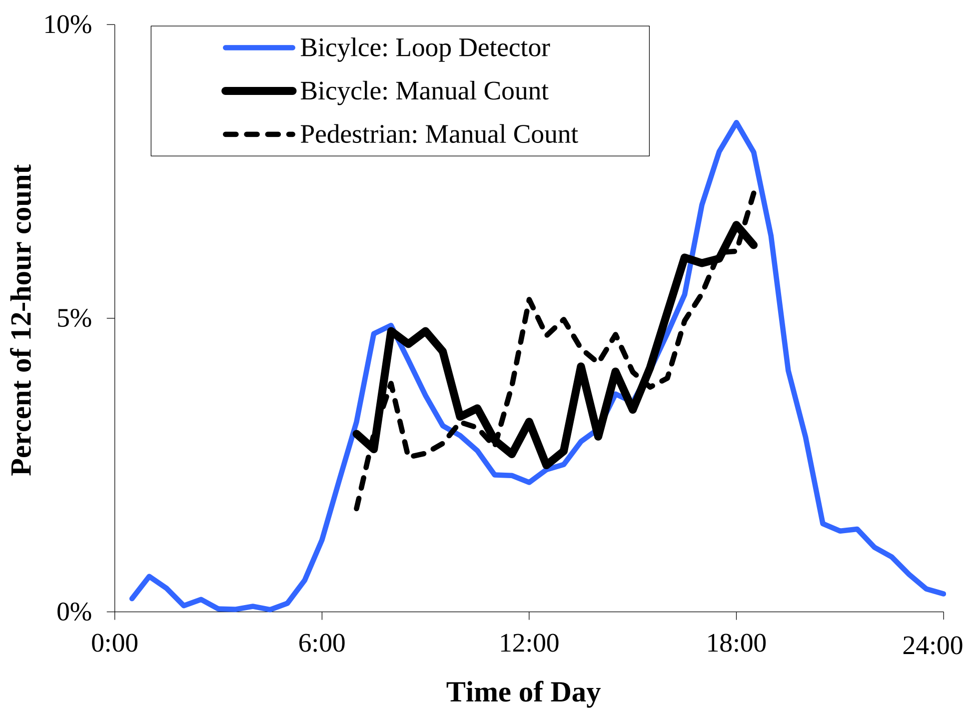

Figure 5.1. Hourly bicycle (manual and loop detector) and pedestrian (manual only) count patterns. All 30-minute counts are normalized to a percentage of the 12-hour count (6:30-18:30).

Hourly scale factors were calculated from 7am-6pm for the manual count data. A scale factor is a multiplier used to estimate near full day counts (e.g., 12-hour counts) from short counts (e.g., 1-or 2-hour counts). The scaling factors shown here scale hourly and bi-hourly counts to 12-hour counts (6:30-18:30). For example, a count of 10 bicyclists from 8-9am would be multiplied by ~10.7 (see Table 5.1) to estimate a 12-hour count of 107. Scaling factors for pedestrians are generally largest during morning hours while they are largest for bicycles in the late morning and early afternoon. This highlights the fact that pedestrian and bicycle behavior is not consistent during the day. All bicycle scaling factors are shown in Table 5.1; all pedestrian scaling factors are shown in Table 5.2 (along with the share of 12-hour flow).

The strength of correlation between 1- and 2-hour counts and the total 12-hour count (shown by the R^2 value in Tables 5.1 and 5.2) were calculated for each 1- and 2-hour period of the day. This calculation yields insight into the relative confidence the data gives for the scale factor during each time period (high confidence is given by values closest to 1). For example, we have more confidence in the 4-5pm scaling factor for bicycles (R^2 = 0.93) than the noon-1pm scaling factor (R^2 = 0.77).

5.1 Temporal Variations in Bicycle Traffic

5.1.1 Hourly Variations in Bicycle Traffic

Table 5.1 shows the scaling factors developed for adjusting 1- and 2-hour counts of bicycle traffic to 12-hour counts. The method used to develop these scaling factors as well as examples of their application are described above. In general, peak hour counts (4-6pm) were better predictors of 12-hour counts than off-peak counts. Figure 5.2 shows scatter plots of actual counts vs. 12-hour counts estimated using the peak hour scaling factors. This validation suggests that both 1- and 2-hour, peak hour counts are strong predictors of 12-hour counts.

Table 5.1. Bicycle scaling factors for the manual count data to 12-hour counts (6:30-18:30).

1-hour scaling factors				**2-hour scaling factors**			
Time period	*Percent of 12-hour count*	*Scale factor*	R^2	*Time period*	*Percent of 12-hour count*	*Scale factor*	R^2
7-8am	7.5%	13.2	0.88	7-9am	16.9%	5.9	0.94
8-9am	9.3%	10.7	0.9	8-10am	17.1%	5.8	0.93
9-10am	7.8%	12.9	0.89	9-11am	14.1%	7.1	0.93
10-11am	6.4%	15.6	0.89	10-noon	12.3%	8.1	0.91
11-noon	5.9%	16.9	0.87	11-1pm	11.2%	9	0.86
noon-1pm	5.2%	19.1	0.77	noon-2pm	12.4%	8.1	0.88
1-2pm	7.2%	14.0	0.88	1-3pm	14.7%	6.8	0.92
2-3pm	7.5%	13.3	0.84	2-4pm	16.8%	6	0.91
3-4pm	9.3%	10.8	0.9	3-5pm	21.2%	4.7	0.97
4-5pm	12.0%	8.4	0.93	4-6pm	24.6%	4.1	0.92
5-6pm	12.6%	7.9	0.89				

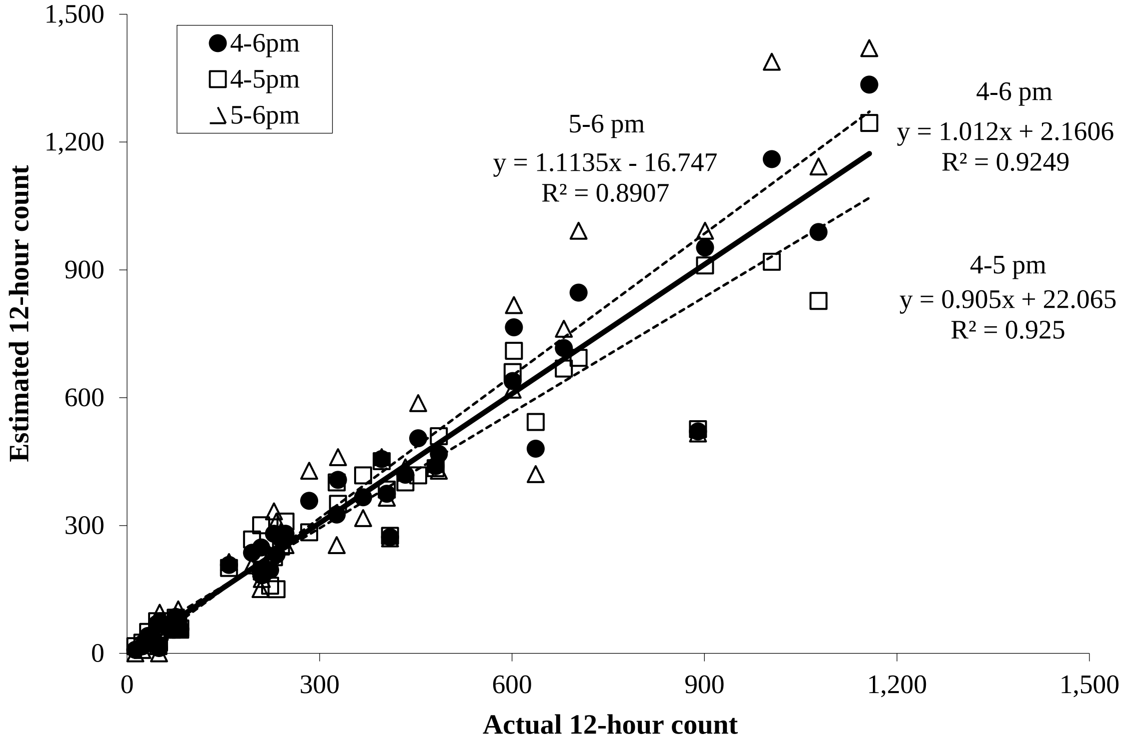

Figure 5.2. Bicycle 12-hour count predictions (n=43) from peak hour measures for hourly (dashed lines) and bi-hourly (solid lines) counts.

5.1.2 Daily Variations in Bicycle Traffic

We explored differences between weekdays and weekends. To do this, the ratio of average daily weekend bicycle traffic compared to average daily weekday bicycle traffic was calculated for each month at the three locations on the Midtown Greenway (see Figure 5.3). We found that this ratio rarely exceeds 2 and is usually near 1.5. This may suggest that there is a heavy utilitarian-use population on this section of the Midtown Greenway. This pattern may or may not be observed for other trails (e.g., Lake Calhoun, Lake Harriet, or Mississippi River trails) where a larger share of the overall traffic is recreational. These patterns also seemed to track well across each location.

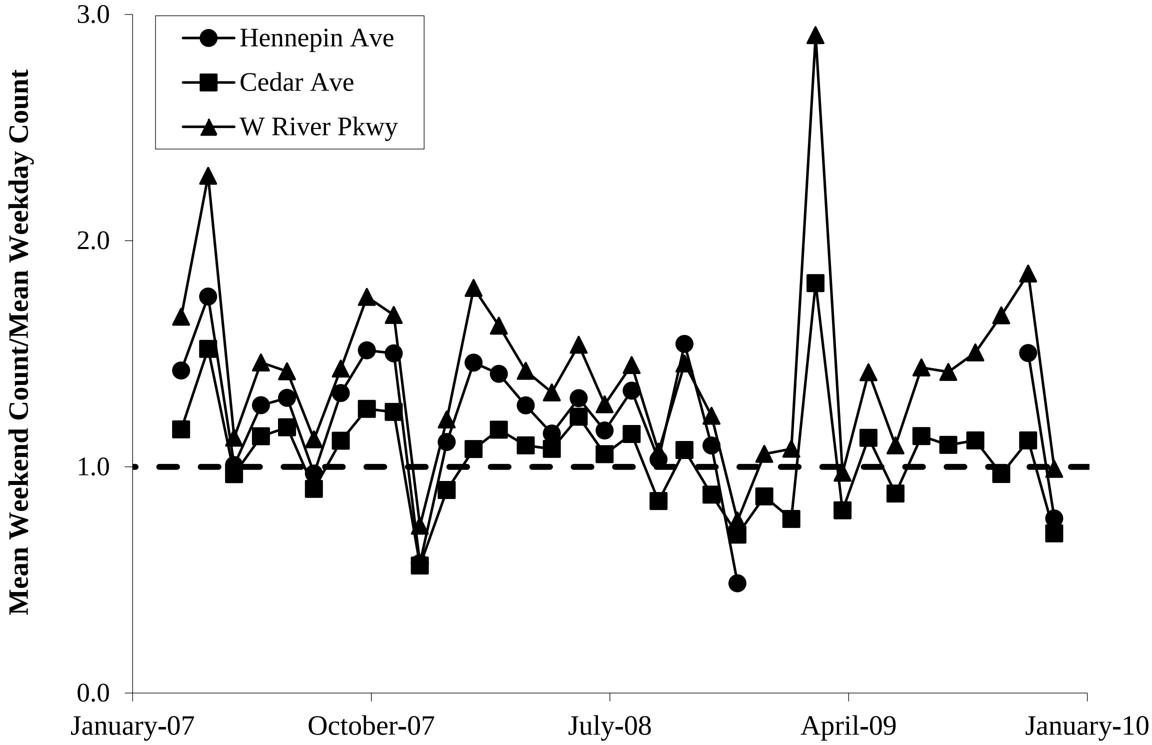

Figure 5.3. Weekend:Weekday ratios for daily bicycle counts on the Midtown Greenway (note: Hennepin Ave detector was broken from January 2009 – October 2009).

5.1.3 Monthly Variations in Bicycle Traffic

Seasonal trends were only analyzed for the Midtown Greenway loop detector data due to data availability. Manual count data was limited to a small number of locations over about 1 year and thus only loop detector data was used to investigate these patterns.

Monthly scaling factors for the Midtown Greenway are shown in Figure 5.4. For each month the average daily count was divided by the average daily count in December of the same year. This procedure shows that monthly traffic on the Midtown Greenway increases by a factor of 15-30 during the summer months (as compared to winter months). The absolute value of the scaling factors changes by location but the overall seasonal pattern seems to hold across all locations (for the Midtown Greenway only).

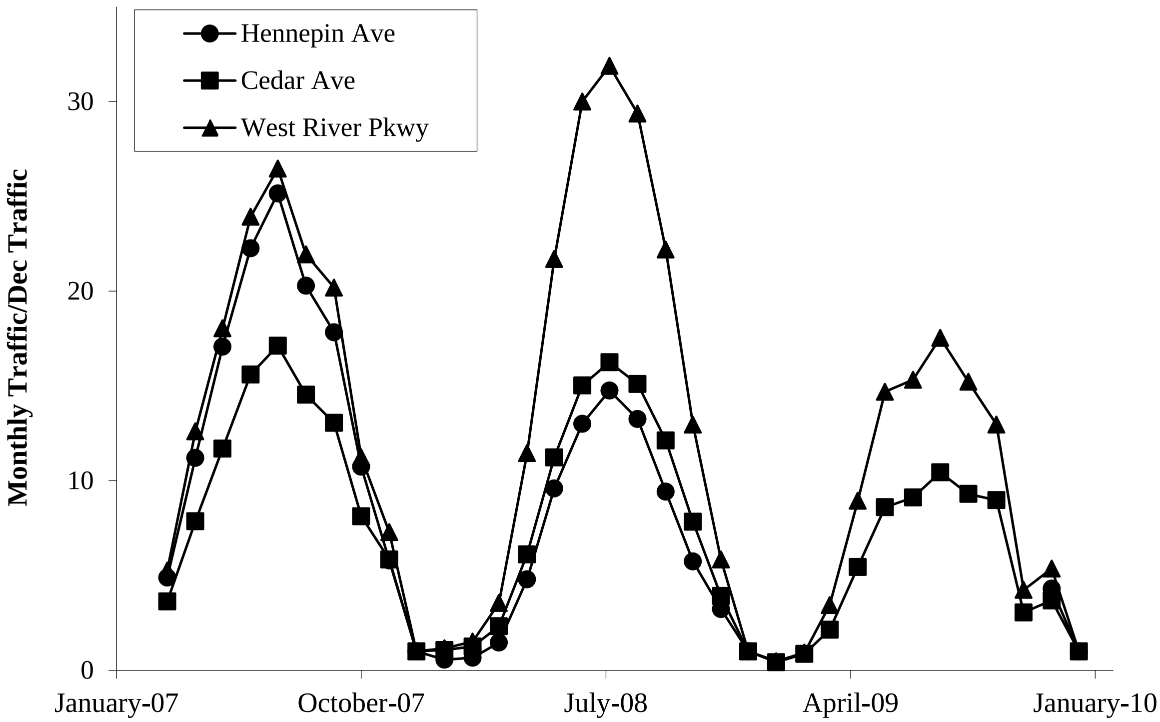

Figure 5.4. Monthly scaling factors for each loop detector on the Midtown Greenway as compared to December of each (note: Hennepin Ave detector was broken from January 2009 – October 2009).

5.2 Temporal Variations in Pedestrian Traffic

5.2.1 Hourly Variations in Pedestrian Traffic

Table 5.2 shows the scaling factors developed for adjusting 1- and 2-hour counts of pedestrian traffic to 12-hour counts. The method used to develop these scaling factors as well as examples of their application are described above. In general, peak hour counts (4-6pm) were better predictors of 12-hour counts than off-peak counts. Figure 5.5 shows scatter plots of actual counts vs. 12-hour counts estimated using the peak hour scaling factors. This validation suggests that both 1- and 2-hour, peak hour counts are strong predictors of 12-hour counts.

Table 5.2. Pedestrian scaling factors for the manual count data to 12-hour counts (6:30-18:30).

1-hour scaling factors				**2-hour scaling factors**			
Time period	*Percent of 12-hour count*	*Scale factor*	R^2	*Time period*	*Percent of 12-hour count*	*Scale factor*	R^2
7-8am	6.9%	14.5	0.91	7-9am	12.2%	8.2	0.95
8-9am	5.3%	18.7	0.96	8-10am	11.4%	8.7	0.99
9-10am	6.1%	16.4	0.97	9-11am	12.0%	8.3	0.98
10-11am	5.9%	16.8	0.96	10-noon	15.1%	6.6	0.99
11-noon	9.2%	10.9	0.99	11-1pm	18.8%	5.3	0.99
noon-1pm	9.7%	10.3	0.99	noon-2pm	18.4%	5.4	0.99
1-2pm	8.7%	11.5	0.99	1-3pm	17.5%	5.7	0.99
2-3pm	8.8%	11.4	0.98	2-4pm	16.6%	6	0.98
3-4pm	7.8%	12.8	0.98	3-5pm	18.2%	5.5	0.98
4-5pm	10.4%	9.6	0.97	4-6pm	22.6%	4.4	0.99
5-6pm	12.3%	8.2	0.996				

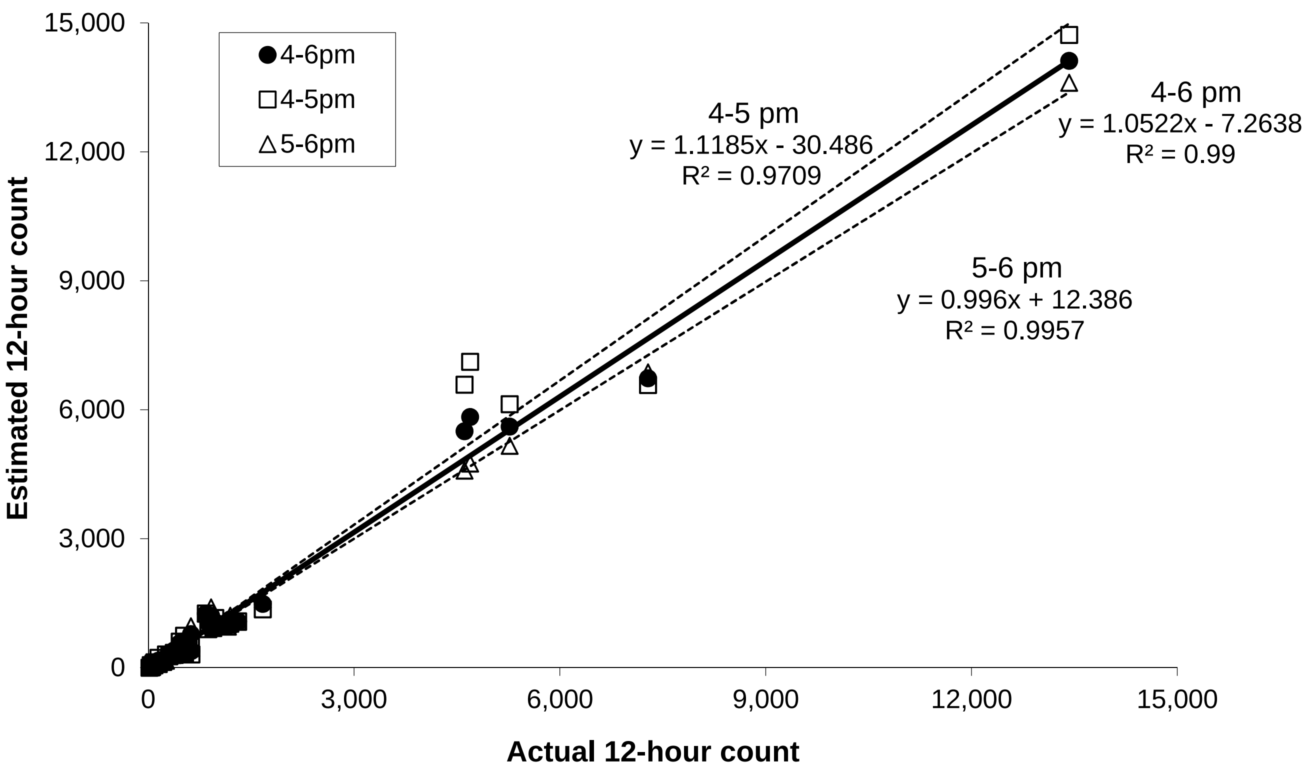

Figure 5.5. Pedestrian 12-hour count predictions (n=43) from peak hour measures for hourly (dashed lines) and bi-hourly (solid lines) counts.

5.2.2 Daily and Monthly Variations in Pedestrian Traffic

Currently we lack sufficient information on daily and monthly variability in pedestrian traffic. The only dataset that explicitly counts pedestrians is the set of manual counts administered by the DPW and TLC. Those data are cross-sectional counts taken in September of each year for ~2 hours each. In the future it may be possible to develop correction equations for the infrared (multi-mode) infrared counters that have been deployed in the past year.

5.3 Temporal Variations in Mixed-Mode Trail Traffic

5.3.1 Hourly Variations in Mixed-Mode Trail Traffic

Figures 5.6 and 5.7 show hourly patterns for one location with an infrared monitor – Lake Nokomis. The patterns at the other six locations are similar and can be found in Appendix B. In general the patterns at these locations seem to be stable over time but are different between weekdays and weekends. Namely, weekdays show a small peak in the morning followed by a large peak in the afternoon (likely, coinciding with recreational uses); weekends have a single peak near midday and subsequently decreased use in the morning and evening hours. Figure 5.6 shows hourly traffic volumes as well as their monthly variability. While the patterns are consistent between months the overall volumes are much higher during the summer months with peak flows occurring during the month of July for both weekends and weekdays.

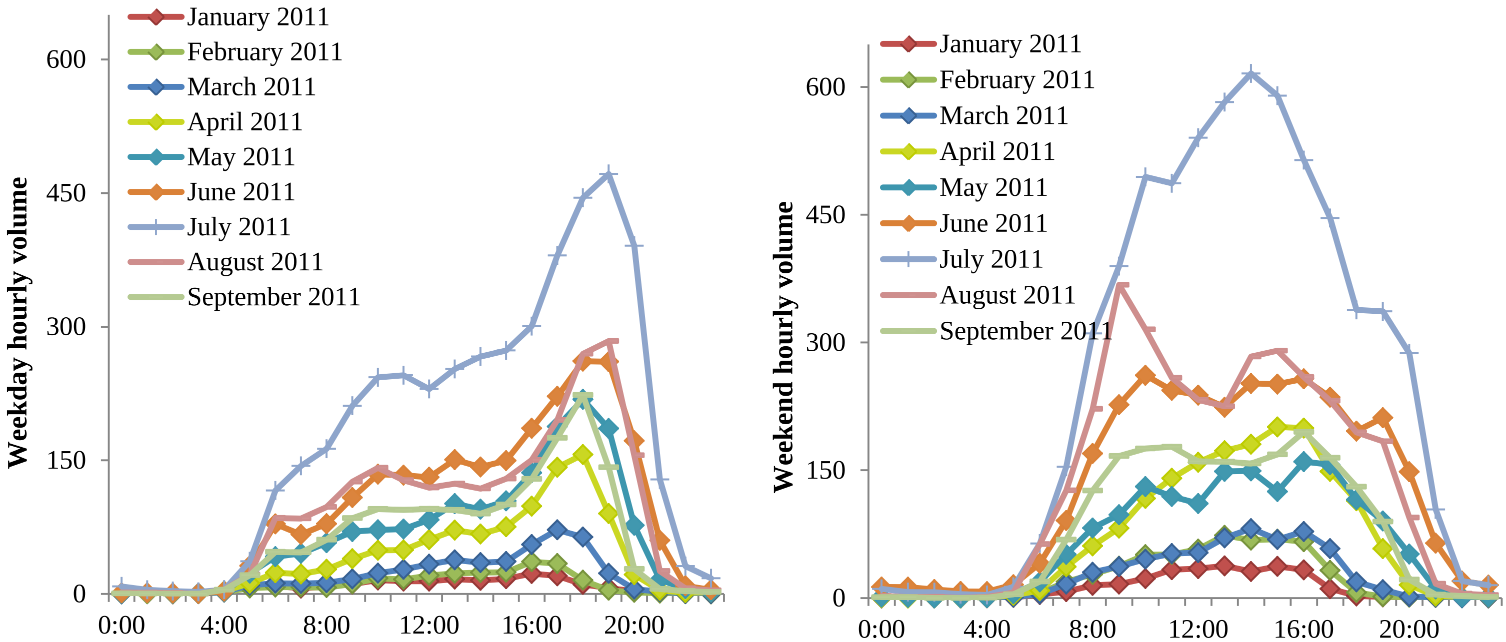

Figure 5.6. Average hourly non-motorized traffic volumes by month for one location with an infrared counter – Lake Nokomis.

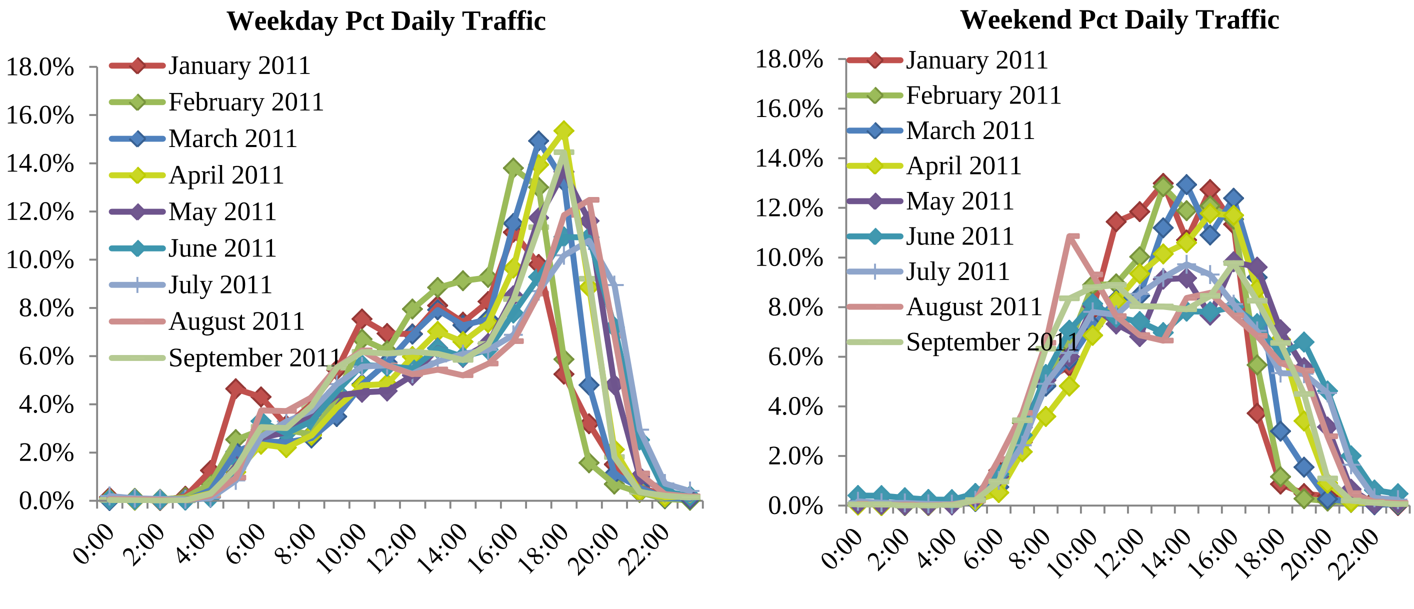

Figure 5.7. Percent of daily non-motorized traffic volumes by month for one location with an infrared counter – Lake Nokomis.

5.3.2 Daily Variations in Multi-Mode Trail Traffic

Figure 5.8 illustrates weekend to weekday average count ratios (i.e., average daily weekend traffic divided by average daily weekday traffic) for each Chain of Lakes location by month. Ratios greater than a value of one indicate average daily traffic on weekends is greater than on weekdays. Ratios greater than one may indicate that routes are used more for recreational use, while ratios near or less than one may indicate routes where commuters account for a higher proportion or majority of users. All three locations experienced spikes in the weekend-weekday traffic ratio during February, which could be partially explained by an extended period of warm weather in mid-February. All three locations also had below average values for May. This is likely due to bad weather on weekend days in May or possibly the influence of Memorial Day recreational traffic. For the first quarter of 2011, the weekend-weekday traffic ratios are highest for the Lake Calhoun location indicating that recreational traffic increases proportionately more on weekends at Lake Calhoun than at the other locations. However, during the second quarter of 2011 ratios were similar among locations and trended closer to a value of one for each month.

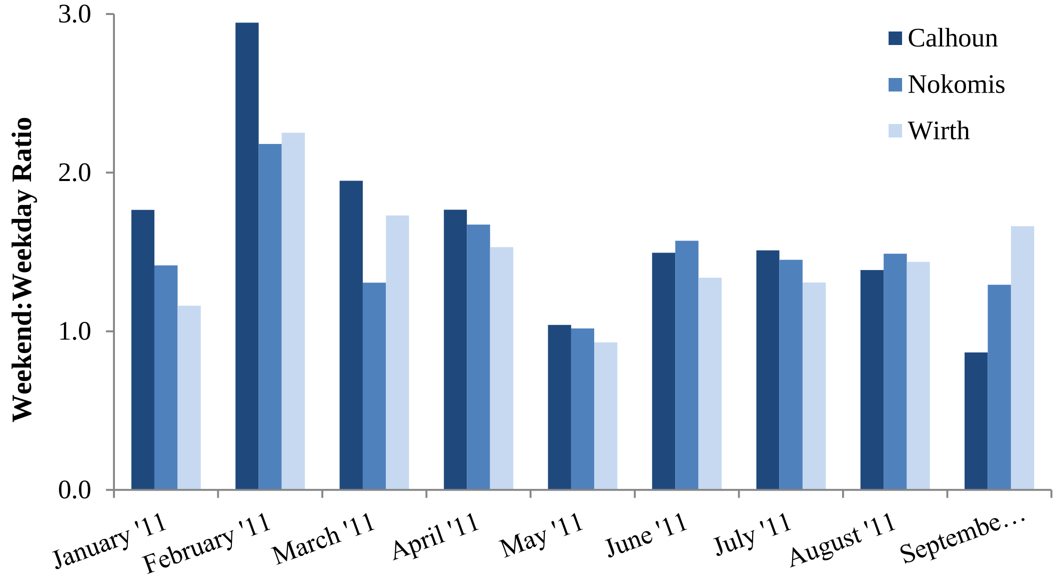

Figure 5.8. Weekend:Weekday average adjusted daily count ratio.

5.3.3 Monthly Variations in Mixed-Mode Trail Traffic

Figure 5.9 depicts the average adjusted daily count for each count location, separated by weekend versus weekday. In each successive month, from January to September 2011, the average counts increase for all three locations until late summer and then start to decline. The largest counts are on the Lake Calhoun trail. Weekend counts are generally higher than weekday counts, for corresponding months and locations.

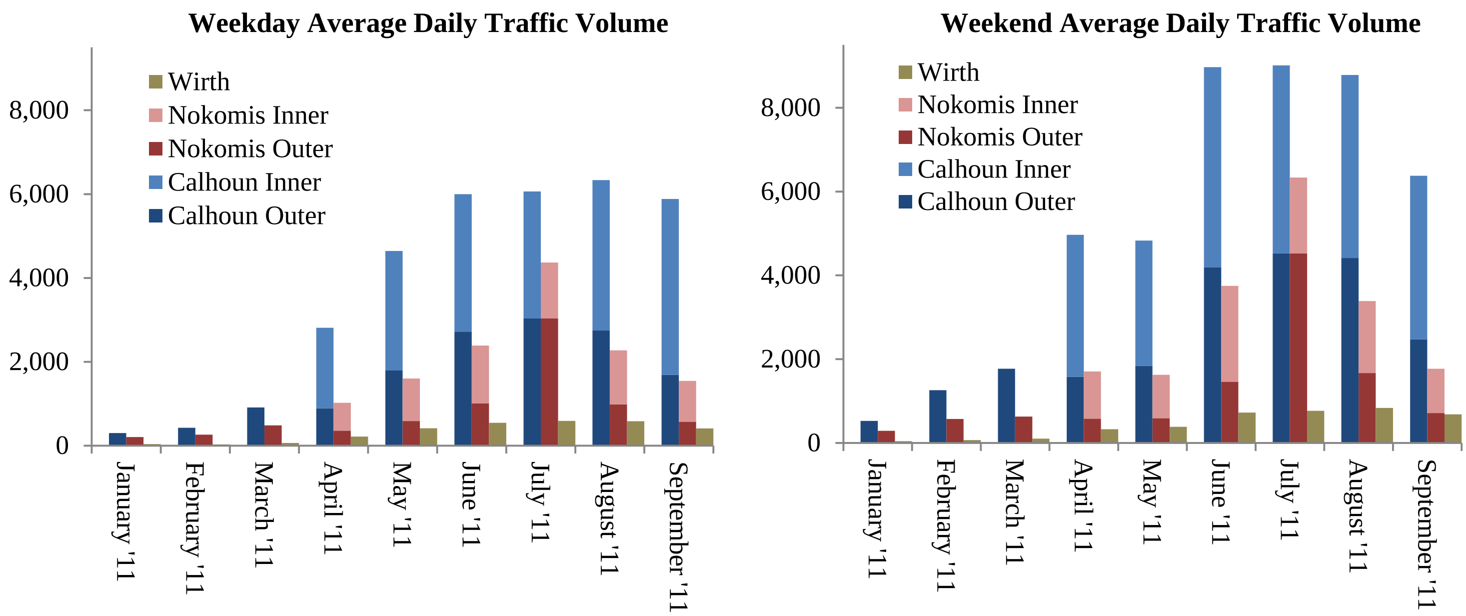

Figure 5.9. Average daily traffic volumes. Light colors represent inner trails (pedestrian) and dark colors represent outer trails (bicycle) for each location.

Chapter 6
Models of Bicycle, Pedestrian, and Mixed-Mode Trail Traffic

In this chapter we describe two sets of models we developed for the datasets described above:

1. Ordinary least squares and negative binomial models of pedestrian and bicycle traffic (Section 6.1). These models use the manual count data to explore spatial trends in non-motorized traffic in Minneapolis, MN.
2. Negative binomial models of mixed-mode traffic (Section 6.2). These models use the active infrared, mixed-mode data set to explore trends in off-street trail use in Minneapolis, MN.

Negative binomial regression can be used when the dependent variable is a non-negative integer in which events occur during equal-length time periods. Negative binomial models naturally fit the characteristics of bicycle and pedestrian traffic very well. No models are estimated from the DPW's automated counts of bicycles on the Midtown Greenway.

6.1 Models of Pedestrian and Bicycle Traffic

We used the manual (short) counts from TLC and DPW to estimate regression models for non-motorized traffic. To illustrate importance of functional form for predicting traffic flows, bicycle and pedestrian traffic models were estimated using both ordinary least squares and negative binomial regression routines in STATA ©.

In these models we used the variables listed in Table 6.1 as independent variables. Table 6.1 also shows the expected effect each variable will have on pedestrian and bicycle traffic volumes. For example, since increased population density and land use mix represent closer proximity to a large variety of destinations we expect that these variables will each have a positive impact on bicycle and pedestrian traffic volumes. Street functional types (both with and without bicycle facilities) were modeled using dummy variables. In both the bicycle and pedestrian traffic models, local streets with no facilities are the suppressed case as they are expected to have the lowest non-motorized traffic. Interpretations of significance for other street types are made relative to traffic on local streets without bicycle facilities.

The model results reported here (Table 6.2) include data from counts during 2007-2010. To test the predictive power of our models we re-estimated each model for data during 2007-2009 and predicted counts which occurred during 2010. We predicted bicycle and pedestrian counts at 85 locations and compared our model results to the actual count values reported by TLC and DPW.

We also use the results of the regression models to estimate 12-hour bicycle and pedestrian traffic counts for all street segments in the City of Minneapolis. Using a Geographic Information System (ArcGIS 9.3©) values for each model variable (street type, weather, household income, population density, etc.) were applied to the street segments based on their individual characteristics and geographic location. We assumed a temperature of 25ºC and no precipitation. Since our input data is from the month of September our results should be interpreted as typical traffic volumes during the fall season. We generated an estimate for non-motorized traffic for each street segment. The street segments were provided by DPW within one GIS file consisting of 12,868 individual street segments. This was reduced to 12,481 by removing interstates, on and off ramps, and other unique road segments that do not allow bicyclists or pedestrians.

Table 6.1. Independent variables used for regression of manual count data.

Continuous variable	Description	Mean	Units/notes	Expected effect on bicycles	Expected effect on pedestrians
			Socio-demographic variables		
Pct_nonwhite[a]	Percentage of neighborhood residents that are non-white	0.33	Areal unit: Census block group	Negative	Negative
Pct_under5_over65[a]	Percentage of neighborhood residents over the age of 65 or under the age of 5	0.15	Areal unit: Census block group	Negative	Positive
Pct_4yrdegree[a]	Percentage of neighborhood residents with a college education	0.39	Areal unit: Census block group	Positive	Positive
MedianHHInc[a]	Median household income	39	Areal unit: Census block group; Variable unit: Thousands of dollars	Positive	Positive
Crime[b]	Average number of violent crimes per year	50	Areal unit: City defined neighborhood (n=87)	Negative	Negative
			Built environment variables		
PopDens[a]	Population density	3,299	Areal unit: Census block group; Variable unit: Persons per square kilometer	Positive	Positive
LUMix[c]	Measure of mixing of land uses	0.56	Areal unit: Census block group; Index (range: 0-1) with 1 indicating high mixing and 0 low mixing. See supplementary material for calculation details	Positive	Positive
Water_dist	Distance from nearest body of water	2.9	Distance measured in kilometers	Negative	Negative
CBD_dist	Distance from the central business district (CBD)	1.3	Distance measured in kilometers	Negative	Negative
Employment[d]	Number of jobs accessible by transit	30,215	Areal unit: Census block group; Number of jobs within a 30 minute transit ride (< 3 transfers)	Positive	Positive
			Weather and temporal variables		
Tmax[e]	Recorded daily high temperature	23	Variable unit: Degrees Celsius	Positive	Positive
Precip[e]	Recorded precipitation	0.2	Variable unit: Centimeters	Negative	Negative
Categorical variable	**Description**	**Freq.**	**Notes**	**Expected effect on bicycles**	**Expected effect on pedestrians**
			Road and facility variables		
Principal[f]	Principal arterial	8	Designed for 15,000-100,000 ADT and 40-50 mph	Negative	Negative
Arterial[f]	Minor arterial	200	Designed for 5,000-30,000 ADT and 35-45 mph	Positive	Positive
Collector[f]	Major collector	57	Designed for 1,000-15,000 ADT and 30-40 mph	Positive	Positive
Local[f]	Local street	82	Designed for less than 1,000 ADT and 30 mph	(base case)	(base case)
BusRoute[g]	Presence of one or more bus routes	227		N/A	Positive
OnStreet[f]	On-street bicycle facility	70	Bike lane or shared space	Positive	N/A
Offstreet[f]	Off-street trail	89	Bicycle or pedestrian trails separate from roads	Positive	Positive
			Temporal variables		
Year	Level variable indicating year count occurred	N/A	Base case: Year-2007	N/A	N/A

[a]US Census (2000).
[b]City of Minneapolis crime statistics (http://www.minneapolismn.gov/police/crime-statistics/).
[c]Land use data: Metropolitan Council (2005); Calculation method: Frank (2004).
[d]Fan et al. (2012).
[e]University of Minnesota Climatology Working Group (climate.umn.edu).
[f]City of Minneapolis Department of Public Works (data available upon request).
[g]MetroTransit schedules accessed via: www.datafinder.org.

Table 6.2. Regression results for 12-hour bicycle and pedestrian counts.

	Bicycle Models					Pedestrian Models				
	Ordinary least squares		*Negative binomial*			*Ordinary least squares*		*Negative binomial*		
	Coefficient	*Significance*	*Coefficient*	*Significance*	*Marginal*	*Coefficient*	*Significance*	*Coefficient*	*Significance*	*Marginal*
Constant	-20.9	0.912	**4.766**	**0.000**	-	788.6	0.094	**5.565**	**0.000**	-
Socio-demographic variables										
Pct_nonwhite	189.7	0.080	**0.514**	**0.046**	**67.2%**	-29.8	0.910	**0.743**	**0.022**	**110.2%**
Pct_under5_ over65	461.7	0.073	0.640	0.202	89.6%	32.5	0.958	-0.919	0.159	-60.1%
Pct_4yrdegree	**688.9**	**0.000**	**1.348**	**0.000**	**285.0%**	371.4	0.335	**1.391**	**0.001**	**301.9%**
MedianHHInc	**-4.1**	**0.005**	**-0.0089**	**0.002**	**-0.9%**	2.1	0.560	0.004	0.386	0.4%
Crime	-0.2	0.755	-0.0008	0.453	-0.1%	**2.9**	**0.013**	0.002	0.109	0.2%
Built environment variables										
PopDens	-0.0076	0.310	-0.00003	0.108	0.0%	-0.035	0.056	0.00001	0.498	0.0%
LUMix	12.9	0.906	**0.613**	**0.009**	**84.6%**	**-919.9**	**0.001**	-0.532	0.078	-41.3%
Water_dist	17.6	0.229	0.056	0.083	5.8%	-21.6	0.548	**-0.116**	**0.004**	**-11.0%**
CBD_dist	**-55.2**	**0.000**	**-0.196**	**0.000**	**-17.8%**	-40.3	0.296	**-0.151**	**0.000**	**-14.0%**
Employment	0.0011	0.337	0.000005	0.054	0.0%	**0.0**	**0.000**	0.000005	0.123	0.0%
Weather and temporal variables										
Tmax	-2.6	0.645	-0.015	0.195	-1.5%	-26.0	0.074	-0.012	0.442	-1.2%
Precip	**-54.3**	**0.025**	**-0.163**	**0.001**	**-15.0%**	**-127.8**	**0.033**	**-0.150**	**0.023**	-13.9%
Road and facility variables										
Principal	-115.6	0.434	-0.275	0.369	-24.0%	66.4	0.859	**-0.823**	**0.038**	**-56.1%**
Arterial	**140.6**	**0.008**	**0.396**	**0.000**	**48.6%**	**391.8**	**0.012**	**0.774**	**0.000**	**116.8%**
Collector	3.3	0.960	0.098	0.473	10.3%	**611.1**	**0.001**	**0.853**	**0.000**	**134.7%**
Local	(base case)			(base case)		(base case)			(base case)	
BusRoute	N/A			N/A		100.3	0.438	0.211	0.183	23.5%
OnStreet	98.8	0.060	**0.317**	**0.003**	**37.3%**	N/A			N/A	
Offstreet	**690.8**	**0.000**	**1.463**	**0.000**	**331.9%**	253.8	0.094	0.190	0.267	20.9%
Temporal variables										
Year	**61.6**	**0.004**	**0.045**	**0.001**	**4.6%**	-5.9	0.909	0.001	0.987	0.1%
	Adj R^2	*0.381*	*Cox-Snell R^2*	*0.476*		*Adj R^2*	*0.302*	*Cox-Snell R^2*	*0.418*	

[a]Values in bold are significant (p=0.05).

We found better goodness of fit for the models of bicycle traffic (OLS: adj. R^2 = 0.381; Negative binomial: Cox-Snell Pseudo R^2 = 0.476) than for the models of pedestrian traffic (OLS: adj. R^2 = 0.302; Negative binomial: Cox-Snell Pseudo R^2 = 0.418). More independent variables were significant (at the five percent level) for the bicycle model than for the pedestrian model. Furthermore, there were more significant variables in the negative binomial models than in the OLS models for both bicycles and pedestrians. For most statistically significant variables, the direction of effect (i.e., increasing or decreasing traffic) was the same for pedestrians and bicycles.

Neighborhood design and urban form play a role in explaining bicycle traffic. Bicycle facilities have a significant impact on bicycle traffic, and this effect is much larger for off-street (332% increase in traffic) than for on-street (37% increase in traffic) facilities. Furthermore, we found that a one-unit increase in the measure of land use mix (i.e., an entropy index of four land use types) increased bicycle traffic by 85% and that traffic decreased 18% per kilometer in distance from the central business district (CBD). We also found that certain neighborhood socio-demographic characteristics (i.e., percent non-white, percent with a college degree, and median household income), precipitation, and arterial roads had significant effects on bicycle traffic. Finally, our models indicate that overall bicycle traffic is increasing 4.6% per year (see Table 6.2) suggesting that efforts by local government agencies to improve the number and quality of bicycling facilities may be impacting the number of cyclists.

Road classification, proximity to amenities, and activity centers are important explanatory variables for pedestrian traffic. Roads typically associated with destinations or retail corridors (arterial and collectors) significantly increased pedestrian traffic. Additionally, pedestrian volumes are larger near the CBD (15% decrease per kilometer from the CBD) and bodies of water (11% decrease per kilometer from the nearest body of water [i.e., lakes or rivers]). Neighborhood socio-demographics (i.e., percent non-white and percent with a college degree) and precipitation also impact pedestrian traffic. Unlike for bicycle traffic, we did not find that pedestrian traffic is increasing over time.

The bicycle and pedestrian models were used to estimate and map bicycle and pedestrian traffic for all street segments in the City of Minneapolis except interstates and on- and off-ramps (n=12,481; Figure 6.1). As expected, given the relative significance of variables in the models, the maps reflect the importance of street functional class (i.e., higher levels of traffic on arterials and collectors), measures of neighborhood design (higher levels of traffic in the downtown area and near neighborhood or strip shopping areas), and presence of bicycle facilities.

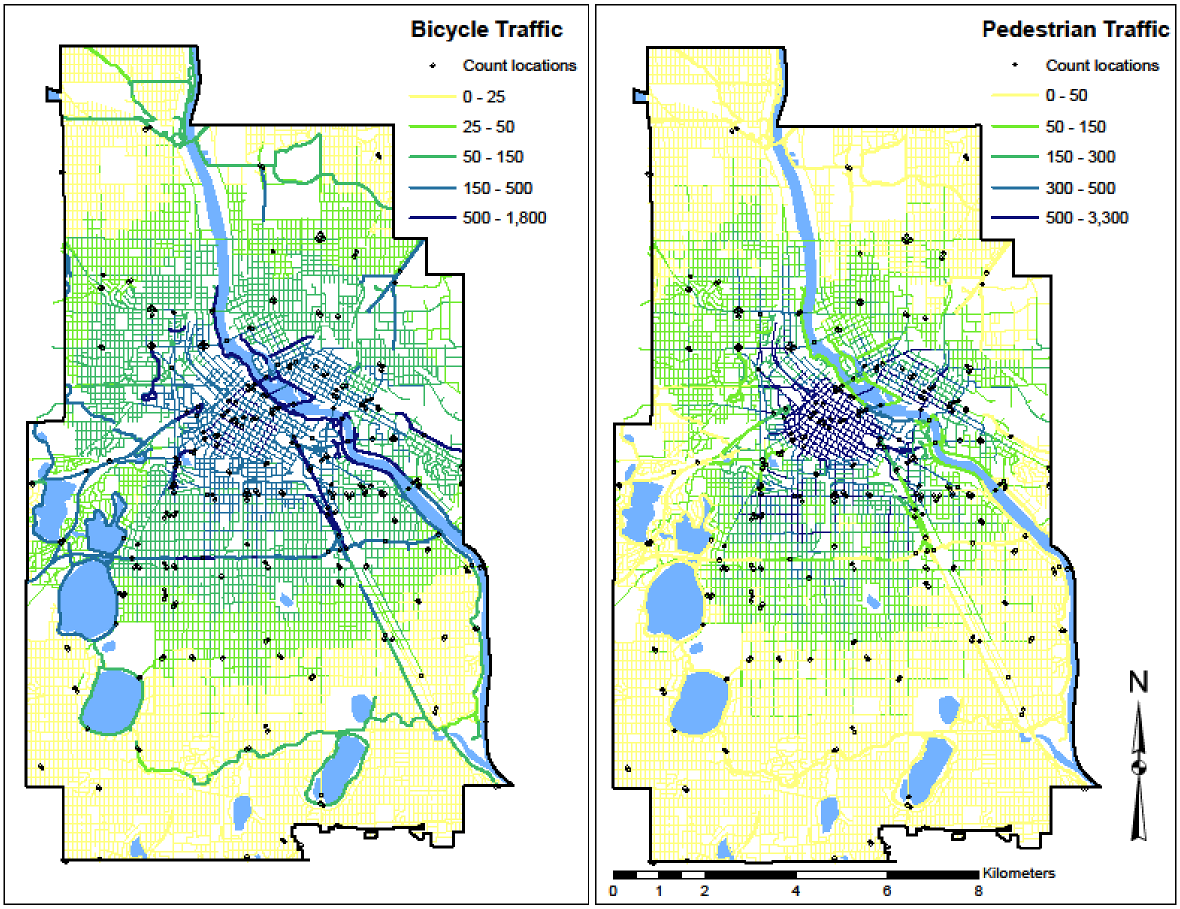

Figure 6.1. Estimated non-motorized traffic for street and trail segments in Minneapolis, MN.

As shown in Figure 6.2 the negative binomial models generally do a better job of estimating both bicycle and pedestrian traffic. No model completely captures the variability among (as well as within) locations, but because the negative binomial models do not predict negative values, they capture the general trends in non-motorized traffic better. This outcome is illustrated by presence of many predicted negative values in the images comparing OLS predictions with actual values.

One problem with comparing model estimates to counts collected on any given day is that there is not only variability in counts among locations but significant variability within each location among count days (and years). Once more data are available it may be possible to aggregate location data (by either averaging or using modeling techniques specific to panel data) to generate 'typical' values for each location and build models that investigate between-location variability more accurately.

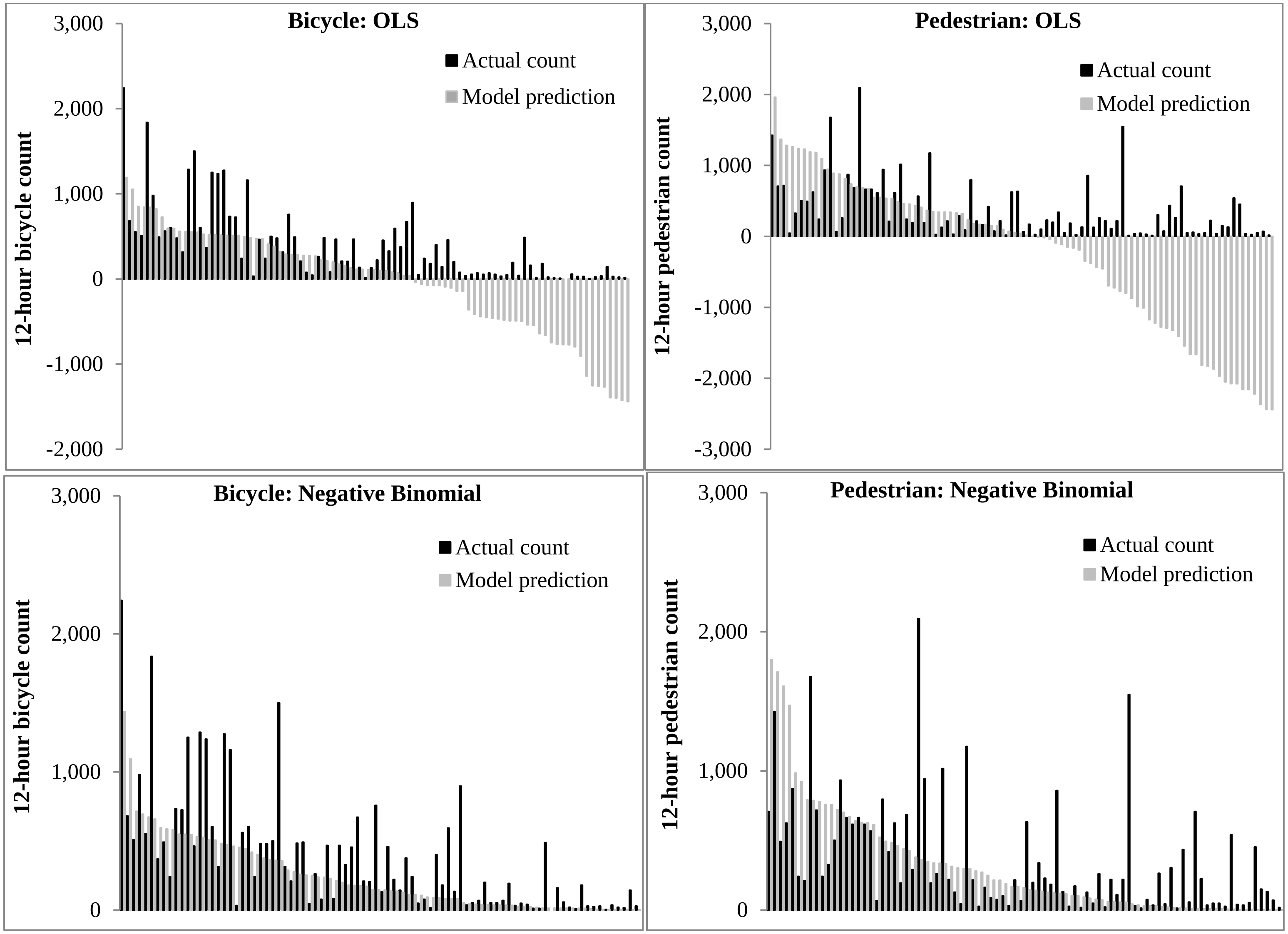

Figure 6.2. Comparison of model predictions (model data: 2007-2009) to actual counts (year-2010) for pedestrians and bicycles. Upper left: Bicycle ordinary least squares; Upper right: Pedestrian ordinary least squares; Lower left: Bicycle negative binomial; Lower right: Pedestrian negative binomial.

6.2 Models of Mixed-Mode Trail Traffic

Here we present eight negative binomial models for estimating urban trail traffic using 1,020 mixed-mode daily traffic counts from active infrared counters at six locations in Minneapolis, Minnesota. Based on the studies described in the literature, we identified 11 independent variables to include in models as correlates of daily trail traffic, some of which are the same as variables included in the models of bicycle and pedestrian traffic presented in the preceding section. These independent variables include neighborhood socio-demographic characteristics, weather, and temporal factors, and characteristics of the built environment of the neighborhood in which the counter is located. Mean values for each variable, together with the dummy variables used are presented in Table 6.3.

The four socio-demographic variables, race (*blkpct*), education (*collegepct*), age (*ynoldpct*) and income (*medincthd*), are all percentages and are estimated from the 2000 Census for the Census block group in which the traffic monitor is located. Trail traffic is expected to correlate positively with neighborhood income, education and proportion of middle-aged population.

The two built environment variables are a land use mix index, *lumix*, and population density, *popden*. *Lumix* is calculated by dividing the area of retail, office and commercial land use in the Census block group in which the monitor is located by the number of housing units in the block group (in 2000). *Popden* also is calculated for the Census block group**.** Non-motorized traffic volumes are hypothesized to correlate positively with greater mixes of land use because commercial and other non-residential land uses are both traffic generators and destinations for traffic. Non-motorized traffic volumes are believed to be higher in areas with greater population density because these areas potentially generate more trips.

The four weather variables are retrieved from monthly and daily weather archives in Minneapolis and St. Paul Area from the Minnesota Climatology Working Group website. Mean daily traffic is expected to correlate positively with temperature and negatively with precipitation and average wind speed. The direction of the variable *maxdev*, the deviation of daily high temperature from the long-term monthly average of daily high temperatures, is expected to vary by season and direction of variation.

The only temporal variable is a dummy variable indicating whether the day of the count is a weekend day or a weekday. Greater volumes of trail traffic are expected on weekend days than on weekdays in any given location because of the time available to individuals to engage in outdoor recreation.

Table 6.3. Variables selected for model 1 building and expected signs.

Variables	Notes	Mean	Expected Sign
Neighborhood Socio-demographic Characteristics			
blkpct	Percentage of African American residents.	6.095	-
collegepct	Percentage of residents with a college degree.	60.68	+
yngoldpct	Percentage of population over 65 or below 5 (including 65 and 5).	17.99	-
medincthd	Median Household income. (1,000 dollars)	45.60	+
Neighborhood Built Environment			
lumix	Acres of retail, office and commercial area per housing unit	0.032	+
popden	Population density (per acre).	9.284	+
Weather Conditions			
tmax	Recorded high temperature.(in Fahrenheit)	41.10	+
maxdev	Deviation from the monthly average daily high temperature.	0.248	+/-
precip	Precipitation.(inches)	0.074	-
windavg	Average wind speed. (miles per hour)	8.620	-
Temporal Dummies			
weekend	Saturday or Sunday (equals 1, otherwise 0)	0.288	+
Location Dummies			
henn	Hennepin @ Midtown Greenway counter	0.269	+/-
wrp	West River Parkway @ Midtown Greenway counter	0.246	+/-
cedar	Cedar @ Midtown Greenway counter	0.126	+/-
calhoun	Lake Calhoun Counter	0.119	+/-
nokomis	Lake Nokomis Counter	0.115	+/-

To support different types of practical applications, we estimate and present here eight different models:

- A general model (Model 1) that incorporates 11 independent socio-demographic, built environment, weather, and temporal variables;
- A six-location model (Model 2) estimated from all 1,020 daily counts that includes dummy variables for the monitoring locations and omits the socio-demographic and built environment variables; and
- Six trail-specific models (Models 3 – 8), one for each of the six locations where traffic counts have been taken, that include only the weather and temporal variables.

The general model can be used to estimate traffic at locations where traffic counts have not been taken or for proposed new trails because values for the independent variables can be computed for any location on an existing or proposed trail. The six-location model is useful because it takes advantage of the entire data set and can be used to estimate counts for all six locations simultaneously. The six site-specific models can be used to estimate traffic for each monitoring location when counts are missing or if the TrailMaster © counters are moved to other sites.

Table 6.4. Estimation results of the models.

Variables	1-General Model	2-Six-location Model	Trail-specific Models 3-8					
			3-Hennepin	4-WRP	5-Cedar	6-Calhoun	7-Nokomis	8 Wirth
	n=1020	n=1020	n=274	n=251	n=1299	n=121	n=117	n=128
Pseudo-R^2	0.1450	0.1450	0.1255	0.1447	0.1005	0.1172	0.1358	0.1442
(Constant)	**-1.470*** **	**2.768*** **	**4.828*** **	**3.997*** **	**5.008*** **	**4.745*** **	**4.647*** **	**2.472*** **
Social Demographic Characteristics								
blkpct	0.190***	-	-	-	-	-	-	-
collegepct	**0.038*** **	-	-	-	-	-	-	-
yngoldpct	**-0.439*** **	-	-	-	-	-	-	-
medincthd	**0.166*** **	-	-	-	-	-	-	-
Built Environment								
lumix	(dropped)	-	-	-	-	-	-	-
popden	**0.295*** **	-	-	-	-	-	-	-
Climate Conditions								
tmax	**0.047*** **	**0.047*** **	**0.045*** **	**0.045*** **	**0.054*** **	**0.065*** **	**0.051*** **	**0.058*** **
maxdev	**-0.006*** **	**-0.006*** **	**-0.008*** **	**-0.005* **	**-0.027*** **	**-0.009**	**-0.0003**	**-0.019*** **
precip	**-0.617*** **	**-0.617*** **	**-0.491*** **	**-0.623*** **	**-0.765*** **	**-0.868*** **	**-1.882*** **	**-0.254**
windavg	**-0.038*** **	**-0.038*** **	**-0.031*** **	**-0.032*** **	**-0.038*** **	**-0.061*** **	**-0.057*** **	**-0.055*** **

Table 6.4. Estimation results of the models (Continued).

				Temporal Dummy				
weekend	**0.317*****	**0.317*****	**0.212*****	**0.268*****	-0.308***	**0.820*****	**0.516*****	**0.542*****
				Location Dummies				
henn	-	**1.984*****	-	-	-	-	-	-
wrp	-	**1.165*****	-	-	-	-	-	-
cedar	-	**2.270*****	-	-	-	-	-	-
calhoun	-	**2.504*****	-	-	-	-	-	-
nokomis	-	**1.880*****	-	-	-	-	-	-
				Dispersion Factor				
lnα	-1.630	-1.630	-1.855	-1.872	-1.791	-1.655	-2.127	-1.694

The coefficients with bold numbers are consistent with expected signs.
Coefficients which are significant at 0.1 level, 0.05 level and 0.01 level are labeled as *, **, and ***.
"-" indicates "not applicable to this model."

In our general model (Model 1), the signs on the coefficients of most variables are in the expected direction and all are significant at a less than 1% level. For the built environment variables, *lumix*, the index of land use mix, was dropped from the model because of multicollinearity. Trail traffic is correlated positively and significantly with neighborhood education, income, proportion of population between 6 and 64, and population density.

Our six-location model (Model 2) illustrates the effects of different locations on daily trail traffic counts when controlling for the five weather and temporal variables. The coefficients of all variables are also significant at a less than 1% level. The value of each location dummy variable indicates the daily traffic count relative to that of Wirth Parkway, the location with the lowest mean daily traffic, when the weather and temporal factors are equal. Lake Calhoun Parkway attracts the highest trail traffic volume, 12.2 times the Wirth Parkway volume, followed by Cedar Avenue & Midtown Greenway with 9.7 times, Hennepin Avenue & Midtown Greenway with 7.3 times, Nokomis Parkway with 6.6 times, and West River Parkway & Midtown Greenway with 3.2 times respectively.

Our trail-specific models (Models 3-8) include only the weather variables and the weekend dummy variable. All variables in each of the six models are significant with the expected sign except the weekend variable at the Cedar location on the Midtown Greenway. This unexpected outcome may have to do with unique traffic patterns such as high levels of commuting or utilitarian use relative to recreational use on this section of the Greenway.

To validate our models, we used them to predict trail traffic for each monitoring location for a week not included in the dataset, Sunday, April 24, 2011 – Saturday, April 30, 2011. For each location, trail traffic was predicted using the general model, the six-location model, and the relevant trail specific model. To illustrate the relative performance of these negative binomial models, we also predicted traffic for each location using models with the same variable but estimated with OLS regression. The predictions for each negative binomial model, together with the actual counts for each location, are graphed in Figure 6.3. The predicted values generally track the actual values, although, across all models, the divergence between predicted and actual values is greater for the higher traffic volumes. The traffic volumes predicted with the general model (Model 1) and the six-location model (Model 2) are quite similar. The performance of the six trail-specific models (Models 3-8) varies across the six monitoring sites, but the trail-specific models do better in tracking the highest traffic volumes at four locations (Cedar/Midtown Greenway, Calhoun Parkway, Nokomis Parkway and Wirth Parkway).

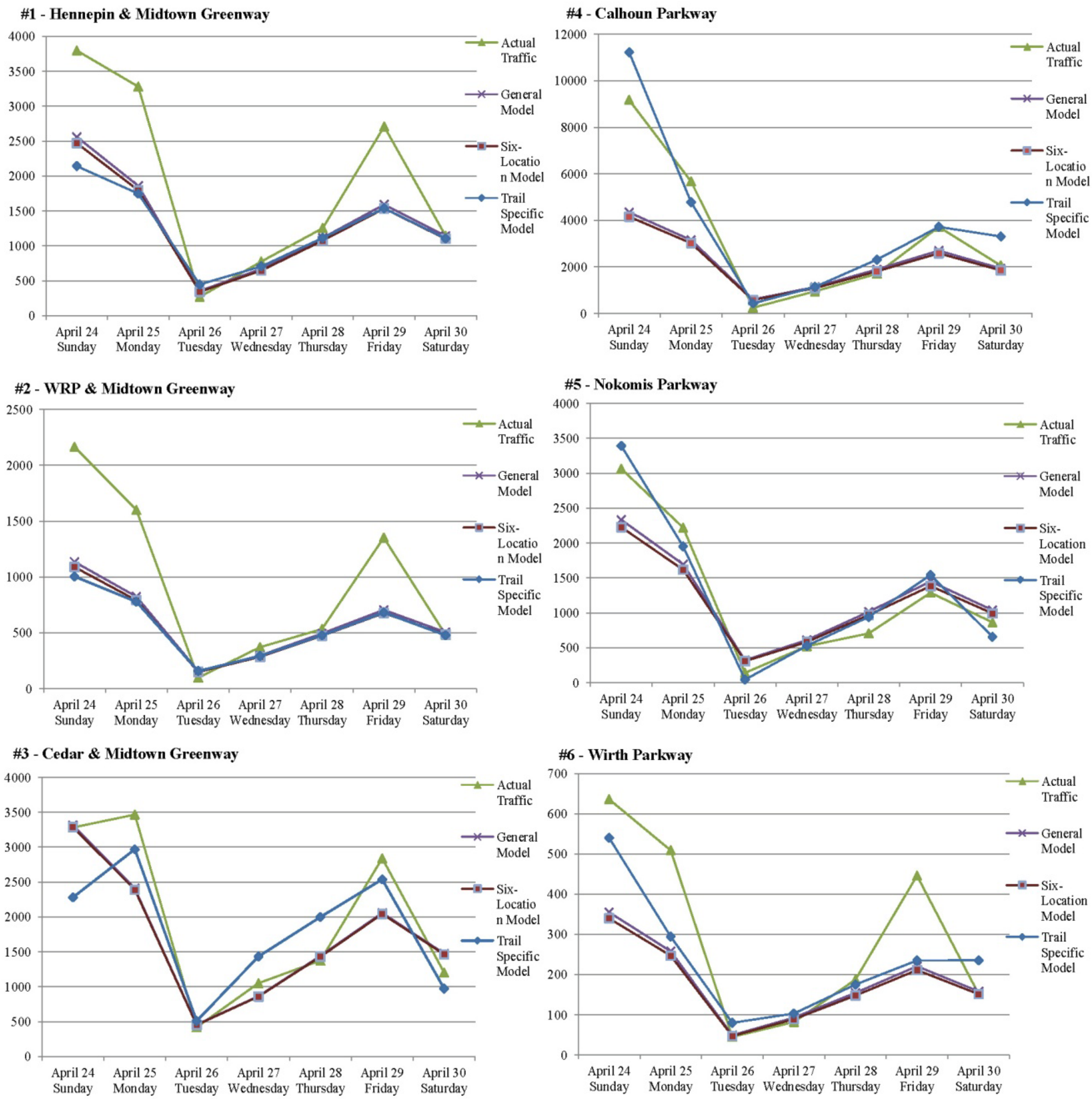

Figure 6.3. Predicted and actual trail traffic, April 24-30, 2011.

Chapter 7
Findings and Implications for Transportation Planning and Management

7.1 Findings about Measurement and Use of Non-Motorized Facilities

Bicyclists and pedestrians have been counted in Minneapolis since at least 2007 using different approaches and methodologies. Short-duration, manual counts of bicyclists and pedestrians on streets and sidewalks have been counted at more than 450 locations. Twenty-four hour counts of bicyclists have been taken with magnetic loop detectors at three locations on the Midtown Greenway more or less continuously since 2007. Twenty-four hour counts of mixed-mode trail traffic (bicyclists and pedestrians) were initiated in this project with active-infrared counters at three locations on the Midtown Greenway and at three locations on paved, multi-use trails around lakes on in parks. Although the magnetic loop detectors and the active infrared counters are designed to count traffic continuously, counters occasionally malfunction, lose power, or are vandalized. In addition, human error in data collection occasionally results in loss of data. For the period analyzed in this study, the percentage of usable days of traffic counts for the three magnetic loop detectors ranged from 61% to 89%, with an overall average of 79%. For the infrared counters deployed during this study, the percentage of usable days of data obtained at the six locations ranged from 86% to 93%, with an overall average of 90%.

All traffic counts regardless of approach or technology used, including manual counts, include errors and therefore are estimates. An estimate of the magnitude of error in manual counts based on simultaneous, replicate counts at a small number of locations is between one and two percent. Using manual counts taken at the location of automated counters as “true” values, the error in the mean hourly count from the three magnetic loop detectors ranged from an undercount of -5% to an over-count of approximately 25%. The reason(s) why these detectors both over-count and undercount are not known. The error in the mean hourly count from active infrared monitors ranged from an undercount of -2% to an undercount of -12%. The reason for systematic undercounting is that the infrared monitors record only a single event when users pass simultaneously. Hourly correction equations estimated for counts from the magnetic loop detectors and the infrared monitors have high goodness-of-fit (Adj. R^2 = 0.94 - 0.99) and can be used to adjust counts to obtain more accurate estimates of actual traffic volumes.

Bicycle and pedestrian volumes vary significantly by location and by time of day, day of week, and month of year or season. Analyses of both bicycle and pedestrian flows taken with manual counts indicate that peak hour traffic volumes correlate strongly (Adj. R^2 = 0.92 - 0.99) with 12-hour traffic volumes. The strength of these correlations means that counts of short duration (i.e., one to two hours) can be used to estimate 12-hour bicycle or pedestrian volumes.

Mean and median estimates of 12-hour bicycle volumes on Minneapolis streets and paths were 502 and 269, respectively, for fall months on days without rain, with significant variation across facility type and street functional class. Higher bicycle traffic volumes were observed on off-street paths, minor arterials, and collector streets. Regardless of street functional class, bicycle volumes were higher streets with bicycle lanes than on streets of the same functional class without bicycle lanes, although for some functional classes, the differences were not statistically significant. Limitations of the bicycle traffic volume data in Minneapolis from manual counts are that counts are not available for all months of the year and the counting locations are not representative of the city as a whole.

Mean daily (24-hour) bicycle traffic across three locations on the Midtown Greenway varied significantly by month, with mean daily bicycle volumes ranging from lows of fewer than 100 bicycles per day in winter months to highs in excess of 3,000 bicycles per day in summer months.

Mean and median estimated 12-hour pedestrian volumes on Minneapolis sidewalks and paths were higher than bicycle volumes (934 and 443, respectively) for the same days. Pedestrian traffic volumes also varied significantly across street functional class and facility type, with higher traffic volumes on collector streets and minor arterials. For all types of streets except principal arterials, pedestrian volumes were higher on streets with bus lines than on streets of the same functional class without bus lines, although for some functional classes, the differences were not statistically significant. Limitations of the pedestrian traffic volume data in Minneapolis from manual counts is that counts are not available for all months of the year and the counting locations are not representative of the entire city.

Mean daily (24-hour) mixed-mode trail volumes (i.e., undifferentiated bicycle and pedestrian traffic) across six locations ranged from a low of 36 on a trail in Theodore Wirth Park for weekdays in January to nearly 9,000 per weekend day in June on the trail around Calhoun Lake. This significant variation is associated with both differences in weather associated with the temperate climate in Minnesota and also differences in location.

Bicycle, pedestrian, and mixed-mode trail traffic follow similar but distinct temporal patterns, with variations associated with distinct characteristics of nearby locations. Bicycle traffic on streets on weekdays generally includes an early-morning peak (e.g., 8:00 - 9:00 a.m.: ±9% of 12-hour volume), with a larger peak in the late afternoon/early evening (e.g., 5:00 - 6:00 p.m.; ±12.6% of 12-hour volume). Weekday bicycle traffic on off-street paths generally followed similar time-of-day patterns, although evening peak hour generally accounted for a higher percentage of daily traffic, presumably because of recreational riders using trails following work.

Weekday pedestrian traffic on sidewalks also generally includes an early-morning peak (e.g., 9:00 - 10:00 a.m.: ±6% of 12-hour volume), with a larger peak a noon-time (e.g., ±10% between noon and 1:00 p.m. of 12-hour volume, followed by a higher in the late afternoon/early evening (e.g., 5:00 - 6:00 p.m.; ±12.3% of 12-hour volume). Mixed-mode trail traffic follows similar patterns, though with relatively higher evening peak hour volumes associated with increases in recreational traffic.

Sufficient data from manual observations are not available to characterize weekend time-of-day patterns for bicycle traffic on streets or pedestrian traffic on sidewalks. Automated counts of bicycle trail traffic and mixed-mode trail traffic permit show that average daily weekend trail traffic generally is higher than average daily weekday trail traffic, except during some winter months at specific locations. Across the six locations for which automated counts were analyzed, the weekend-weekday ratios of mean daily mixed-mode traffic generally ranged between one and two, indicating that high levels of weekend bicycle and pedestrian trail use. Monthly ratios of less than one were uncommon for recreational trails and may have been influenced by weather and holiday traffic (e.g., on Memorial Day or Labor Day Mondays). For bicycle traffic, ratios of less than one were recorded along the Midtown Greenway principally in winter months, indicating that at least some sections of this off-street facility may be used more for commuting than recreation in the winter.

These automated counts of bicycle and mixed-mode trail traffic also show that time-of-day patterns of weekend trail traffic differ significantly from weekday trail traffic. As noted previously, weekday trail traffic is characterized by small a.m. and noon-time peaks with a larger peak in late afternoon/early evening. On weekends, traffic volumes increase later in the morning (e.g., 9:00 – 10:00 a.m.), remain relatively constant or increase slightly between late morning and mid-late afternoon, and then begin to decline after 3:00 p.m. or 4:00 p.m. These patterns generally are maintained throughout the year, though the magnitude of flows varies, with lower volumes in winter.

In addition to providing useful descriptive information about the magnitude of bicycle, pedestrian, and mixed-mode, non-motorized traffic, both the manual counts and automated counts were used to develop statistical models of non-motorized traffic that have a number of potential applications. Our statistical models of bicycle and pedestrian traffic developed from manual counts provide insight into factors that are correlated with traffic volumes and can be used to predict bicycle and pedestrian traffic city-wide. Bicycle traffic volumes are positively and significantly correlated with neighborhood socio-demographic characteristics (percent non-white; education); neighborhood built environment (land use mix); and infrastructure type (arterial street, presence of a bike lane, or an off-street facility). Bicycle traffic volumes are negatively and significantly correlated with neighborhood household income, distance from the CBD, and precipitation. Bicycle traffic also is correlated positively with year, indicating bicycle traffic is increasing over time.

The bicycle models have reasonably good fit for cross-sectional data (OLS: adj. R^2 = 0.381; Negative binomial: Cox-Snell Pseudo R^2 = 0.476). Although the models do not fully capture the variability in the actual traffic flows, the models do a reasonably good job of estimating traffic. A limitation of the model estimated with OLS regression is that it predicts negative values in some circumstances.

Pedestrian traffic is correlated significantly with fewer, but similar variables, and the pedestrian models explain less of the variation in traffic volumes than the bicycle models (OLS: adj. R^2 = 0.302; Negative binomial: Cox-Snell Pseudo R^2 = 0.418). Pedestrian traffic volumes are positively and significantly correlated with neighborhood socio-demographic characteristics (percent non-white; education) and infrastructure type (arterial and collector street). Pedestrian traffic volumes are negatively and significantly correlated with distance from the CBD, distance from water, principal arterial, and precipitation. We found no evidence pedestrian traffic is increasing over time.

We estimated eight different models of mixed-mode traffic on off-street trails to support different types of practical applications. These models indicate trail traffic is correlated positively and significantly with neighborhood education and income, neighborhood population density, temperature, and weekend. Mixed-mode trail traffic is correlated negatively and significantly with the percentage of very young and old in the surrounding neighborhood, precipitation, and wind. Trail specific models generally appear to do better in predicting traffic at monitoring locations than the models estimated for all six monitoring locations.

7.2 Implications for Counting Pedestrians and Cyclists

Despite widespread recognition of the need for systematic measurement of bicycle and pedestrian traffic few studies have reported systematic collection of counts. Our research adds to the both the academic literature and professional practice by reporting robust counts of non-motorized traffic and illustrating how counts taken over time by collaborating teams of professionals and volunteers from the public and nonprofit sectors can be used to understand traffic and support the development of tools to improve management. For example, in planning applications where no counts exist and no tools are available to account for location-specific factors like land use, analysts can use these counts of 12-hour and time-of-day traffic to illustrate ranges or to bound estimates of the magnitude of non-motorized traffic on different types of streets.

The approach of normalizing a set of counts to a common time period (i.e., 12-hour counts) by using scaling factors derived from analyses of time-of-day traffic is a step towards development of robust measures that analysts can use to inform both plans for counting and analyses of traffic. The existence of scaling factors for each hour of the day means that counts taken ad hoc can be integrated and used in analyses with greater confidence that results will be reasonable. The fact that peak hour counts correlate strongly with 12-hour counts means that analysts can focus on counting during the peak hour without sacrificing much in terms of understanding 12-hour or daily traffic levels. Similarly, the fact that one-hour peak hour counts correlate as well with 12-hour counts as do two-hour counts means that analysts generally can limit counts to a single peak hour without great loss of information, thereby increasing the efficiency of data collection or permitting a greater number of locations to be sampled with the same overall level of effort. In most practical applications, it will be important to do additional longer counts (e.g., 12- or 16-hour counts to ensure that scaling factors are current).

7.3 Implications for Modeling Non-Motorized Traffic

The models reported here provide new evidence on the types of factors that correlate with non-motorized traffic and can be used in a general way to understand the implications of land use and transportation decisions. They also confirm that different factors influence bicycle and pedestrian traffic and that these modes need to be measured and modeled separately, although in a common context. For instance, because bicycle trips are generally much longer than pedestrian trips, the socio-demographic and built environment characteristics of the neighborhoods in which counts are taken may need to be interpreted differently for bicycle and pedestrian models. Because cyclists make longer trips, locations of the counts may represent both the origins and destinations of pedestrian trips, but may be the destinations or the middle of routes of bicycle trips.

A long term objective of modeling bicycle and pedestrian traffic is to develop a general, robust set of models that can be used in a wide variety of settings and applications to produce information to inform management decisions. In the development of any particular model, researchers must choose which variables to include and make decisions about how to construct them. Alternative measures of variables (e.g., land use mix or access to bus service) are available, and inclusion of different measures may affect the outcomes of the modeling exercise. Hence, as part of the broader national effort to develop widely applicable models, additional research into the effects of using different practical measures of the same theoretical constructs would be useful. In particular, in addition to land use mix and access to bus service, different measures of income, education, population age distribution, access to employment, access to recreation and other destinations, and even street classification could be tested. For example, in situations where actual vehicle counts are available for locations where bicycle and pedestrian counts have been taken, vehicle counts rather than street functional class could be used as an independent variable. However, limitations of different measures, including the availability of data, need to be kept in mind. If actual vehicle counts were used as an independent variable, then estimating non-motorized traffic for each street segment would become impossible, since the vehicular counts would not be available for every street segment (especially local streets).

An important decision central to all GIS-based models of bicycle and pedestrian traffic concerns the areal unit used to construct variables that have a geographic component. For example, socio-demographic variables used in this study were values for census block groups. Other options exist, including census tracts or areas-linked by street or sidewalk networks. Lindsey et al.[21] have illustrated the tradeoffs in quality of forecasts for trail traffic from using census tracts rather than network-based areal units as the base area for constructing independent variables. Similar research for on-street bicycle and sidewalk-based pedestrian traffic would be informative.

Another general choice in modeling has to do with the overall approach to inclusion of variables, specifically whether to include all those theoretically relevant or to take a more parsimonious approach and include only those variables that add to the explanatory power of the model. This choice depends partly on the purposes of the model, specifically whether the principal purpose is to test hypotheses or to predict. This choice also depends on the challenges and resources required to assemble the information necessary to run the model in any particular application. In this paper, emphasis has been placed on the former, though it is clear that from a theoretical perspective the models can be improved. For example, we use one of many measures of land use mix which is a proxy for access to destinations, including employment. Many other measures of accessibility to employment and to shopping exist, and these could be tested. In contrast to this analysis, Haynes and Andrezejewski[13] take a parsimonious approach, limiting the number of variables, which seems appropriate given their principal objective of informing decision-making in the most efficient way possible. In the long term, a useful approach may be for researchers to develop and report both fully-specified and reduced forms of models so that users will understand the trade-offs and implications associated with using different specifications.

It is clear from initiatives in the field of transportation that the demand for information regarding planning for non-motorized transportation will increase in the future. Another useful strategy for the development of models would be a series of meta-analyses in which counts and other data from multiple cities are combined in order to develop more robust models and test hypotheses related to community-specific or cultural factors. These approaches will require coordination and will be more expensive, but given the magnitude of proposed investments, particularly in times of financial austerity, greater collaboration and investment in the development of tools that will increase the efficiency of infrastructure investments seems warranted.

A challenge for researchers is to replicate these types of models and assess their applicability in other urban locations. The models presented in this report add to our understanding of the distinct ways that bicycle and pedestrian traffic are linked to transportation infrastructure, land use, and neighborhood characteristics. As these types of models are validated and generalized, practitioners in communities across the nation will be able to adapt them for use in their particular communities and situations.

7.4 Implications for Transportation Planning and Management

The findings of this study, including information about methods for counting and modeling non-motorized traffic, can be used by transportation professionals to improve transportation planning and management. Examples of potential practical applications include using information from these traffic counts to help design new counting programs and using models to estimate traffic where counts are unavailable or unlikely to be taken.

State and local planners and engineers can apply, test, and extend these findings through additional implementation projects. For example, this report summarized manual counts of pedestrians and bicyclists on sidewalks and streets, automated counts of bicycles on a multi-use trail, and mixed mode traffic (i.e., pedestrians and bicyclists) on multi-use trails. To extend these findings, state and local officials can plan manual counts of pedestrians and bicyclists for more than 12 hours, the longest duration thus far reported in the state. These findings also can be augmented by testing automatic bicycle counters deployed in streets, a technology that has not been deployed in Minnesota previously, and by testing continuous counting of pedestrians on sidewalks using active or passive infrared counters. As practitioners obtain experience working with different approaches and technologies for counting, the evidence base for planning for non-motorized transportation will grow, improving decisions that depend on knowledge of non-motorized traffic volumes.

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Appendix A: Normalization of Manual Pedestrian and Bicycle Count Data

Method used to normalize manual count data:

1. Select applicable data
   a. Pulled all 43 manual count observations that had 12-hours or more of data and included full data from 6:30am – 6:30pm.
   b. Pulled 15-minute interval data from the 3 loop detectors on the Midtown Greenway for each day there was a manual count observation.
      i. Aggregated the loop detector data to 30-minute intervals.
2. Normalize each count observation
   a. Normalized each count observation (or day of loop detector data) by dividing each 30-minute interval by the 12-hour count (6:30am – 6:30pm) for that observation.
   b. Yields a percent of 12-hour count for each 30-minute period for each count observation.
3. Deriving an average curve
   a. Averaged each normalized curve across each 30-minute increment to give an 'average' hourly traffic curve.
   b. We did not weight this 'average' curve by level of volume for each count observation. Future analysis might include investigating some sort of weighting strategy.
4. Overlay on similar plot
   a. Show all normalized 'average' curves on same plot to investigate patterns by facility type or count method.
   b. Curves for each data set (bikes: loop detector; bikes: manual count; pedestrians: manual count) are shown below.

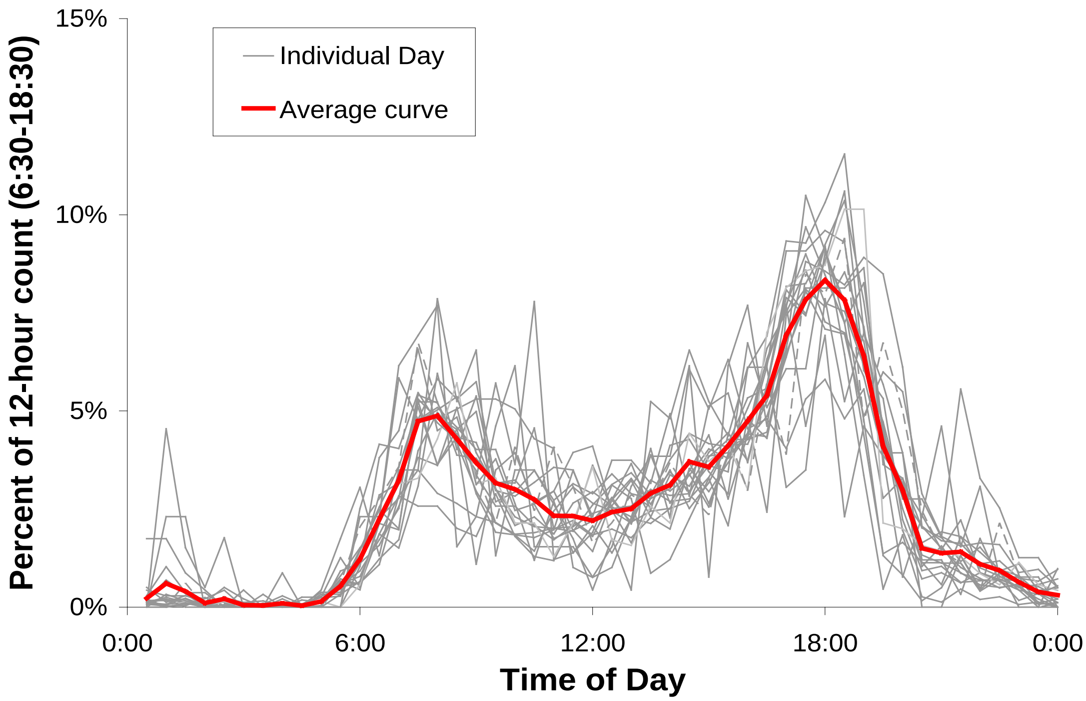

Figure A.1. 30-minute loop detector counts normalized by 12-hour counts (6:30-18:30) for the Midtown Greenway.

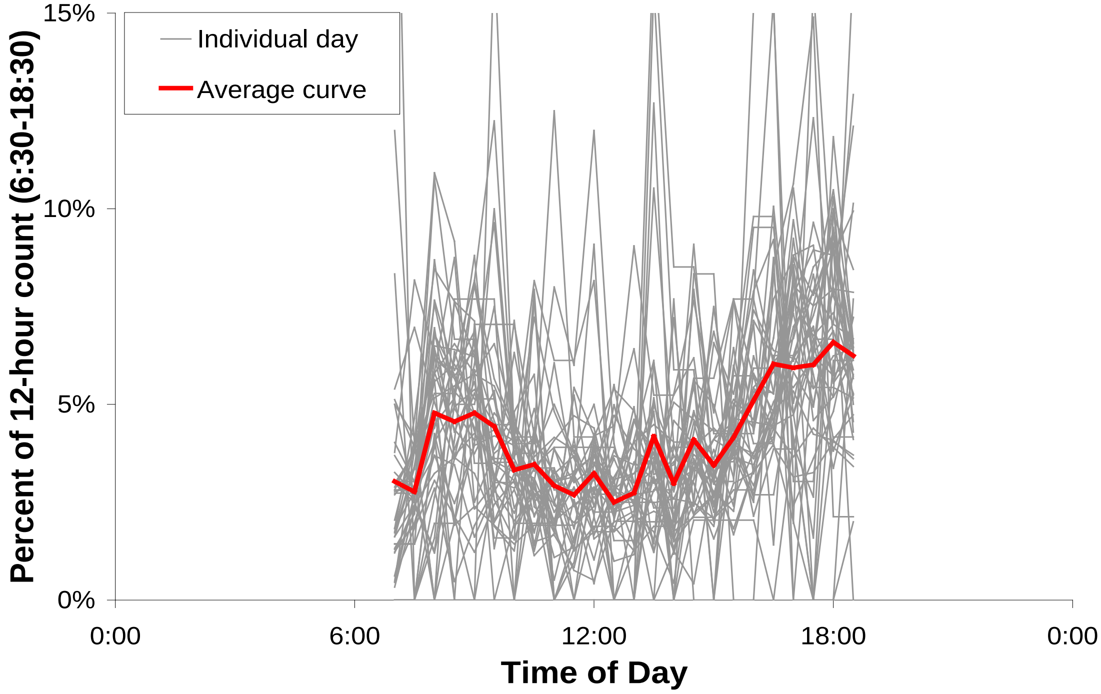

Figure A.2. 30-minute manual bicycle counts normalized by 12-hour counts (6:30-18:30) for 43 count locations.

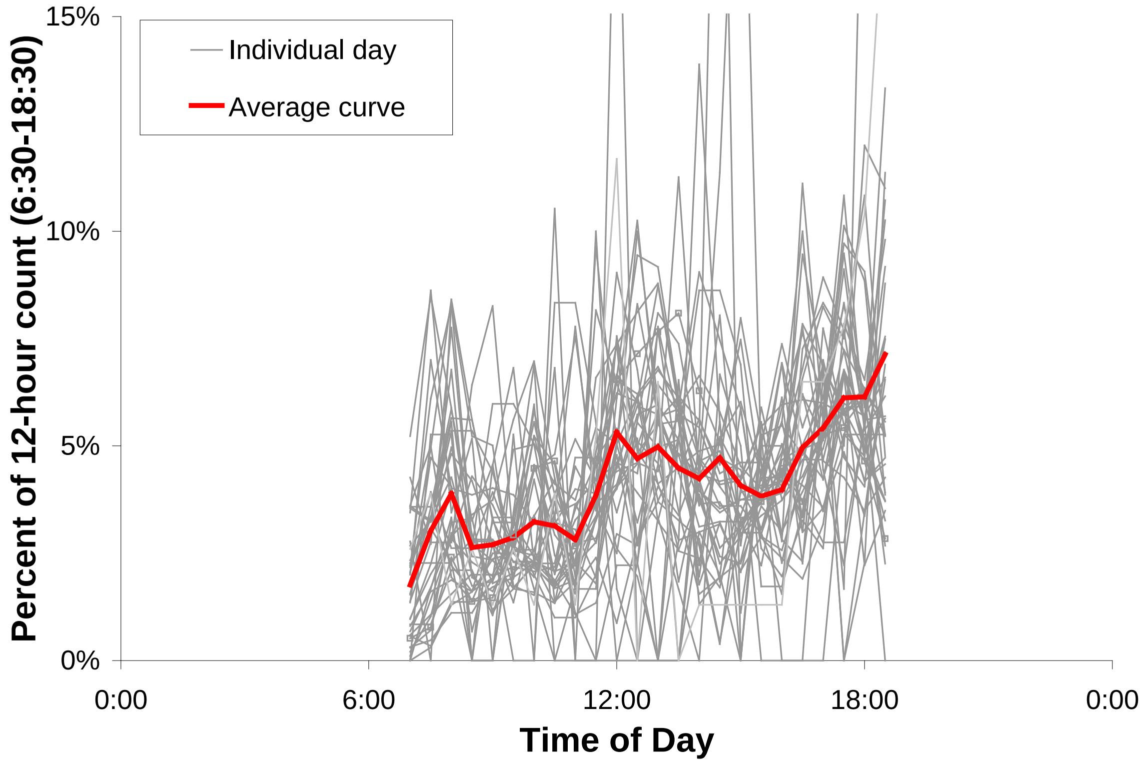

Figure A.3. 30-minute manual pedestrian counts normalized by 12-hour counts (6:30-18:30) for 43 count locations.

Appendix B: Daily Traffic Patterns for Mixed-Mode Locations

Here we present the daily patterns for all locations with infrared mixed-mode trail monitors:

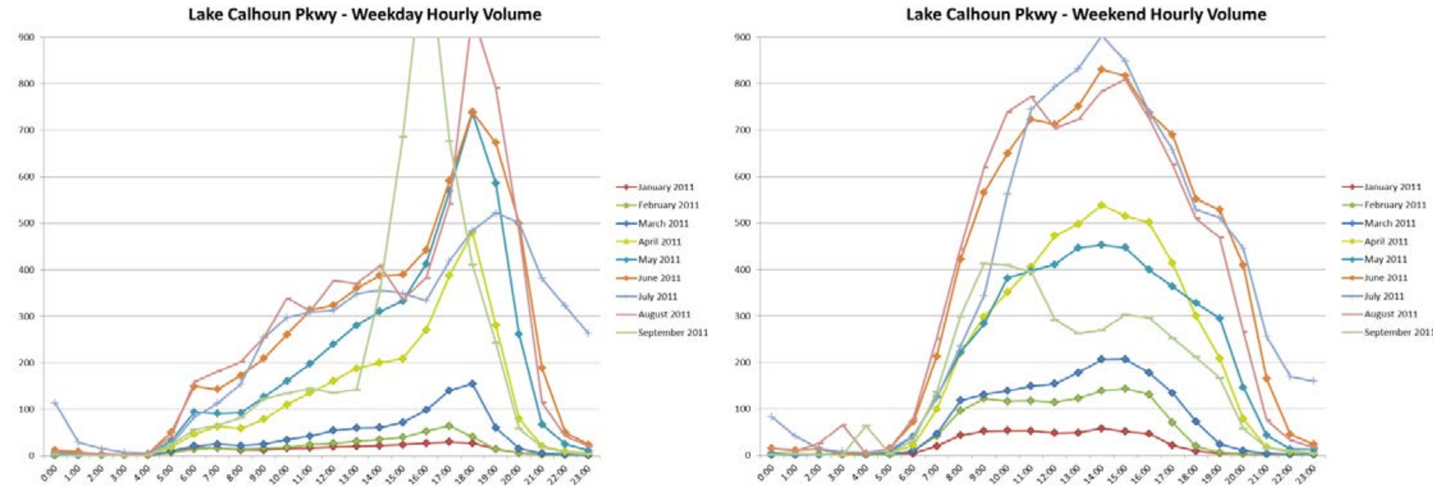

Figure 3. Weekend and weekday average adjusted hourly counts for Lake Calhoun Parkway.

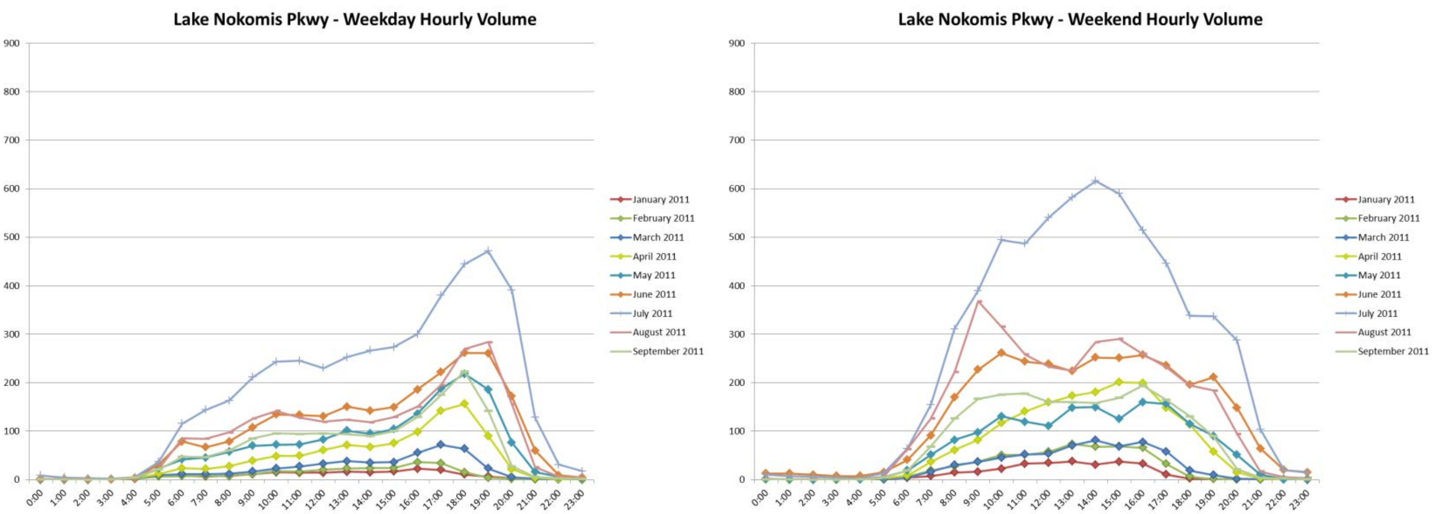

Figure 4. Weekend and weekday average adjusted hourly counts for Lake Nokomis Pkwy.

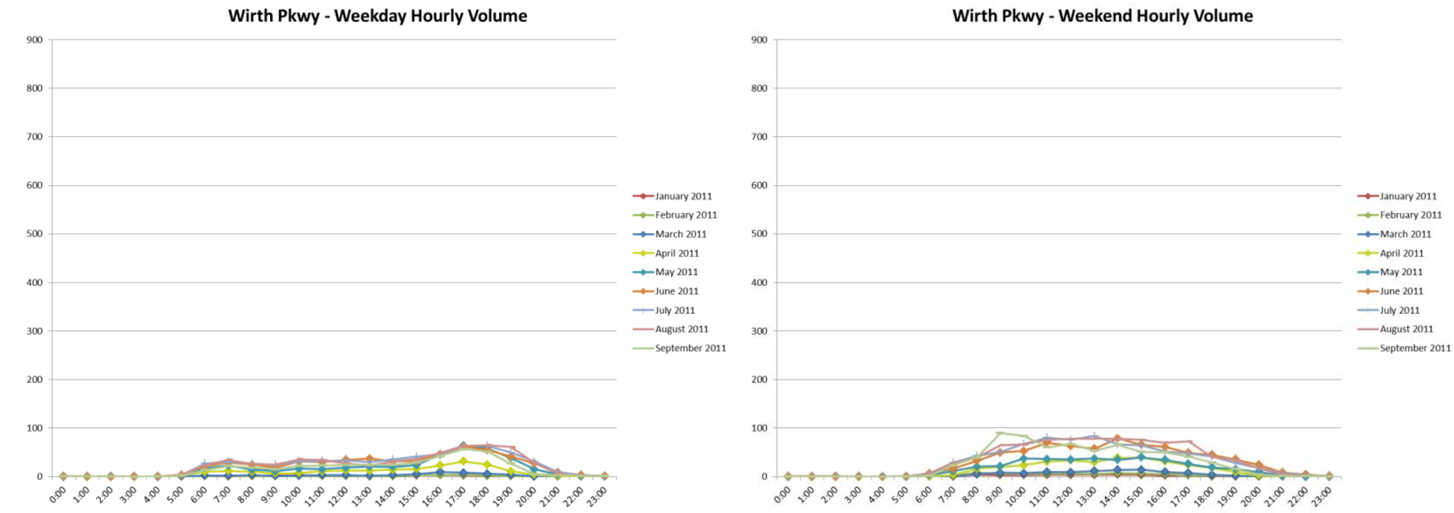

Figure 5. Weekend and weekday average adjusted hourly counts for Theodore Wirth Parkway.

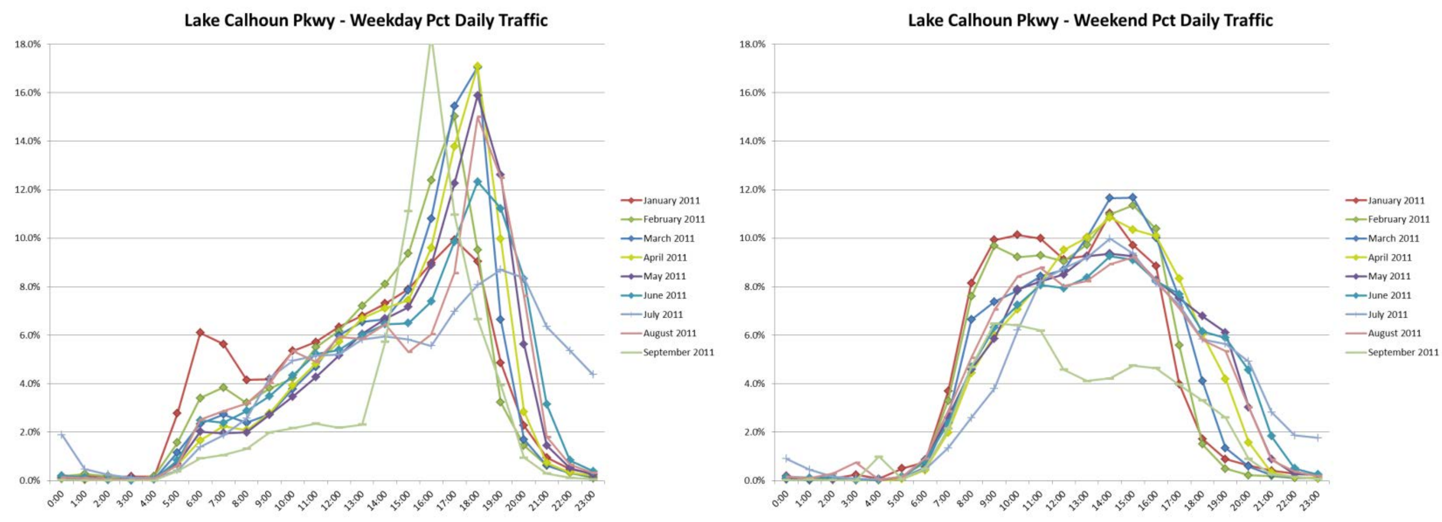

Figure 6. Percentage of adjusted daily counts, by hour – Lake Calhoun Parkway.

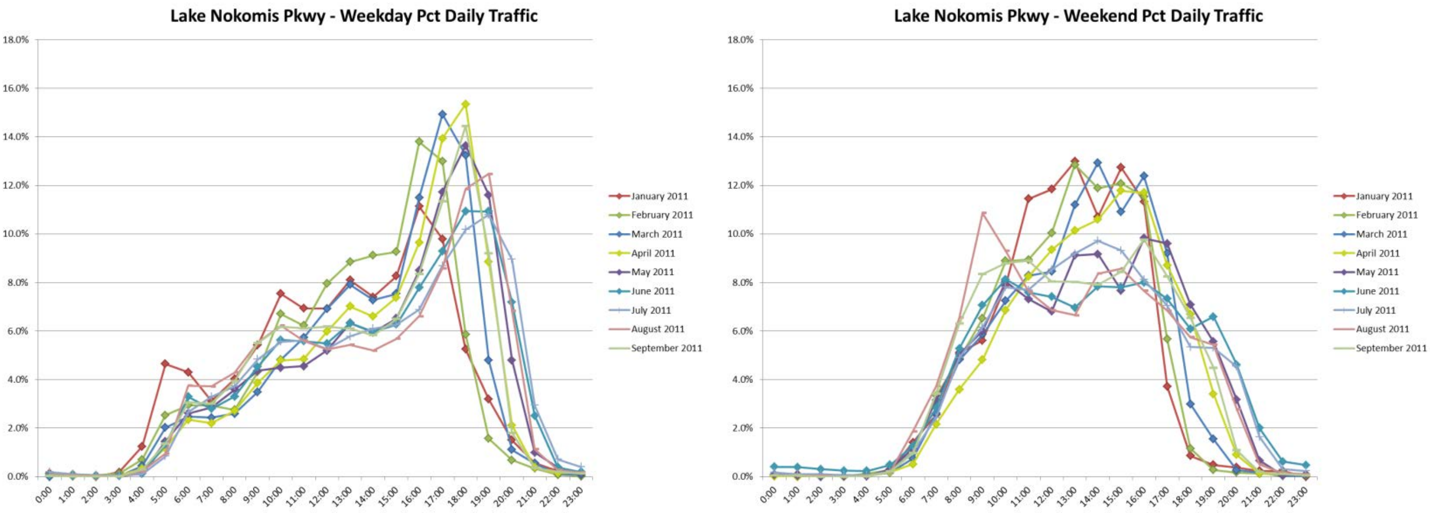

Figure 7. Percentage of adjusted daily counts, by hour – Lake Nokomis Parkway.

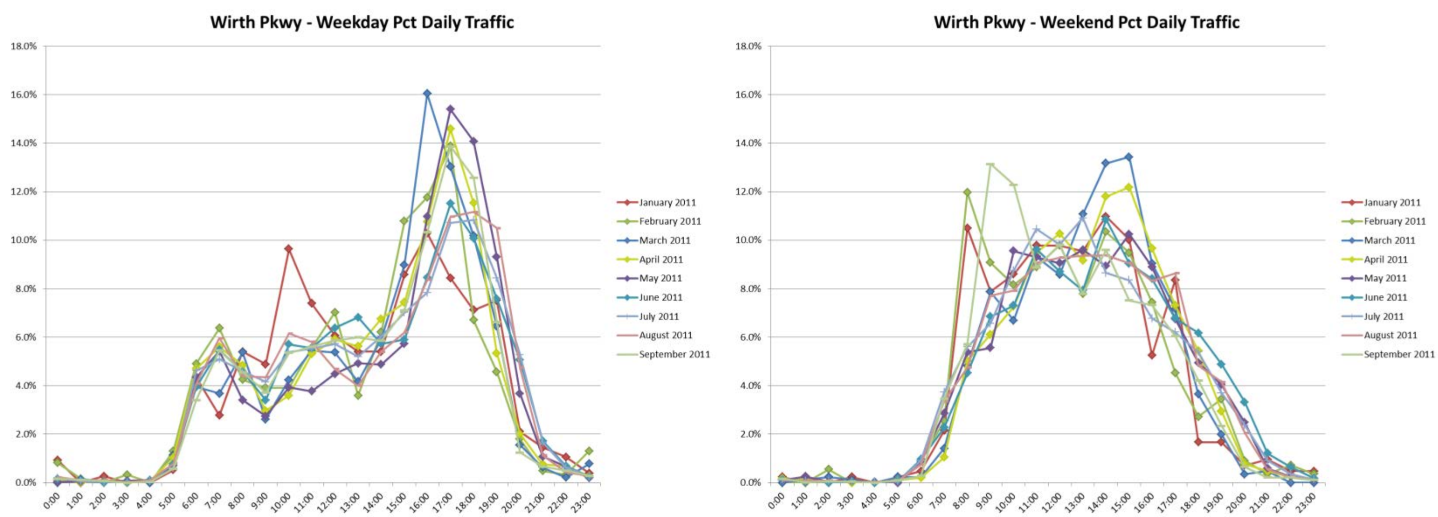

Figure 8. Percentage of adjusted daily counts, by hour – Theodore Wirth Parkway.