EVALUATION OF SURROGATE MEASURES FOR PEDESTRIAN SAFETY IN VARIOUS ROAD AND ROADSIDE ENVIRONMENTS

Final Report

CTLS 11-04

by

John N. Ivan
Nalini Ravishanker
Md. Saidul Islam
Volodymyr Serhiyenko
University of Connecticut

for
Center for Transportation and
Livable Systems (CTLS)
270 Middle Turnpike
Storrs, CT 06269

October 2012

Technical Report Documentation Page

1. Report No. 11-04	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle EVALUATION OF SURROGATE MEASURES FOR PEDESTRIAN SAFETY IN VARIOUS ROAD AND ROADSIDE ENVIRONMENTS		5. Report Date October 18, 2012
		6. Performing Organization Code 11-04-1
7. Author(s) John N. Ivan, Nalini Ravishanker, Md. Saidul Islam, Volodymyr Serhiyenko		8. Performing Organization Report No. 11-04
9. Performing Organization Name and Address University of Connecticut, Unit 3037, Storrs, CT 06269-3037		10. Work Unit No. (TRAIS)
		11. Contract or Grant No.
12. Sponsoring Agency Name and Address Center for Transportation and Livable Systems (CTLS) 270 Middle Turnpike Unit 5202 Storrs, CT 06269-5202		13. Type of Report and Period Covered Final
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

This report presents an investigation of pedestrian conflicts and crash count models to learn which exposure measures and roadway or roadside characteristics significantly influence pedestrian safety at road crossings. Negative binomial models were estimated for pedestrian conflicts and crash counts except for fatal and incapacitating crashes for which binary logistic models were estimated. Also models for predicting highest severity at a location were estimated using an ordered proportional odds (PO) technique. Pedestrian counts and conflicts data were collected using a variation of the Swedish Traffic Conflict Technique (TCT) at 100 locations throughout Connecticut. Pedestrian crash data for the latest available three years (2009, 2008, and 2007) were collected from the Connecticut Crash Data Repository (CTCDR). The results show that minor and serious conflicts are marginally significant in predicting total pedestrian crashes together with crossing distance and building setback. This suggests that these conflicts, when observed over a longer period of time, may be a good surrogate for crashes in analyzing pedestrian safety. Greater crossing distance and small building setbacks are both found to be associated with larger numbers of pedestrian-vehicle crashes. This latter effect is not expected, since we expect vehicle speeds to be lower in areas where the building setback is small. This factor may account for the greater pedestrian activity and more complex interactions in such areas. Further research aimed at identifying a minimum length of time for accurate estimation of pedestrian volume and conflicts to relate to crashes is the subject of continuing investigation by the authors.

17. Key Words Pedestrian safety, traffic conflict analysis, crash analysis, negative binomial modeling, crash severity modeling		18. Distribution Statement No restrictions. Copies available from CTLS: www.ctls.uconn.edu	
19. Security Classification (of this report) Unclassified	20. Security Classification (of this page) Unclassified	21. No. of Pages 52	22. Price

ACKNOWLEDGMENTS

This project was funded by the Center for Transportation and Livable Systems (CTLS).

DISCLAIMER

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

EXECUTIVE SUMMARY

This report presents an investigation of pedestrian conflicts and crash count models to learn which exposure measures and roadway or roadside characteristics significantly influence pedestrian safety at road crossings. Negative binomial models were estimated for pedestrian conflicts and crash counts except for fatal and incapacitating crashes for which binary logistic models were estimated. Also models for predicting highest severity at a location were estimated using an ordered proportional odds (PO) technique. Pedestrian counts and conflicts data were collected using a variation of the Swedish Traffic Conflict Technique (TCT) at 100 locations throughout Connecticut. Pedestrian crash data for the latest available three years (2009, 2008, and 2007) were collected from the Connecticut Crash Data Repository (CTCDR). The results show that minor and serious conflicts are marginally significant in predicting total pedestrian crashes together with crossing distance and building setback. This suggests that these conflicts, when observed over a longer period of time, may be a good surrogate for crashes in analyzing pedestrian safety. Greater crossing distance and small building setbacks are both found to be associated with larger numbers of pedestrian-vehicle crashes. This latter effect is not expected, since we expect vehicle speeds to be lower in areas where the building setback is small. This factor may account for the greater pedestrian activity and more complex interactions in such areas. Further research aimed at identifying a minimum length of time for accurate estimation of pedestrian volume and conflicts to relate to crashes is the subject of continuing investigation by the authors.

INTRODUCTION

Crashes involving pedestrians are a serious problem in the United States, as in many countries. There were 49,128 pedestrian fatalities during the period of 1997 to 2006 in the USA which represents 12 percent of all motor vehicle crash fatalities (424,840). Though the probability of a pedestrian crash was in decline from 1997 to 2006, the probability of a pedestrian fatality in a crash increased during this time period (*NHTSA 2008*). Thus, providing a safer environment to pedestrians to protect them from motor vehicle crashes remains a major concern for traffic safety professionals.

Various studies have been performed to identify factors which affect pedestrian crashes and severity. One such study in the State of Virginia showed that the age of the pedestrian, location of the crash, the type of facility, the use of alcohol, and the type of traffic control at the site are associated with pedestrian conflicts and the likelihood of severe injury in motor vehicle crashes (*Garber and Lienau 1996*). This same study also found that pedestrian involvement rates are significantly higher at locations within 150 feet of an intersection stop line. Also vehicle speed is seen as a significant contributor to crash severity. According to a mathematical model, a speed of 50 km/hour increases the risk of death almost eight-fold compared to a speed of 30 km/hour (*Pasanen and Salmivaara 1993*).

This paper describes an investigation of how roadway and roadside characteristics are associated with pedestrian-vehicle conflicts and crashes at various levels of severity, and also the extent to which pedestrian-vehicle conflicts are associated with crashes. Observational data were collected from 100 pedestrian crossings throughout Connecticut. A variation of the Swedish conflict technique was used for observing conflicts between pedestrian and vehicles in each location. Traffic data and crash data were collected from the Connecticut Department of Transportation (ConnDOT) and Connecticut Crash Data Repository (CTCDR) respectively. Negative binomial count models and binary logistic models for crash predictions were estimated using the SAS software (*SAS 2002*) to identify which roadway characteristics and exposure measures are most strongly associated with pedestrian crashes and severity.

1.0 STUDY DESIGN AND DATA COLLECTION

1.1 LOCATION CHARACTERISTICS

We selected 100 pedestrian crossings throughout Connecticut for collecting observational data to represent ranges of values for each of several road characteristics that were considered to be potentially associated with the occurrence of pedestrian-vehicle conflicts and collisions. This section describes these location characteristics.

1.1.1 Crossing Type

Three types of crossing were observed: type 1 - midblock crosswalks, type 3 – 3 three-leg intersections, and type 4 – four-leg intersections. Among these three categories, midblock crossings do not have traffic signals except in a few cases, which sometime confuse the driver and the pedestrians, as in some cases, sometime both of them might think they have the right of way.

1.1.2 Traffic Control

We defined two types of traffic control - ‘signal’ and ‘no-signal’. At signalized intersections there is less possibility of pedestrian/vehicle interactions if both obey the traffic signal. However, in some cases vehicles or pedestrians disregard the traffic control, creating the possibility of a serious conflict or a crash. In non-signalized locations, vehicles may be required to stop for pedestrians, or yield to pedestrians, or pedestrians may be required to yield to vehicles. As there is less control over vehicles in this type of location, pedestrian crossing can be more hazardous. Also some drivers may travel slowly while approaching these non-signalized intersections due to interactions with pedestrians and other vehicles. These low vehicle speeds would be beneficial for pedestrian crossings as the car would have more time to stop for crossing pedestrians.

1.1.3 Speed Limit

As observing actual speed of the vehicles was beyond the scope of the project, speed limit in miles per hour has been used for the analysis. Pedestrian crossing is expected to be safe at the locations with lower speed limit as it is easy for the pedestrian to react when vehicles are at low speed. Higher vehicle speeds are expected to be associated at least with greater pedestrian crash severity, if not also greater numbers of pedestrian crashes.

1.1.4 Median/Island

A median or pedestrian refuge in the middle of a crossing may sometimes act positively for the pedestrians as it provides a safe area for pedestrians to wait when crossing wide intersections and requires them to wait for gaps in only one direction at a time. A median may also act negatively for pedestrians as it separates the flow of traffic which may cause drivers to approach the intersection at greater speeds because they feel safer knowing that the opposing lane is physically separated. This increase in speed could prove hazardous to pedestrians crossing the street.

1.1.5 Crossing Distance

A longer crossing distance requires more time for the pedestrian to cross the street putting him/her in danger for a longer time, potentially increasing the risk of a crash.

1.1.6 Number of Lanes

Number of lanes is similar to crossing distance, but gives some extra information. For example, a crossing forty feet wide may be either one or two lanes traveling in each direction. More lanes of traffic implies more vehicles to which the pedestrians must pay attention to when choosing gaps for crossing the street. There is also the multiple-threat risk when a driver thinks that someone in a parallel lane will not yield to the pedestrian.

1.1.7 On Street Parking

On street parking may create a visual barrier between a pedestrian and a driver, thus creating a possible conflict between them. On the other hand, on street parking is known to cause drivers to travel slower (*Hansen et al. 2007*) which may be beneficial for the pedestrian crossing as noted above for speed limit.

1.1.8 Building Setback

This is the relative distance at which buildings are located from the edge of the road. We defined three types of setback – small, medium, and large (*Hansen et al. 2007*). A small setback is when the buildings begin at the outer edge of the sidewalk, or within fifteen feet of the edge of the road. There were very few cases with ‘large’ setback, so they were combined with the “medium” setbacks into a category including all observations other than those with small setbacks.

1.2 CONFLICT OBSERVATION

Conflicts between pedestrians and vehicles at each location were observed using a variation of the Swedish Traffic Conflict Technique (TCT) (*Hyden 1987*). The Swedish TCT is very easy to use and does not require any complicated equipment, so that with a few days of training an observer is ready to carry out observations. For this modified Swedish TCT, pedestrian crossings were categorized into four types: Undisturbed passages, Potential conflicts, Minor (slight) conflicts, and Serious conflicts. Conflict data were collected for periods ranging from one to six hours at each location, with the observation period varying due to rain, unusual local events, and low pedestrian volumes. Easy to use observation sheets were used for recording the four types of pedestrian crossings through the intersections, which are defined in more detail as follows.

1.2.1 Undisturbed Passages

This means that the pedestrians cross the intersection without having any possibility of getting in collision with vehicles. One example of this happening is when vehicles are stopped at a red signal and a pedestrian crosses the street, or when a pedestrian crosses an uncontrolled crosswalk with no vehicles in the vicinity. Any pedestrian crossing the street without having any moving vehicles in the vicinity is considered an undisturbed passage.

1.2.2 Potential Conflicts

This type of passage does not rise to the level of a conflict, in that there was a relatively low likelihood of a collision occurring. There was, however, some low level interaction between the pedestrian and a vehicle. For example, the vehicle may have been slowing to a stop as the pedestrian crossed the street.

1.2.3 Minor Conflicts

A minor conflict occurs when there was a chance of a collision between the pedestrian and a vehicle. During a minor conflict, vehicle speed is usually slow which allows the driver to maneuver out of pedestrian's path or come to a quick stop if that is required to avoid hitting the pedestrian in the crosswalk. The vehicle normally would stop a few feet away from the pedestrian during a minor conflict. This type of conflict would likely not result in a fatality if it were to turn into a collision because of the slow speed of the moving vehicle. Also the pedestrian has enough time to react since the vehicle is moving at a slower speed.

1.2.4 Serious Conflicts

This is the case when a pedestrian and a vehicle are on a collision course with very late evasive action taken to avoid the collision. This is very close to an actual collision. In a serious conflict, a vehicle must make a strong evasive action in order to avoid a collision with a pedestrian, or a pedestrian must make an erratic, unplanned movement (*e.g.*, jumping back onto the sidewalk or springing out of the vehicle's path) in order to avoid a collision with a vehicle. This type of incident is very rare among the interactions observed in this study.

1.3 VEHICLE AND PEDESTRIAN VOLUMES

The vehicular traffic volume is another important piece of information for pedestrian crash analysis as it helps us determine the exposure to risk that pedestrians are facing when they cross the road. AADT data was collected from ConnDOT. Further, for conflict analysis to be consistent, it was necessary to calculate traffic data for the time period in which observations were done at each location. It was not practical to observe the actual vehicle traffic counts during our observation period. Instead, the latest available hourly traffic counts for each observational time period ($\widetilde{V}_C$) were collected from ConnDOT. Because these counts were not on the same day as the observations were made, we adjusted them using seasonal factors provided by ConnDOT's Traffic Monitoring and Data Analysis section. The traffic volume for the time period when our observations were taken was estimated as follows:

$$\widetilde{V}_O = \left(\frac{\widetilde{V}_C}{V_C}\right)\left(\frac{V}{F_O}\right)$$

where:

$\widetilde{V}_O$ =Traffic volume for the desired time period on the day of the conflict observations

F_O = Factors for expanding 24-hr traffic counts to the AADT for the day of the conflict observations

V = AADT for the observation location

V_C = Average daily traffic (ADT) on the day of the traffic count for the observation location

To illustrate the procedure, consider the following intersection. The observational time period was 8:00AM to 1:00PM on a Saturday in May, 2012. The following information was collected for this intersection: V = 19,900, V_C = 21,222, $\widetilde{V}_C$ = 5,854, and the F_O value for urban streets on Saturdays in May is 1.04.

Thus $\widetilde{V}_O$ is calculated to be:

$$\widetilde{V}_O = \left(\frac{5{,}854}{21{,}222}\right)\left(\frac{19{,}900}{1.04}\right) = 5{,}278$$

In order to perform the crash analysis, it was necessary to convert the pedestrian counts observed during our observation time periods to a comparable Annual Average Daily Pedestrian Volume (AADPV). This AADPV was calculated under the assumption that pedestrian volumes vary throughout the day and the year in the same way as the vehicle volume. While this may not be an accurate assumption, it is the best approach available for this analysis. The following formula was used:

$$AADPV = AADT * \frac{P}{\widetilde{V}_O}$$

where: P is the total pedestrian during the observed time period.

So for the same location as above, AADPV was estimated as:

$$AADPV = 19{,}900 * \frac{923}{5{,}278} = 3{,}480$$

where: P = Undisturbed pedestrians + Potential conflicts + Minor conflicts + Serious conflicts = 908 + 9 + 4 + 1 = 923.

1.4 ASSEMBLY OF DATA SET

Pedestrian crash data for the latest available three years (2009, 2008, and 2007) at all 100 observation locations were collected from the Connecticut Crash Data Repository (CTCDR), a web tool housed by the University of Connecticut for the State of Connecticut. This data repository provides access to information from crash reports generated by state and local police. The CTCDR is comprised of crash data from two separate sources; the Department of Public Safety (DPS) and the Connecticut Department of Transportation (ConnDOT). From the repository, pedestrian crash data with different level of severity (K=fatal injury, A=incapacitating injury, B=non-incapacitating evident injury, C=possible injury, N=no injury) was collected for the observation locations. Crashes involving pedestrians and occurring within 200 feet from the pedestrian crosswalk were included in the dataset.

Descriptive statistics of the continuous variables used are shown in Table 1. This table reports the values of the mean, medium, maximum, minimum, and standard deviation for the variables. Frequency distribution for the binary and discrete variables and highest crash severity at location is reported in Table 2.

Table 1 Descriptive Statistics of Continuous Variables

Variable	Minimum	Maximum	Median	Mean	Std Dev
KA	0	2	0	0.09	0.321
B	0	3	0	0.3	0.644
CN	0	3	0	0.26	0.676
KAB	0	3	0	0.39	0.737
KABCN	0	5	0	0.65	1.14
PC	0	225	11.5	18.97	27.297
MC	0	48	3	5.09	7.097
SC	0	6	0	0.26	0.733
Hours of Observation	1	6	4	4.033	1.448
Crossing Distance	25	120	53.5	56.24	17.504
Log (Vehicle Volume)	5.9	9.491	8.293	8.212	0.741
Log (Pedestrian Volume)	3.555	8.182	5.751	5.837	1.016
$Log\left(\frac{3yearAADT}{10^6}\right)$	1.155	3.943	2.857	2.788	0.559
$Log\left(\frac{3yearAADPV}{10^6}\right)$	-2.305	2.429	0.465	0.413	1.076
$Log\left(\frac{3yearAADPC}{10^4}\right)$	-8.277	4.033	1.823	1.5	1.456
$Log\left(\frac{3yearAADMSC}{10^4}\right)$	-1.342	3.161	0.439	0.566	0.997

Table 2 Frequency Distribution for Categorical Variables

Variables	Levels	Frequencies
Highest Crash Severity at Location	None	65
	CN	9
	B	18
	KA	8
Setback	Small	71
	Medium/Large	29
Type of Intersection	Mid-block/3-leg	42
	4-leg	58
Day of The Week	Monday	5
	Tuesday	4
	Wednesday	19
	Thursday	21
	Friday	42
	Saturday	9
Weather	Rain	10
	Cloudy	15
	Sunny	75
Traffic Control	No signal	18
	Signal	82
Median/Islands	No	86
	Yes	14
On Street Parking	No	41
	Yes	59
Speed Limit	25 mph	73
	30 mph or more	27

2.0 METHODOLOGY

2.1 ANALYSIS FRAMEWORK

There were two objectives for this study: 1) to identify roadway and roadside characteristics associated with pedestrian safety, defined by the occurrence of pedestrian-vehicle conflicts and crashes, and 2) to investigate the extent to which pedestrian – vehicle conflict counts can used as a surrogate for crashes in analyzing pedestrian safety. For both objectives we estimated models for predicting counts of pedestrian – vehicle conflicts and crashes. We also estimated models of pedestrian crash severity. The following sections describe the statistical methods used.

2.2 CRASH AND CONFLICT COUNT MODELING

Various types of statistical models have been developed and tested recently for modeling highway crashes. The general consensus among crash modeling researchers is that the negative binomial distribution provides the best distribution for modeling crash counts because of its ability to capture the commonly observed overdispersion in crash count data (*Usman et al. 2011*). Negative binomial modeling was used for modeling pedestrian crash counts at different levels of severity using various measures of exposure, including pedestrian – vehicle interactions and road characteristics as predictors. For modeling KA crashes (fatal and life-threatening injury), binary logistic modeling was used because the KA count was greater than 1 for only one case.

Let Y_i be a response variable with k ordinal levels. Then $Y_i \sim NB(\mu_i,k)$, with probability distribution function given by:

$$f(y_i) = \frac{\Gamma(y_i + 1/k)(k\mu_i)^{y_i}}{\Gamma(y_i + 1)\Gamma(1/k)(1 + k\mu_i)^{y_i + 1/k}}$$

where μ_i is the mean;

k is overdispertion parameter;

$Var(Y_i) = \mu_i + k\mu_i^2$.

The model equation for linear predictor is given by the following:

$$\log(\mu_i) = \vec{x}_i^{'}\vec{\beta}$$

which is estimated by:

$$\log(\hat{\mu}_i) = \vec{x}_i^{'}\hat{\vec{\beta}}$$

where $\hat{\vec{\beta}}$ is the Maximum Likelihood Estimator (MLE) of $\vec{\beta}$. Estimated values of the mean response variable are given by:

$$\hat{\mu}_i = e^{\vec{x}_i^{'}\hat{\vec{\beta}}}$$

where $\hat{\mu}_i$ – estimated mean of the response in the i^{th} observation;

$i=1, \ldots, n$, n – number of observations;

$\vec{x}_i^{'}$ is a fixed vector of explanatory variables;

$\hat{\vec{\beta}}$ is estimated vector of unknown parameters.

Logistic regression is a suitable technique to use when the response variable has only two possible outcomes (levels), either 1 or 0 (binary responses). This type of models has been successfully used in crash analysis in many instances (*Rahman et al. 2011*).

Let Y_i be a response variable. Then $Y_i \sim Bernoulli(p_i)$. Probability p_i is connected to the linear predictors through *Logit* link function and model equations are given below:

$$Logit(\hat{p}_i) = \vec{x}_i^{'}\hat{\vec{\beta}}$$

$$\hat{p}_i = \frac{1}{1 + e^{-(\vec{x}_i^{'}\hat{\vec{\beta}})}}$$

where $\hat{p}_i$ is estimated probability of the response variable in the i^{th} observation;

$i=1, \ldots, n$, n – number of observations;

$\vec{x}_i^{'}$ is a fixed vector of explanatory variables;

$\hat{\vec{\beta}}$ is estimated vector of unknown parameters (MLE for $\vec{\beta}$).

2.3 CRASH SEVERITY MODELING

The proportional-odds (PO) model is used for severity analysis where each location is assigned to the severity category (None, CN, B, KA) according to the most intense (highest severity) crash that had occurred during 3 year period. This model is a class of generalized linear models used for modeling response variable that has multiple levels (more than two) as a function of discrete or continuous covariates.

Let Y_i be a response variable with k ordinal levels and let $p_{ij} = P(Y_i \le j \mid x)$ be the cumulative response probability given a vector of explanatory variables $\boldsymbol{x}$. The proportional-odds model is linear logistic model in which the intercepts depend on j, but the slopes are all equal. The model equation for linear predictor is the following:

$$logit(p_{ij}) = \alpha_j + \boldsymbol{x}_i'\boldsymbol{\beta}$$

which is estimated by:

$$\widehat{logit(p_{ij})} = \hat{\alpha}_j + \boldsymbol{x}_i'\widehat{\boldsymbol{\beta}}$$

where $\widehat{\alpha}_j$ and $\widehat{\beta}$ are the MLEs of α_j and β. In other words the estimated cumulative probabilities are given by:

$$\widehat{p}_{ij} = \frac{1}{1 + e^{-(\widehat{\alpha}_j + x_i'\widehat{\beta})}}$$

where $\widehat{p}_{ij}$ is the set of estimated cumulative probabilities;

$j = 1, \ldots, k$, k – number of ordinal levels for response variable;

$i = 1, \ldots, n$, n – number of observations;

$\mathbf{x}_i'$ is the vector of model covariates;

$\widehat{\alpha}_j$ is the estimated intercept for response variable on level j;

$\widehat{\boldsymbol{\beta}}$ is the estimated vector of model regression coefficients.

3.0 RESULTS AND DISCUSSION

Three different analyses were performed to satisfy the objectives of the paper:

- Modeling pedestrian conflict with pedestrian and vehicle volumes or potential conflicts as exposure, and including all roadway and roadside characteristics as potential predictors variables,

- Modeling different levels of crash severity with pedestrian and vehicle volumes, minor and serious conflicts, or potential conflicts as exposure, and including all roadway and roadside characteristics as potential predictor variables,

- Modeling highest severity at a location, including all volumes and roadway and roadside characteristics as potential predictor variables.

This section describes three different analysis methods and the results we found. For all of our statistical tests we used a 90 percent level of confidence to test for significance.

3.1 PEDESTRIAN CONFLICT COUNT MODELS

Models for minor and serious pedestrian conflicts (MSC) were estimated using two distinct exposure measures – i) potential conflicts (as defined above) and ii) observed pedestrian counts and estimated traffic volume – in conjunction with other relevant variables (crossing distance, weather, intersection type, setback, traffic control, median/island, on street parking, speed limit, and day of the week). Table 3 presents the results of the best models with each exposure measure. The table also includes values of dispersion parameter, deviance, Akaike Information Criterion (AIC) (a measure of relative goodness-of-fit for a statistical model), AICC (the corrected version of AIC for small sample size), and Bayesian Information Criterion (BIC). Values in bracket indicate Wald 90% confidence interval.

From the results, it is observed that when potential conflict (PC) was used as the exposure measure, intersection type was the only significant variable together with day of the week (Thursday). If pedestrian count and traffic volume are used, no road characteristics or other variables except days of the week (Wednesday and Thursday) were significant. But in both cases, exposure measures were significant in predicting MSC. In terms of goodness-of-fit criteria, the pedestrian and vehicle volume model has better fit as it has smaller AIC and BIC values. The exposure measures explain most of the variation in estimating pedestrian conflict. Day of week may capture driver and/or pedestrian behavioral differences or possibly differences that are artifacts of observational logistics.

Table 3 Model Estimation Results for Predicting Minor and Serious Conflicts

Predictors	Model 1	Model 2
Intercept	-1.3500 (0.0001) [-2.0403,-0.6597]	-4.2608 (0.0017) [-6.9201,-1.6014]
Log (PC)	0.8143 (<.0001) [0.5955,1.0330]	
Log (Pedestrian Volume)		0.4841 (<.0001) [0.2903,0.6778]
Log (Vehicular Volume)		0.3102 (0.0481) [0.0025,0.6179]
Intersection Type *4-leg*	0.6159 (0.0020) [0.2249,1.0070]	
Monday	0.3373 *(0.4103)* [-0.4656,1.1403]	0.6345 *(0.1617)* [-0.2542,1.5232]
Tuesday	0.4610 *(0.3327)* [-0.4717,1.3936]	0.7890 *(0.1140)* [-0.1895,1.7676]
Wednesday	0.3596 *(0.1539)* [-0.1346,0.8539]	0.8761 (0.0013) [0.3405,1.4117]
Thursday	0.5023 (0.0387) [0.0261,0.9785]	0.4761 (0.0739) [-0.0459,0.9981]
Saturday	-0.2979 *(0.4343)* [-1.0447,0.4489]	-0.3372 *(0.4169)* [-1.1514,0.4770]
Dispersion	0.5216 [0.3322,0.8190]	0.7250 [0.4899,1.0728]
Deviance	113.0023	111.2247
Log Likelihood	560.9139	605.0079
AIC	493.0853	525.4551
AICC	495.0853	527.4551
BIC	516.5319	548.9016

3.2 PEDESTRIAN CRASH COUNT MODELS

Crash prediction models were estimated for three different levels of crash severity: i) KABCN (all pedestrian crashes together), ii) KAB (crashes with K, A, and B severity), and iii) KA (crashes with severity K and A). The following exposure measures were considered: i) Annual average daily traffic (AADT) along with Annual average daily pedestrian volume (AADPV), ii) Annual average daily potential conflict (AADPC), and iii) Annual average daily minor and serous conflicts (AADMSC). AADPC and AADMSC are calculated the same was as AADPV as described earlier. Including the conflict values as exposure allowed us to investigate the association between conflicts and crashes, in order to satisfy the second objective of investigating whether or not conflicts can be used as surrogates for crashes. Including both pedestrian and vehicular volumes accounts for the potential effects of both the pedestrian and vehicle traffic intensity at the location on crash incidence.

All of these exposure variables were multiplied by the number of days in the period for which crashes were collected, that is, three years times 365 days per year. These variables were also scaled by 10^4 (in the case of conflicts) or 10^6 (for the vehicle and pedestrian counts) considering their relatively large values. Some cases had no observed conflicts, so those values were incremented by 1 across the board to avoid instances of zeros in the dataset which were problematic for taking natural logs.

Tables 4, 5, and 6 show the estimation results for the KABCN, KAB, and KA models, respectively. Initially, full models were estimated using different exposure measures and road or roadside characteristics (crossing distance, setback, speed limit, traffic control, median/islands, and on street parking). The tables show only significant variables together with exposure measures as well as some statistics for comparing goodness-of-fit among models.

Minor and serious conflicts, potential conflicts, and pedestrian volumes are not significant, although minor and serious conflicts when predicting KABCN have a significance level of just over 13 percent. For predicting all three crash severities, AADT is the only exposure measure found to be significant. In all but the KA models, crossing distance and building setbacks are found to be significant. Parameter estimates for crossing distance have positive sign, indicating that crash counts increase with longer crossing distance. Parameter estimates for building setback have a negative sign which means larger building setback decreases crashes.

The minor and serious conflict count, which is found to be marginally significant in the KABCN model, thus has potential as a surrogate for pedestrian crashes in conjunction with other road characteristics – in this case crossing distance and building setback. The positive sign on crossing distance parameter estimates is expected as longer crossing distance means pedestrians are more exposed to danger, so we would expect great risk of crashes. We note that median/island is not significant for predicting any of the crash count levels, most likely because there were only 14 locations with such features, and physical design varied substantially from one to another. Most notably, not all were designed to accommodate or facilitate pedestrian crossing.

Table 4 Model Estimation Results for Predicting KABCN

Predictors	Model 1	Model 2	Model 3
Intercept	-2.5976 (<.0001) [3.6774,-1.5178]	-2.3944 (<.0001) [-3.3707,-1.4181]	-4.2912 (<.0001) [-5.9496,-2.6328]
$Log\left(\frac{3yearAADPC}{10^4}\right)$	0.2035 *(0.2428)* [-0.0831, 0.4900]		
$Log\left(\frac{3yearAADMSC}{10^4}\right)$		0.2218 *(0.1318)* [-0.0203, 0.4639]	
$Log\left(\frac{3yearAADT}{10^6}\right)$			0.9492 (0.0114) [0.3319,1.5665]
$Log\left(\frac{3yearAADPV}{10^6}\right)$			0.1391 *(0.3148)* [-0.0885,0.3667]
Crossing distance	0.0334 (0.0001) [0.0192, 0.0476]	0.0334 (0.0001) [0.0193,0.0476]	0.0195 (0.0319) [0.0046,0.0345]
Setback	-2.9955 (0.0034) [-4.6777,-1.3132]	-3.0157 (0.0032) [-4.6995,-1.3320]	-2.9468 (0.0039) [-4.6239,-1.2696]
Dispersion	0.4263 [0.1372, 1.3251]	0.4111 [0.1300,1.2997]	0.2473 [0.0492,1.2429]
Deviance	74.5389	74.2243	73.3492
Log Likelihood	-60.0958	-59.6571	-55.9206
AIC	188.6537	187.7764	182.3035
AICC	189.2920	188.4147	183.2067
BIC	201.6796	200.8022	197.9345

On the other hand, the negative sign on the building setback parameter estimates is the opposite of what we originally had expected. Vehicle speeds are known to be higher with medium and large building setbacks (*Hansen et al. 2007*), so we would expect higher vehicle speeds to also be associated with more pedestrian crashes. We note that the locations with small setbacks are all in downtown type areas, where the pedestrian volumes are higher. Also we observe that the pedestrian volume coefficient was not significant in the crash count models, probably because our pedestrian counts were extrapolated to three years from counts of several hours. So it is possible that building setback is acting as a surrogate for the actual pedestrian count rather than reflecting a physical association with crash risk.

Table 5 Model Estimation Results for Predicting Fatal, Life-threatening and Non-life-threatening Visible Injury Crashes

Predictors	Model 1	Model 2	Model 3
Intercept	-2.7837 (.0001) [-3.9684,-1.5989]	-2.5036 (<.0001) [-3.5422,-1.4649]	-3.9925 (0.0004) [-5.8521,-2.1329]
$Log\left(\frac{3yearAADPC}{10^4}\right)$	0.2378 *(0.2293)* [-0.0876,0.5631]		
$Log\left(\frac{3yearAADMSC}{10^4}\right)$		0.2291 *(0.1628)* [-0.0409,0.4990]	
$Log\left(\frac{3yearAADT}{10^6}\right)$			0.7557 (0.0805) [0.0446,1.4668]
$Log\left(\frac{3yearAADPV}{10^6}\right)$			0.0622 *(0.7078)* [-0.2106,0.3349]
Crossing distance	0.0274 (0.0029) [0.0123,0.0426]	0.0271 (0.0027) [0.0123,0.0420]	0.0172 (0.0981) [0.0001,0.0342]
Setback	-2.5204 (0.0138) [-4.2032,-0.8377]	-2.5257 (0.0134) [-4.2054,-0.8461]	-2.5008 (0.0143) [-4.1806,-0.8211]
Dispersion	0.2296 [0.0113,4.6757]	0.1987 [0.0066,6.0047]	0.1328 [0.0010,17.6296]
Deviance	71.5400	72.0835	72.1300
Log Likelihood	-59.5997	-59.4019	-58.3744
AIC	148.8430	148.4474	148.3925
AICC	149.4813	149.0857	149.2957
BIC	161.8689	161.4733	164.0235

Table 6 Model Estimation Results for Predicting Fatal and Life-threatening Injury Crashes

Predictors	Model 1	Model 2	Model 3
Intercept	-4.9891 (0.0010) [-7.4923,-2.4858]	-5.2063 (0.0002) [-7.4950,-2.9177]	-6.6469 (0.0144) [-11.1152,-2.1786]
$Log\left(\frac{3yearAADPC}{10^4}\right)$	-0.1296 *(0.7223)* [-0.7295,0.4703]		
$Log\left(\frac{3yearAADMSC}{10^4}\right)$		-0.3872 *(0.3245)* [-0.0409,0.4990]	
$Log\left(\frac{3yearAADT}{10^6}\right)$			1.4651 (0.0965) [0.0150,2.9152]
$Log\left(\frac{3yearAADPV}{10^6}\right)$			-0.4477 *(0.2121)* [-1.0380,0.1425]
Crossing distance	0.0445 (0.0239) [0.0121,0.0768]	0.0473 (0.0177) [0.0145,0.0801]	
Log Likelihood	-25.1749	-24.7295	-25.7084
AIC	56.3498	55.4590	57.4168
AICC	56.5998	55.7090	57.6668
BIC	64.1653	63.2745	65.2323

3.3 PREDICTING HIGHEST CRASH SEVERITY AT A LOCATION

We considered that because the known effect of building setback is related to vehicle speeds, it is possible that its effect related to pedestrian safety is on the severity of crashes experienced, rather than the crash count. Therefore we estimated models for predicting the highest crash severity at each location using three exposure measures described above for modeling crashes along with all of the roadway and roadside characteristics as potential predictors. For this analysis, each location was assigned to the severity level None, CN, B, and KA according to the most severe pedestrian crash that occurred during the three years period (with “None” indicating no crash having occurred). Table 7 shows the model estimation results. Again pedestrian volume is not significant, but crossing distance and setback are significant in the same ways as for the crash count models. So we draw the same conclusion as was made for the counts models that building setback is likely acting as a surrogate for the actual pedestrian count.

The AIC value in Table 7 indicates that the pedestrian and traffic volume model (Model 3) has better goodness-of-fit compared with the other two models. Figures 1 through 3 depict the predicted severity probabilities for this model.

Table 7 Model Estimation Results for Predicting Highest Crash Severity at a Location

Predictors	Model 1	Model 2	Model 3
Intercept KA	-6.4658 (<.0001) [-8.3898,-4.5417]	-6.5393 (<.0001) [-8.4304,-4.6483]	-8.8578 (<.0001) [-11.7762,-5.9394]
Intercept B	-4.8192 (<.0001) [-6.5787,-3.0598]	-4.8788 (<.0001) [-6.5976,-3.1599]	-7.1802 (<.0001) [-9.9475,-4.4129]
Intercept CN	-4.2616 (<.0001) [-5.9776,-2.5456]	-4.3068 (<.0001) [-5.9796,-2.6340]	-6.5909 (<.0001) [-9.3132,-3.8686]
$Log\left(\frac{3yearAADT}{10^6}\right)$			1.1575 (0.0506) [0.1836,2.1313]
$Log\left(\frac{3yearAADPV}{10^6}\right)$			0.0483 *(0.8270)* [-0.3148,0.4113]
$Log\left(\frac{3yearAADPC}{10^4}\right)$	0.0488 *(0.8348)* [-0.3365,0.4342]		
$Log\left(\frac{3yearAADMSC}{10^4}\right)$		0.2732 *(0.2162)* [-0.0902,0.6367]	
Crossing distance	0.0428 (0.0020) [0.0201, 0.0656]	0.0418 (0.0026) [0.0189,0.0646]	0.0263 *(0.1014)* [-0.00011,0.0526]
Setback	-1.5901 (0.0027) [-2.4609,-0.7193]	-1.6058 (0.0025) [-2.4800,-0.7317]	-1.6223 (0.0024) [-2.5016,-0.7430]
AIC	180.277	178.860	177.487
SC	195.908	194.491	195.723
-2 Log L	168.277	166.860	163.487

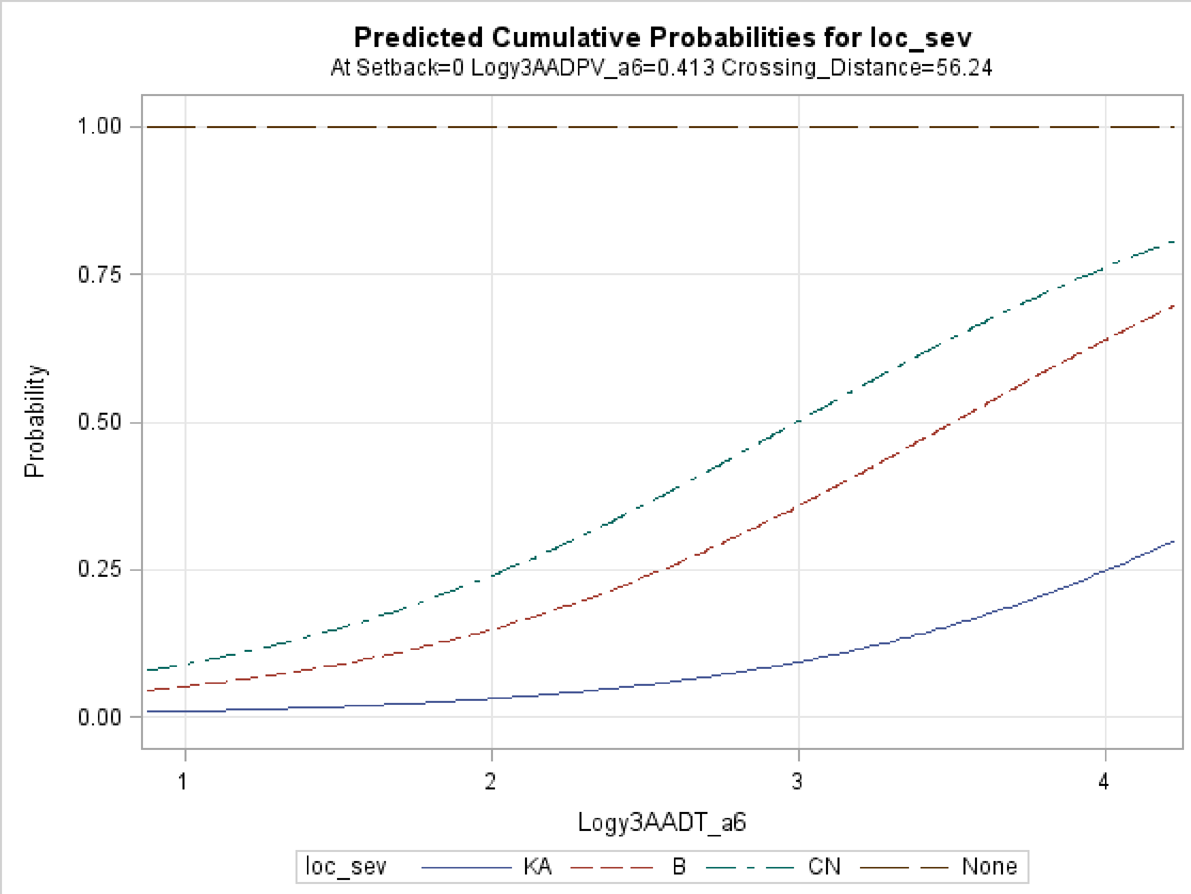

Figure 1 Predicted Cumulative Probabilities by AADT for the Highest Crash Severity at a Location

We observe that with an increase in traffic volume, probability for the location to be in a higher severity category also increases. Holding Building Setback to be small, $Log\left(\frac{3yearAADPV}{10^6}\right)$ to be 0.413 and Crossing Distance to be 56.24, we can conclude the following:

- when the traffic volume is small, it is more likely to observe locations with no pedestrian crashes (severity level = None) than locations with crashes;
- with the increase in traffic volume we can notice increase in probability for locations to have pedestrian crashes (for all three highest severity categories KA, B and CN) and decreasing probability to observe locations with no crashes;
- with the large traffic volume, it is more likely to observe locations with pedestrian crashes (all severity categories) than locations with no crashes.

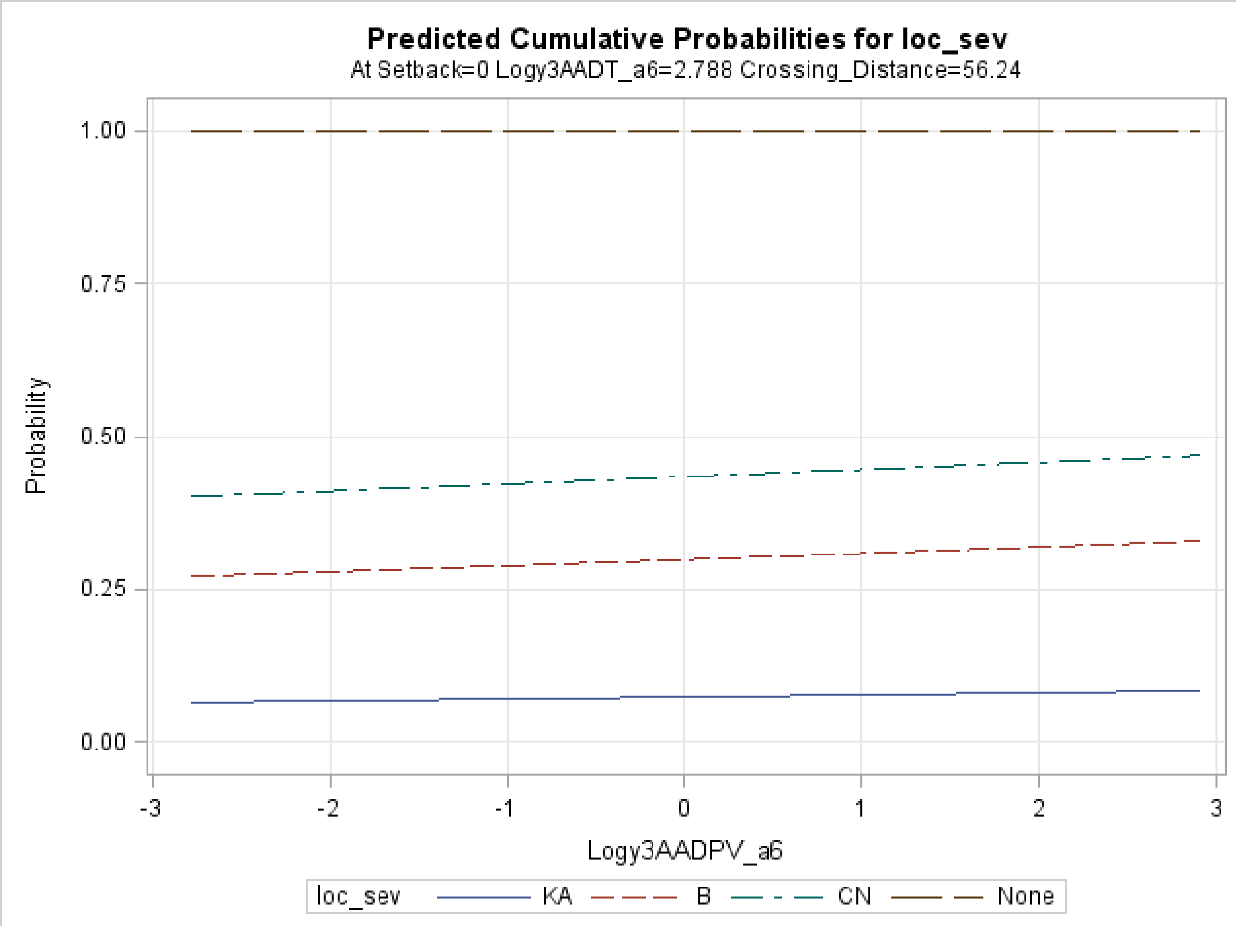

Figure 2 Predicted Cumulative Probabilities by AADPV for the Highest Crash Severity at a Location

On the other hand, we see little effect for pedestrian volume on the probability of higher severity for pedestrian crashes. Here Building Setback is held to be small (Setback=0), Crossing Distance to be 56.24 and $Log\left(\frac{3yearAADT}{10^6}\right)$ to be 2.788.

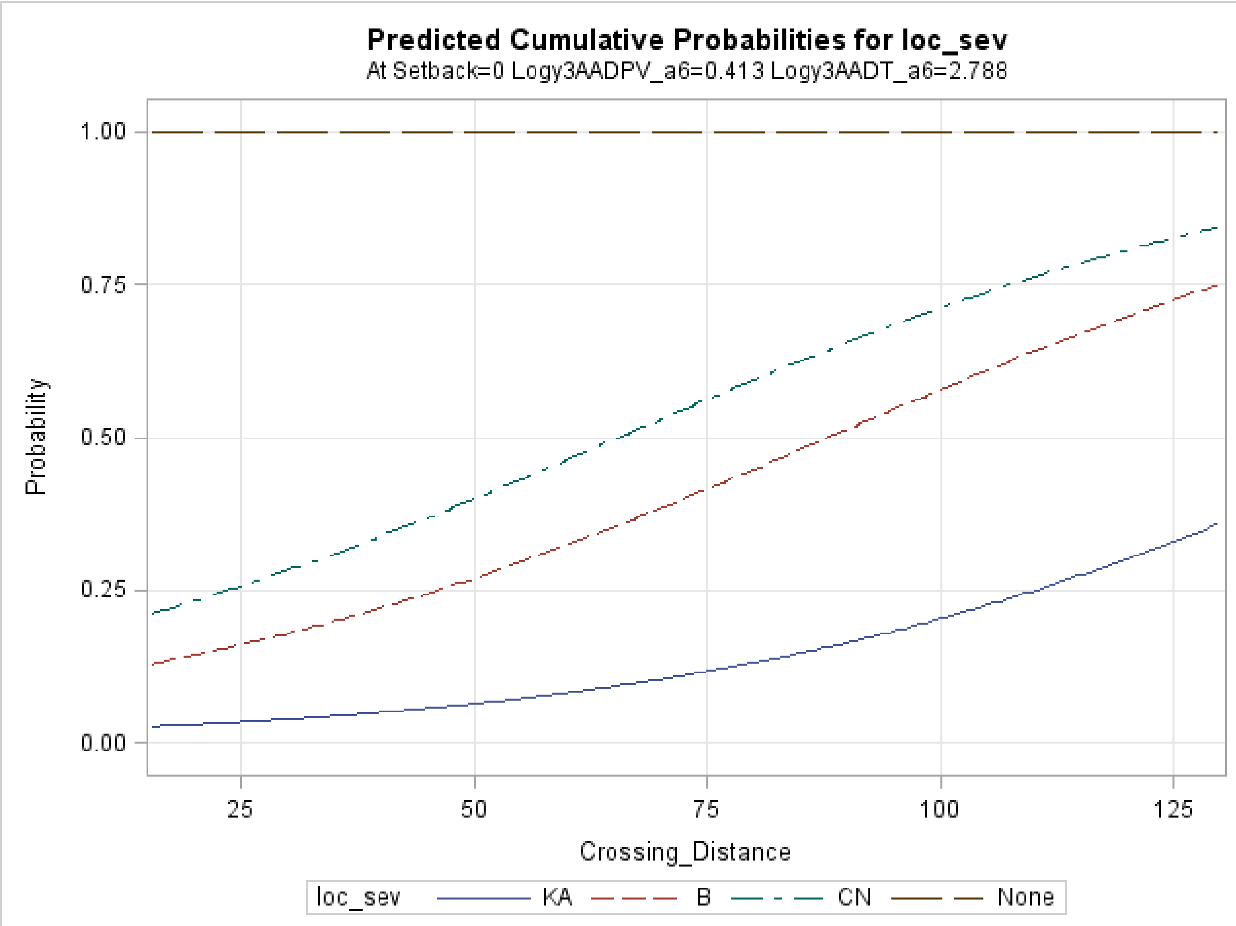

Figure 3 Predicted Cumulative Probabilities by Crossing Distance for the Highest Crash Severity at a Location

As crossing distance increases we observe an increase in probability for the location to be in the higher severity categories. Holding Building Setback to be small (Setback=0), $Log\left(\frac{3yearAADPV}{10^6}\right)$ to be 0.413 and $Log\left(\frac{3yearAADT}{10^6}\right)$ to be 2.788, we can conclude the following:

- when the Crossing Distance is small, it is more likely to observe locations with no pedestrian crashes (None severity category) than locations with crashes;
- with the increase of Crossing Distance we can notice significant increase in probability for locations to have pedestrian crashes (for all three highest severity categories KA, B and CN) and decreasing probability to observe locations with no crashes;
- with the long Crossing Distance, it is more likely to observe locations with pedestrian crashes (all severity categories) than locations with no crashes.

4.0 CONCLUSIONS

This study focused on estimating and evaluating models of conflicts and crash count to investigate which road characteristics and exposure measures are associated with the safety of pedestrian crossing at road intersections and mid-blocks. From the analysis results we found that minor and serious conflicts were marginally significant for predicting total pedestrian crashes along with crossing distance and building setback. This suggests that these conflicts can be a good surrogate for crashes in analyzing pedestrian safety. Observing conflicts over a longer time period would likely increase the significance of this relationship.

The positive parameter estimate for crossing distance in the crash count models means longer crossing distance increases the occurrence of pedestrian crashes. To reduce pedestrian crashes at such locations, it is suggested to take measures to reduce the crossing distance perhaps with curb extensions, reducing curb return radii or installing pedestrian refuge islands specifically designed to accommodate pedestrians.

It was originally expected that large setbacks which allow drivers to travel faster would be associated with more crashes, but model results suggest otherwise as setback coefficients were found to be negative in count as well as severity models. This may actually not be surprising. Locations with small setback are all in downtown type areas where the pedestrian volumes are higher and the general complexity also is higher such that drivers are more alert and proceeding slower with frequent stops to let passengers off, etc. So, not only may setback act as an indicator of pedestrian volume, but there may also be causal relationships that are not directly 'caused' by the setback but correlate with it.

It was noted that pedestrian volume was not significant in any of the count models, and locations with small setback are all in downtown type areas. It may very well be that setback is acting as a surrogate for the actual pedestrian counts. We would expect that more significant results could be experienced by observing pedestrian and vehicle volumes and conflicts over longer periods of time. Sixteen locations in our study were observed for less than three hours, and none for more than six hours. Further research could be aimed at identifying a minimum length of time for accurate estimation of pedestrian volume and conflicts to relate to crashes. The authors are about to undertake a follow up to this study in which we will investigate this.

5.0 REFERENCES

Garber, N.J., Lienau, T.K., 1996. "Traffic and Highway Geometric Characteristics Associated with Pedestrian Crashes in Virginia". Report VTRC 96-R29. Virginia Transportation Research Council, March 1996.

Hansen, G, Garrick, N., Ivan, J. and T. Jonsson. 20007. "Variation in Free Flow Speed due to Roadway Type and Roadside Environment". Presented at 87th Annual Meeting of the Transportation Research Board, Washington, D.C., Paper No. 07-3136, Jan.

Hyden, C. 1987. "The Development of a Method for Traffic Safety Evaluation: The Swedish Traffic Conflicts Technique". Department of Traffic Planning and Engineering. Lund University, Lund, Sweden.

National Highway Traffic Safety Administration (NHTSA), 2008. National Pedestrian Crash Report, http://permanent.access.gpo.gov/lps98115/810968.pdf; Accessed June 2012.

Pasanen, E., Salmivaara, H., 1993. "Driving speeds and pedestrian safety in the City of Helsinki". *Traffic Engineering and Control* 34 (6), 308-310.

Rahman, M.M., Kattan, L., and Tay, R. 2011. "Injury Risk in Collisions Involving Buses in Alberta, Canada" *Transportation Research Record: Journal of the Transportation Research Board*, No.2265, Transportation Research Board of the National Academies, Washington, D.C., pp. 13-26.

SAS Institute Inc.2002. Version 9 of the SAS System for Windows. Cary, N.C.

Usman, T., Fu, L., and Mirando-Morceno, L.2011. "Accident Prediction Models for Winter Road Safety: Does Temporal Aggregation of Data Matter?" *Transportation Research Record: Journal of the Transportation Research Board*, No.2237, Transportation Research Board of the National Academies, Washington, D.C., pp. 144-151.

APPENDIX A – DATA SET

The following pages list the data collected for the analysis. Following is a list of abbreviations and data dictionary to aid in reading the table. All terms are used as defined in the text of the report.

U = undisturbed passages
P = potential conflicts (number of pedestrians)
P-E = potential conflict events (can be more than one pedestrian per event)
M = minor conflicts (number of pedestrians)
M-E = minor conflict events (can be more than one pedestrian per event)
S = serious conflicts (number of pedestrians)
S-E = serious conflict events (can be more than one pedestrian per event)
Setback: 0 = small, 1 = medium or large
Type: 4 = four-leg intersection, 3 = three-leg intersection, 1 = mid-block crossing
Traffic Control: 0 = no signal; 1 = signal
Crossing Distance is in feet
Medians/Islands: 0 = no median or island; 1 = median or island present
Max lanes is total in both directions
On-Street parking: 0 = no on-street parking; 1 = on-street parking present
Vc = as defined in the text
Vo = as defined in the text
K = fatal crash
A = crash with life-threatening injury
B = crash with visible, non-life-threatening injury
C = crash with non-visible injury
N = crash with no injury

APPENDIX B – STATISTICS

	Location Information			Observed Event Counts							
ID	Street 1	Street 2	Town	U	P	P-E	M	M-E	S	S-E	Hours Observed
1	Route 195	Mansfield Road	Storrs	950	45	37	10	8	2	2	6
2	Glenbrook Road	Jorgenson	Storrs	2804	18	11	7	6	0	0	6
3	North Hillside Road	Alumni Drive	Storrs	891	99	75	6	6	0	0	6
4	Hillside Road	Stadium rd	Storrs	2317	6	5	2	1	0	0	4
5	Route 195	Bolton Road	Storrs	771	29	24	5	5	0	0	5
6	North Eagleville Road	Northwest Dormitories	Storrs	1773	225	121	10	7	1	1	6
7	Hillside Road	SRF	Storrs	112	12	11	0	0	0	0	3.5
8	Glenbrook Road	Liberal Arts Building	Storrs	549	37	21	7	6	0	0	5
9	North Eagleville Road	North Dormities	Storrs	810	48	27	8	5	0	0	3.5
10	Hillside Road	McMahon Dorms	Storrs	690	32	24	3	3	0	0	6
11	Main street	Market Street	Norwich	245	39	29	12	11	1	1	6
12	Main street	Chelsea Harbor Drive	Norwich	421	110	85	9	9	0	0	6
13	Water street	Chelsea Harbor Drive	Norwich	180	36	36	19	19	0	0	6
14	Route 74	Elm St	Rockville	77	8	7	0	0	0	0	4
15	Route 74	Park Street	Rockville	135	7	7	0	0	0	0	4
16	Route 32	Windham St	Willimantic	121	17	15	1	1	0	0	4
17	Route 66	Bridge Street	Willimantic	162	6	5	0	0	1	1	3
18	route 66	high street	willimantic	145	20	16	3	3	0	0	5
19	Route 66	North Street	Willimantic	90	8	6	4	3	1	1	4
20	Route 66	Walnut Street	Willimantic	145	8	6	2	2	0	0	3
21	Gilbert Road	By South C	Storrs	592	8	8	1	1	0	0	2.5
22	North Eagleville Road	Hillel/Church Area	Storrs	912	10	6	0	0	1	1	3
23	Route 150	Church st	Wallingford	308	3	3	0	0	0	0	6
24	Route 150	South Whittlesey Ave	Wallingford	140	2	2	3	1	0	0	6
25	Route 150	Route 5	Wallingford	125	14	12	0		1	1	6
26	Route 150	South Orchard Street	Wallingford	149	0	0	1	0	0	0	6
27	Farmington Ave	Dale Street	West Hartford	598	27	20	3	3	0	0	6
28	Farmington Ave	Walden Street	West Hartford	257	18	13	7	7	1	1	6
29	Farmingon Ave	South Main Street	West Hartford	1065	27	22	11	5	0	0	6
30	Rte-10	whitney	Hamden	105	5	5	3	2	0	0	5

	Location Information			Observed Event Counts							
ID	Street 1	Street 2	Town	U	P	P-E	M	M-E	S	S-E	Hours Observed
31	Route 10	School Street	Hamden	272	11	9	2	2	0	0	5
32	Route 72	Main St	Bristol	34	1	1	0	0	0	0	5
33	Route 72	orchard st	Bristol	85	14	9	5	3	0	0	4
34	Route 641	Broad Street	New London	80	14	14	1	1	0	0	3
35	Route 641	Jay Street	New London	86	12	12	8	8	1	1	3
36	route 641	state street	New London	93	20	15	0	0	0	0	3
37	Route 66	Liberty St	Middletown	472	22	20	3	3	0	0	5
38	Washington Street	main st	Middletown	527	20	16	5	4	0	0	6
39	Route 83	Birch St	Manchester	145	11	8	2	2	0	0	5.5
40	route 83	oak street	Manchester	310	7	6	1	1	0	0	6
41	Route 83	Maple st	Manchester	190	4	3	0	0	0	0	6
42	Route 83	Pearl Street	Manchester	211	24	18	2	1	0	0	6
43	Rte-115	Water St	Ansonia	179	8	6	2	2	0	0	3.75
44	State Street	Washington St	New London	147	2	2	0	0	0	0	1.25
45	State street	union street	New london	195	9	9	3	3	1	1	1.5
46	Golden St	Green Street	New London	126	4	3	0	0	0	0	2.5
47	Golden St	Bank Street	New London	56	3	2	0	0	0	0	3
48	Route 195	North Eagleville	Storrs	183	7	6	0	0	0	0	1
49	Route 195	Gurleyville	Storrs	356	11	8	0		0		2.5
50	Route 195	Willowbrook	Storrs	20	7	7	10	10	0	0	6
51	Main Street	Chelsea Harbor Drive	Norwich	261	51	35	21	19	0	0	6
52	Stadium rd	next to co-op	storrs	146	12	12	1	1	0	0	4
53	route 72	tulip street	Bristol	201	2	1	0	0	0	0	5
54	State Street	Eugine Oniell blvd	New London	121	1	1	1	1	0	0	1.5
55	route 83	park street	Manchester	238	1	1	0	0	0	0	6
56	bedford	Broad Street	Stamford	1871	59	36	48	31	6	3	4
57	gold street	Main St	Hartford	1814	18	12	11	8	1	1	5
58	Main street	Asylum ave	Hartford	1857	26	22	2	2	0	0	5
59	Prospect street	antheneum square	Hartford	254	7	5	4	2	0	0	2
60	Main street	Pearl Street	Hartford	2365	21	13	3	2	0	0	5

	Location Information			Observed Event Counts							
ID	Street 1	Street 2	Town	U	P	P-E	M	M-E	S	S-E	Hours Observed
61	asylum ave	Ann st	Hartford	480	8	7	3	1	0	0	3.25
62	arch st.	Main St	Hartford	506	21	14	3	3	0	0	2
63	albany ave	vine st	Hartford	114	9	8	11	10	0	0	1.5
64	Main street	Elm st	Hartford	1212	20	15	9	7	1	1	5
65	Pearl st	Trumbull st	Hartford	651	37	22	15	13	1	1	3
66	columbus blvd	main st	new britain	222	14	12	10	8	0	0	3
67	high st	W.main st	new britain	107	1	1	4	3	0	0	3
68	E.Main st	Myrtle	new britain	144	1	1	2	2	0	0	3
69	lasalle road	farmington ave	West Hartford	221	8	5	3	3	0	0	4
70	W Main street	Washington St	new britain	267	9	8	6	5	0	0	4.5
71	high st	Broad Street	new britain	305	20	17	1	1	0	0	4.5
72	Main street	crescent st	Middletown	76	3	3	2	2	0	0	3
73	union st	Main St	Middletown	139	6	5	2	2	0	0	3
74	william st	Main St	Middletown	233	3	3	0	0	0	0	3
75	ellsworth	s.main st	West Hartford	36	2	2	0	0	0	0	5
76	Farmington Ave	trout brooke	West Hartford	108	3	3	3	2	0	0	4.5
77	franklin st	Broad Street	Stamford	220	32	27	14	14	0	0	3
78	washington blvd	Broad Street	Stamford	586	32	26	5	5	0	0	3.5
79	summer str	Broad Street	Stamford	324	16	13	7	5	2	1	2
80	Temple	Elm St	New haven	569	20	18	7	6	0	0	3
81	Temple	Grove st	New haven	694	21	19	3	1	0	0	3
82	Washington blvd	tresser blvd	Stamford	717	20	16	2	1	0	0	4
83	Tresser	Atlantic	Stamford	640	25	20	6	4	0	0	3.5
84	asylum st	Trumbull st	Hartford	1238	16	12	0	0	1	1	3
85	Elm st	York st	New haven	1269	17	12	15	10	1	1	2
86	grove st.	college st	New haven	987	22	16	16	14	0	0	3
87	college st	crown st	New haven	510	7	5	1	1	0	0	3
88	crown st	york st	New haven	808	8	8	1	1	0	0	3
89	college st	Elm st	New haven	739	7	6	6	5	0	0	2
90	grove st.	whitney	new haven	690	9	7	3	2	0	0	2

	Location Information			Observed Event Counts							
ID	Street 1	Street 2	Town	U	P	P-E	M	M-E	S	S-E	Hours Observed
91	orange st	crown st	New haven	332	8	8	0	0	0	0	3
92	orange st	Elm St	New haven	430	20	20	3	0	0	0	3
93	N main st	E main st	waterbury	3504	45	20	26	14	1	1	5
94	Washington blvd	state street	stamford	368	15	12	5	5	0	0	2
95	E main st	N. Elm st	waterbury	519	6	4	3	2	0	0	4
96	union st	elm st	waterbury	179	2	2	2	1	0	0	5
97	bank st	grand st	waterbury	908	9	5	4	3	1	1	5
98	levenworth st	grand st	waterbury	625	9	5	4	3	0	0	5
99	State Street	segment of the road	stamford	564	4	4	0	0	0	0	2
100	Elm st	church st	New haven	1570	29	19	30	21	0	0	3

	Observation Conditions			Site Characteristics							
ID	Date	Day of Week	Weather	Setback	Type	Traffic Control	Speed limit	Crossing Distance	Medians/Islands	Max Lanes	On-street Parking
1	7-Sep	Wednesday	Light Rain	1	4	1	25	68	1	4	0
2	8-Sep	Thursday	Light Rain	0	3	0	25	40	0	2	0
3	7-Sep	Wednesday	Light Rain	1	4	0	25	50	0	2	0
4	16-Sep	Friday	Sunny	0	4	0	25	38	0	2	1
5	9-Sep	Friday	Sunny	1	3	1	30	55	0	3	0
6	16-Sep	Friday	sunny	1	1	1	25	50	0	3	0
7	10-Sep	Saturday		1	1	0	25	30	0	2	0
8	9-Sep	Friday	Sunny	1	3	0	25	25	0	2	0
9	13-Sep	Tuesday	Sunny	1	1	1	25	45	0	2	1
10	16-Sep	Friday	Sunny, Cold	1	1	0	25	29	0	2	0
11	21-Sep	Thursday	Overcast	0	3	0	25	65	0	2	1
12	21-Sep	Wednesday	sun	0	4	1	30	72	0	3	1
13	21-Sep	Wednesday	Sunny	0	4	1	25	30	0	2	0
14	17-Sep	Saturday	Sunny	0	4	1	25	80	0	3	0
15	17-Sep	Saturday	sun	0	3	1	30	75	0	5	0
16	1-Oct	Saturday		1	3	1	25	47	0	3	0
17	4-Oct	Tuesday	cloudy	1	3	1	25	65	0	4	0
18	7-Oct	Friday	sunny	0	3	1	30	45	0	2	1
19	1-Oct	Saturday	sun	0	3	1	30	55	0	2	1
20	27-Sep	Tuesday	Sunny	0	3	1	30	40	0	2	1
21	23-Sep	Friday	Cloudy/Rain	1	1	0	25	30	0	2	0
22	23-Sep	Friday	Overcast, Humid	1	3	0	25	40	0	2	0
23	30-Sep	Friday	Sunny	1	4	1	25	68	1	3	1
24	30-Sep	Friday	fair	0	4	1	30	50	0	2	1
25	30-Sep	Friday	sunny	1	3	1	30	55	1	4	1
26	30-Sep	Friday	sun	0	4	1	30	50	0	2	1
27	28-Sep	Wednesday	sunny	0	4	1	30	52	0	4	1
28	28-Sep	Wednesday	sunny	1	3	1	30	50	0	2	1
29	8-Oct	Saturday	sunny	0	4	1	25	120	1	5	1
30	6-Oct	Thursday	Sunny Cold	0	4	1	25	100	0	5	1

	Observation Conditions			Site Characteristics							
ID	Date	Day of Week	Weather	Setback	Type	Traffic Control	Speed limit	Crossing Distance	Medians/Isl ands	Max Lanes	On-street Parking
31	6-Oct	Thursday	sunny	0	4	1	30	47	0	4	0
32	7-Oct	Friday	Sunny	0	4	1	25	80	0	5	0
33	7-Oct	Friday	sunny	1	3	0	25	35	0	2	0
34	12-Oct	Wednesday	Cloudy	0	4	1	30	65	1	4	0
35	12-Oct	Wednesday	Cloudy	0	3	0	30	65	0	3	1
36	21-Oct	Friday	cloudy	0	3	1	30	70	0	4	0
37	13-Oct	Thursday	Cloudy Cold	0	3	1	25	65	0	4	1
38	13-Oct	Thursday	Light Rain	0	3	1	30	80	0	4	1
39	21-Oct	friday	cloudy cold	0	3	0	25	55	0	4	1
40	21-Oct	Friday	sun	0	3	1	25	50	0	4	1
41	15-Oct	Saturday	cloudy cold	0	3	1	25	55	0	4	1
42	21-Oct	Friday	Sunny	0	3	1	25	50	0	4	1
43	20-Oct	Thursday	Partly Cloudy	0	3	0	25	45	0	2	1
44	4-Nov	Friday	Sunny	0	3	0	25	40	0	2	1
45	5-Nov	friday	sunny	0	3	1	25	40	0	2	1
46	4-Nov	Friday	sunny	0	4	0	25	25	0	2	0
47	5-Nov	Saturday	cloudy cold	0	3	0	25	40	0	3	1
48	26-Oct	Wednesday		1	3	1	30	45	1	3	0
49	26-Oct	Wednesday		1	3	1	30	50	0	4	0
50	26-Oct	Wednesday	Cloudy/Rain	1	1	0	30	40	0	2	0
51	21-Sep	Wednesday	Sunny	0	4	1	30	70	0	4	0
52	23-Sep	Friday	cloudy/drizzle	0	1	0	25	40	0	2	1
53	7-Oct	Friday	sunny	1	4	1	25	25	0	2	0
54	4-Nov	Friday	sunny	0	4	1	25	35	0	2	1
55	21-Oct	Friday	sunny	0	4	1	25	60	0	4	1
56	12-Mar	Monday	sunny	0	4	1	25	75	1	5	0
57	23-Mar	Friday	sunny	0	4	1	25	83	0	5	0
58	23-Mar	Friday	sunny	0	3	1	25	60	0	4	0
59	29-Mar	Thursday	sunny	1	3	1	25	50	0	2	1
60	23-Mar	Friday	sunny	0	4	1	25	85	0	6	0

	Observation Conditions			Site Characteristics							
ID	Date	Day of Week	Weather	Setback	Type	Traffic Control	Speed limit	Crossing Distance	Medians/Islands	Max Lanes	On-street Parking
61	30-Mar	Friday	sunny	0	4	1	25	45	0	3	1
62	29-Mar	Thursday	sunny	0	4	1	30	75	0	4	1
63	22-Mar	Thursday	sunny	1	4	1	30	80	0	3	0
64	29-Mar	Thursday	cloudy	0	4	1	30	65	0	4	1
65	30-Mar	Friday	sunny	0	4	1	25	50	1	4	1
66	6-Apr	Friday	sunny	0	4	1	25	55	0	4	1
67	6-Apr	Friday	sunny	1	4	1	25	50	0	2	1
68	6-Apr	Friday	sunny	1	4	1	30	100	1	6	0
69	12-Apr	Thursday	sunny	0	3	1	25	50	0	4	1
70	5-Apr	Thursday	sunny	0	3	1	25	40	0	3	1
71	5-Apr	Thursday	sunny	0	4	1	25	40	0	2	1
72	13-Apr	Friday	sunny	0	4	1	25	50	0	3	1
73	13-Apr	Friday	sunny	0	4	1	25	75	0	5	1
74	13-Apr	Friday	sunny	0	4	1	25	75	0	4	1
75	26-Apr	Thursday	sunny	1	3	1	25	55	0	5	0
76	26-Apr	Thursday	sunny	1	4	1	35	80	0	5	0
77	13-Mar	Tuesday	sunny	0	3	1	25	60	0	5	0
78	15-Mar	Thursday	cloudy	0	4	1	25	80	1	6	0
79	14-Mar	Wednesday	sunny	0	4	1	25	60	1	4	1
80	17-May	Thursday	sunny	1	4	1	25	60	0	4	1
81	16-May	Wednesday	sunny	0	4	1	25	50	0	3	1
82	11-May	Friday	sunny	0	4	1	30	80	1	6	0
83	14-May	Monday	sunny	0	4	1	25	80	1	5	0
84	30-Mar	Friday	sunny	0	4	1	25	65	1	5	1
85	11-May	Thursday	sunny	0	4	1	25	45	0	3	1
86	16-May	Wednesday	sunny	0	4	1	25	75	0	3	1
87	16-May	Wednesday	sunny	0	4	1	25	45	0	2	1
88	14-May	Monday	sunny	0	4	1	25	40	0	2	1
89	17-May	Thursday	sunnt	0	4	1	25	55	0	4	1
90	16-May	Wednesday	sunny	0	4	1	25	50	0	4	1

	Observation Conditions			Site Characteristics							
ID	Date	Day of Week	Weather	Setback	Type	Traffic Control	Speed limit	Crossing Distance	Medians/Islands	Max Lanes	On-street Parking
91	18-May	Friday	sunny	0	4	1	25	35	0	2	1
92	18-May	Friday	sunny	0	4	1	25	50	0	3	1
93	9-May	Wednesday	sunny	0	4	1	25	70	0	5	1
94	14-May	Monday	sunny	1	4	1	30	55	0	5	0
95	10-May	Thursday	sunny	0	4	1	25	60	0	4	1
96	11-May	Friday	sunny	0	4	1	25	70	0	4	0
97	12-May	Saturday	sunny	0	4	1	25	60	0	4	1
98	16-May	Wednesday	sunny	0	4	1	25	50	0	2	1
99	14-May	Monday	sunny	1	1	1	25	40	0	3	0
100	18-May	Friday	sunny	0	4	1	25	60	0	4	1

	Traffic Data								Crashes				
ID	AADT	Vc	ADT	Month and Day	Year	Count time	Expansion factor	Vo	K	A	B	C	N
1	12800	4900	13785	Sep,Tue	2008		0.93	4908					
2	2900	800	3085				0.93	791					
3	8600	2846	9214	Sep,Mon	2008	8.40-11.30,1.15-3.45	0.93	2836					
4	8600	6683	9214	Sep,Mon	2008	9-12.00,2-3.00	0.87	6229					
5	12800	4174	13785	Sep,Mon	2008	10-12,1-4	0.87	3911					
6	8600	3501	9214	Sep,Mon	2008	8.20-11.20,2.20-5.20	0.87	3263					
7	8600	1694	9214	Sep,Mon	2008	8.35-12	1.09	1978					
8	8300	2658	8887	Sep,Wed	2008	12-4.50	0.87	2476					
9	8600	1684	9214	Sep,Mon	2008	11-2.30	0.93	1678					
10	8600	3752	9214	Sep,Mon	2008	8-11.3,2-5	0.87	3497					
11	12700	4992	13409	Apr,Mon	2008	9-3.00	0.93	4902					
12	16500	6311	17333	Apr,Mon	2008	9.20-3.45	0.93	6166					
13	20700	8150	21744	Apr,Mon	2008		0.93	7962					
14	12000	3191	13080	May,Mon	2008	10-1.55	1.09	3791					
15	10800	2949	11788	May,Mon	2008	10-2.00	0.86	2768			1		
16	22600	6249	24021	Feb,Thu	2010	10-2.00	1.05	6974					
17	22600	5085	27211	Feb,Thur	2010	12.30-3.10	0.94	5755					
18	24600	9690	25642	Feb,Thu	2010	12.45-3.45,12.30-2.30	0.87	8787					
19	14600	4250	15545	Feb,Thur	2010	9.55-2.00	1.05	4751			1		
20	14600	3411	15545	Feb,Thu	2010	12.30-3.30	0.93	3378					
21	3000	496	3315	Sep, Wed	2008		0.87	477					
22	8300	1145	8887	Sep,Wed	2008	9.15-11.40	0.87	1067					
23	16900	5956	18421	Sep,Wed	2010		0.87	5648					
24	10400	4183	11204	Oct,Wed	2010	9.10-12.25,1.30-3.55	0.87	3921					
25	17700	7065	19032	Oct,Wed	2010	9.35-12.25,1.30-4.05	0.87	6609					
26	10400	4198	11204	Oct,Wed	2010	9.15-12.30, 1.30-4	0.87	3935					
27	21600	21600	8422	Apr,may,Mon	2009	9.3-12.05,1.15-4.10	0.93	7832					
28	18400	6349	20337	Apr,Ma,Mon	2009	9.34-12.00,1.24-4.00	0.93	6526					
29	32800	13026	35645	Apr,May,Mon	2009	10-4.00	1.05	14864			2		1
30	24500	8076	26373	Aug,Mon	2009		0.94	8172		1	1	1	1

	Traffic Data								Crashes				
ID	AADT	Vc	ADT	Month and Day	Year	Count time	Expansion factor	Vo	K	A	B	C	N
31	25700	9309	27542	Aug,Wed	2009	10.15-3.30	0.94	9378				1	
32	14500	5174	15485	Aug,Nov,Mon	2009		0.87	4807		1			
33	12300	3121	13191	Sep,Wed	2009	9.30-12,1.20-3.00	0.87	2912					
34	15800	3168	16833	Sep,Wed	2008	9.35-12.40	0.94	3173					
35	15200	2808	16516	Sep,Wed	2008		0.94	2868			1		
36	12500	2946	13578	Sep,Wed	2008	1-400	0.87	2784		1	2		
37	20600	6748	21905	Apr,Mon	2010	9.50-2.50	0.94	6745			2		
38	32400	13150	35381	May.Mon	2010	10-4.00	0.94	13498					
39	19200	6088	18808	Feb,Wed	2009	9-12,12.50-3.20	0.87	5188					1
40	19200	7119	18808	Feb,Wed	2009	8.50-315	0.87	6067					
41	19200	6767	18808	Feb,Wed	2009	9.30-3.30	1.05	6960	1				
42	17200	5806	16895	Feb,Wed	2009	8.45-12,12.50-3.20	1.05	5988					
43	5900	1541	6244	Oct,Mon	2009	10.45-12.30,1-3	0.94	1533					
44	6700	673	7201	Sep,wed	2008	1.45-3.00	0.95	687					
45	3400	378	3666	Sep, Wed	2008	1.45-3.00	0.96	391					
46	4900	918	5300	Sep,Mon	2008	1.15-3.45	0.89	884					
47	10800	2126	11575	Sep,Wed	2008	10.52-1.52	1.11	2529					
48	28500	1733	30614	Sep,Wed	2008	10.35-11.35	0.94	1750					
49	14200	2048	15253	Sep,Wed	2008	9.20-11.45	0.94	2068					
50	12700	4872	13671	Sep,wed	2008		0.94	4930					
51	12700	5073	13409	Apr,Mon	2008	9.20-3.20	0.93	4981					
52	3100	774	3315	Sep,Wed	2008	9.00-1.00	0.87	720					
53	9200	2627	9742	Aug,Mon	2009	9.20-12,1.20-3.20	0.78	2170					
54	12900	1086	13839	Sep,Wed	2008	1.55-3.00	0.89	1037					
55	19200	6858	18808	Feb,Thu	2009	9-12,1-4	0.87	5845					
56	30000	7985	32253	sep,Tue	2008	10.20-1.15,1.40-2.55	0.97	8327		1			
57	22400	7179	23823	Apr,Ma,Wed	2009	9-11.30,12.40-3.10	0.9	6872			1	3	
58	30800	9387	32560	Apr,Mon	2009	9.10-11.30,12.35-3.10	0.9	8931				1	
59	9500	1141	10416	Apr,May,Wed	2009	12-2.00	0.97	1213					
60	22300	5118	23660	Apr,Wed	2009	9.05-11.30,12.40-3.10	0.9	4887				3	

	Traffic Data								Crashes				
ID	AADT	Vc	ADT	Month and Day	Year	Count time	Expansion factor	Vo	K	A	B	C	N
61	16200	2807	17425	Apr,May,Mon	2009	9.00-12.15	0.90	2717			2		
62	20200	2760	20907	Apr,Ma,Wed	2009	8.40-9.40	0.97	2771					
63	23200	1849	24726	Apr,Mon	2009	9.00-10.20	0.97	1912					
64	18600	6519	19803	Ap,Ma,Wed	2009	8.45-1.50	0.97	6732					
65	11900	2233	12951	May,Mon	2009	9.10-12.12	0.9	2187					
66	18200	3700	19283	Nov,Thur	2009	9.00-12.00	0.88	3450				1	
67	13300	2700	13926	Nov,Mon	2009	9.00-1200	0.88	2488					
68	27000	5375	28428	Nov,Thur	2009	8.55-12.00	0.88	4980					
69	21600	5660	23789	May,Apr,Mon	2009	9.00-1.00	0.94	5860			1		3
70	8300	2330	8858	Oct,Nov, thu	2009	9.00-1.30	0.94	2337				1	
71	9200	2956	9760	Oct,Nov,Thu	2009	9.00-1.30	0.94	2948					
72	11700	2532	12467	Apr,Wed	2010	9.00-12.00	0.88	2374					
73	26300	5523	26300	Apr,Wed	2010	8.50-11.50	0.88	4860					
74	10500	2283	10500	Apr, Wed	2010	9.00-12.00	0.88	2009				1	
75	21400	7442	22700	Apr,Wed	2009	9.00-2.00	0.94	7420					
76	38700	11010	42040	M,Ap Wed	2009	9-1.30	0.94	11243					
77	19600	4057	21013	Sep,Wed	2008	11.45-1.00,1.10-2.55	0.97	4219		2			
78	44600	9456	47873	Sep, Tue	2008	10.00-11.30,12.30-2.30	0.97	9845					
79	32200	4354	34589	Mar,Tue	2008	8.50-10.50	0.97	4537			3		1
80	21000	3971	22047	Sep, Mon	2006	9.50-12.50	0.9	3752			1		
81	12100	2787	12958	Mar, Wed	2009	12.40-3.45	0.9	2686			1		
82	47100	12162	50920	Sep,Teu	2008	12.00-4.00	0.85	11176		1	1	3	
83	43500	9508	46364	Aug,Mon	2008	11.30-3.00	0.9	9121			2	1	
84	20200	3485	21851	Apr, Mon	2009	9.00-12	0.9	3393					
85	22100	2574	22751	Mar, Wed	2009	10.15-12.15	0.9	2385			1		
86	13500	2983	13950	Mar,Wed	2009	12.40-3.40	0.9	2774					
87	10400	1829	10701	Mar,Wed	2009	12.00-3.00	0.9	1694		1			
88	11100	1758	11473	Mar, Wed	2009	9.00-12.00	0.9	1635					
89	22400	2679	23039	Mar, Wed	2009	10.00-12.00	0.9	2480			1		
90	16000	2185	16581	Mar. Wed	2009	12.40-2.40	0.9	2038			2		

	Traffic Data								Crashes				
ID	AADT	Vc	ADT	Month and Day	Year	Count time	Expansion factor	Vo	K	A	B	C	N
91	7300	1066	7549	Mar. Wed	2009	9.15-12.15	0.85	937					
92	18300	3260	18827	Mar,Wed	2009	10-1.00	0.85	2851					
93	14200	5202	15507	May, Mon	2008	9.00-2.00	0.9	5113			2	1	
94	22900	3820	24676	Sep, Mon	2008	7.30-9.30	0.9	3705					
95	19900	5686	21024	Apr, Mon	2008	8.00-1.00	0.9	5406			1		
96	18100	5995	19041	Apr, Thu	2008	8.30-1.30	0.85	5361			1		
97	19900	5854	21222	Apr, Wed	2008	8.00-1.00	1.04	6493				1	
98	11200	4485	11830	Apr, Wed	2008	8.35-1.35	0.9	4264					
99	8900	757	9641	Aug, Mon	2008	11-1.00	0.9	738					
100	24500	4467	25228	Mar,Wed	2009	9.50-12.50	0.85	3910				1	