7-1-2016

Investigating Pedestrian Crash Risk in Albuquerque, New Mexico

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INVESTIGATING PEDESTRIAN CRASH RISK IN ALBUQUERQUE, NEW MEXICO

By

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B.Tech, Acharya Nagarjuna University, 2013

A Thesis

Submitted in Partial fulfillment of the

Requirements for the Degree of

Master of Science

Civil Engineering

Department of Civil Engineering

The University of New Mexico

July 2016

ACKNOWLEDGEMENTS

I would like to take this opportunity to thank my family for giving me the confidence to make decisions and be there in times of need. Their love and support all throughout has been unconditional and I couldn't be more grateful.

I would like to thank my advisor Dr. Gregory Rowangould, for his valuable support and expertise which helped me in completing my degree.

The thesis wouldn't have been possible without the help and encouragement from all my fellow teammates and friends at the university. In particular, I would like to mention Research assistants Mohammed Tayarani, Amir Poorfakhraei, Mahnaz Nadafian and fellow schoolmate Saydra Alvarez Moreno for all the times they've given their opinions and views without a second thought. I would also like to thank my dear friend Pravallika Devineni for having been behind me and making sure I was heading in the right direction.

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Abstract

Walking, being an important and basic form of transportation is crucial in everyday day life. Seen as an alternative to traditional modes of transport, walking is seen as an effective way to reduce dependence on fossil fuels and personal transport. Its health benefits and positive changes to the community are seen as incentives to promote walking as an effective mode of transport.

As such, pedestrian safety is of utmost importance given the increase in pedestrian numbers and correspondingly, pedestrian crashes. The thesis studies pedestrian crash data and computes pedestrian crash rates for different intersections in Albuquerque, New Mexico. Crash rates help to identify intersections deemed to be unsafe for pedestrians and therefore could be used for additional analysis. Additionally, the thesis investigates different demographic and intersection characteristics responsible for pedestrian crashes and their association with pedestrian crash rates. To achieve this, crash risks along with data from the United States Census were employed in statistical models so as to observe associations between the variables used.

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Chapter 1

INTRODUCTION

As one of the most fundamental modes of transportation, walking is very important in everyday life. A small part of everyday work is accomplished by walking and walking is sometimes used as a mode of transportation such as walking to the grocery store or work. Activities that involve leaving the house bring pedestrians into direct contact with vehicles and streets. As such, pedestrians are exposed to a wide range of issues when it comes to safety, mobility and accessibility. Pedestrian safety is one of the most important transportation planning issues. There were 4,884 pedestrian fatalities during 2014 in the United States representing 15% of all traffic related fatalities. In New Mexico there were 74 pedestrian fatalities during 2014 representing 19% of all traffic related fatalities in the state (National Highway Traffic Safety Administration, 2013).

Crash rates (defined as crashes per 100,000 persons) for fatal pedestrian involved traffic accidents and non-pedestrian involved traffic accidents in the United States have been relatively constant over the past five years (Figure 1, Figure 2). In contrast, fatal pedestrian crash rates in New Mexico are increasing. New Mexico's fatal pedestrian and other vehicular crash rates are also much higher than comparable national rates. In fact, New Mexico's pedestrian crash rate was higher than any other state's in 2013 (Figure 3). Furthermore, the pedestrian crash rate in New Mexico's largest city, Albuquerque, was higher than any other major U.S. city's except Detroit, MI (Figure 4).

Figure 1: Pedestrian fatality rates in United States and New Mexico (National Highway Traffic Safety Administration, 2013)

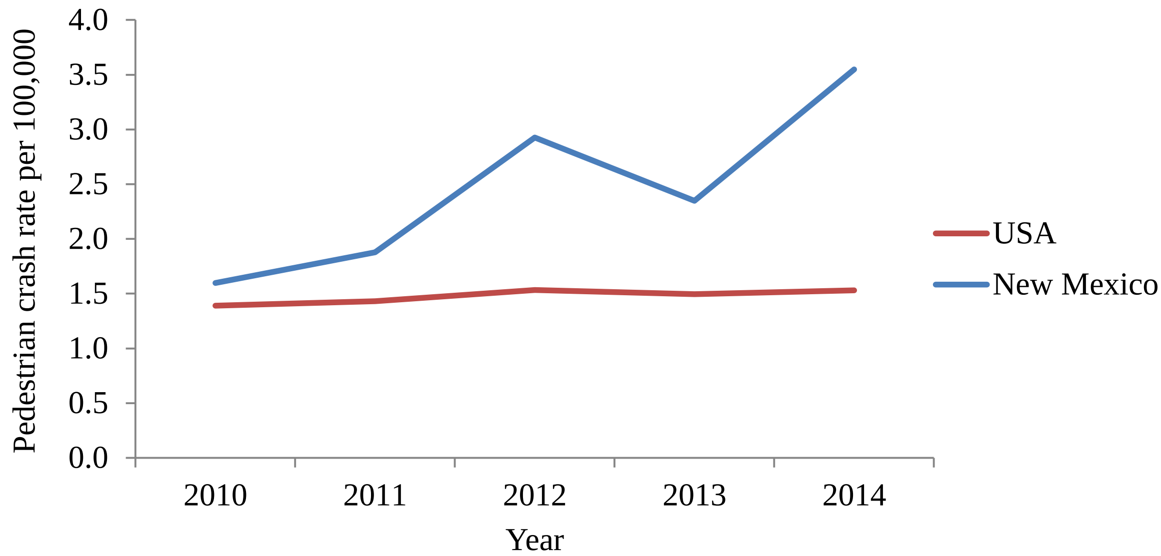


Figure 2: Other vehicular fatalities rates in United States and New Mexico (National Highway Traffic Safety Administration, 2013)

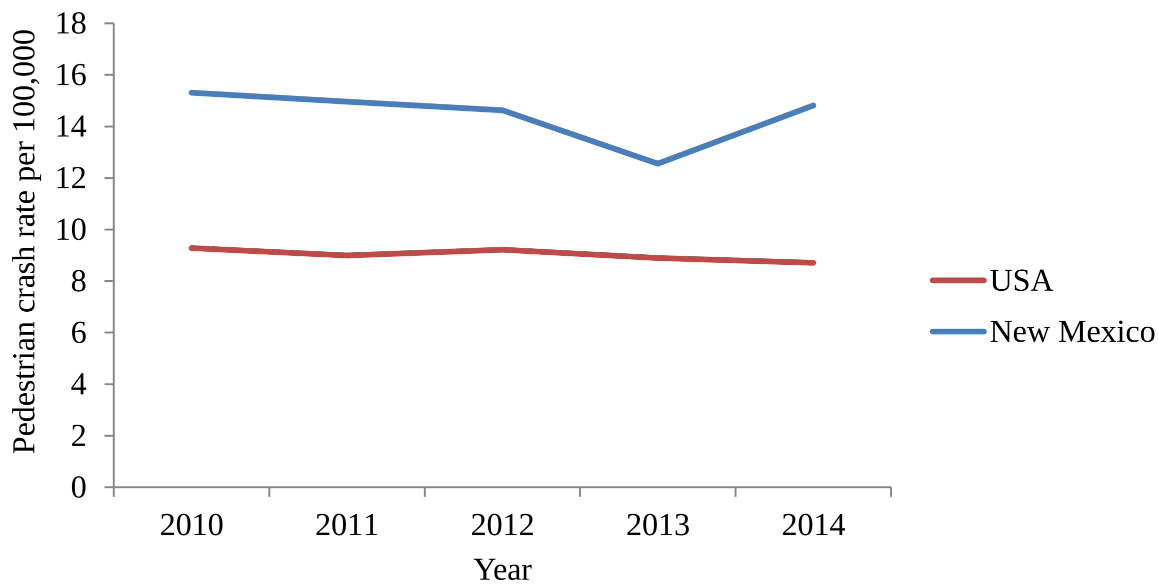


Figure 3: States with highest pedestrian fatalities rates (National Highway Traffic Safety Administration, 2013)

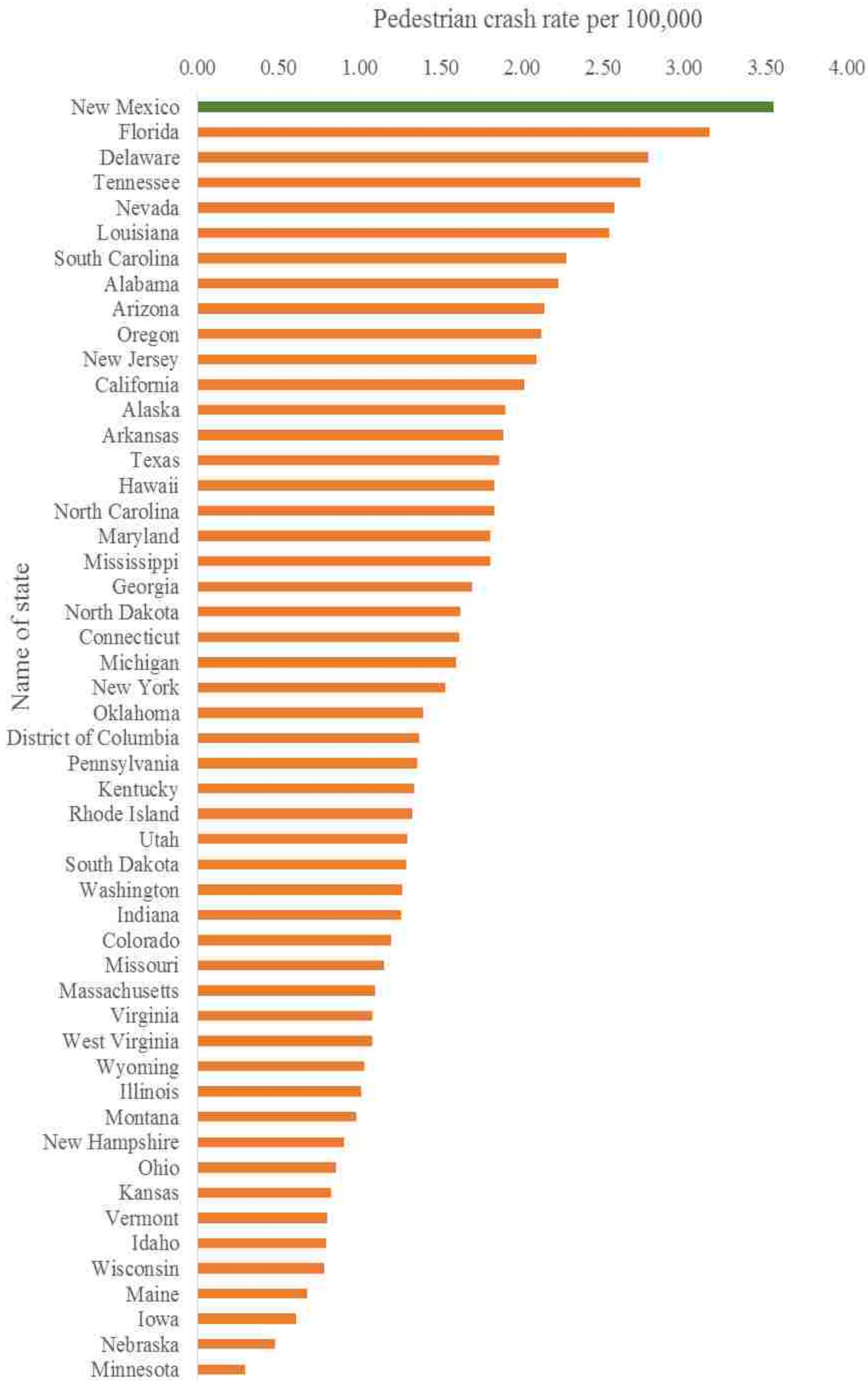
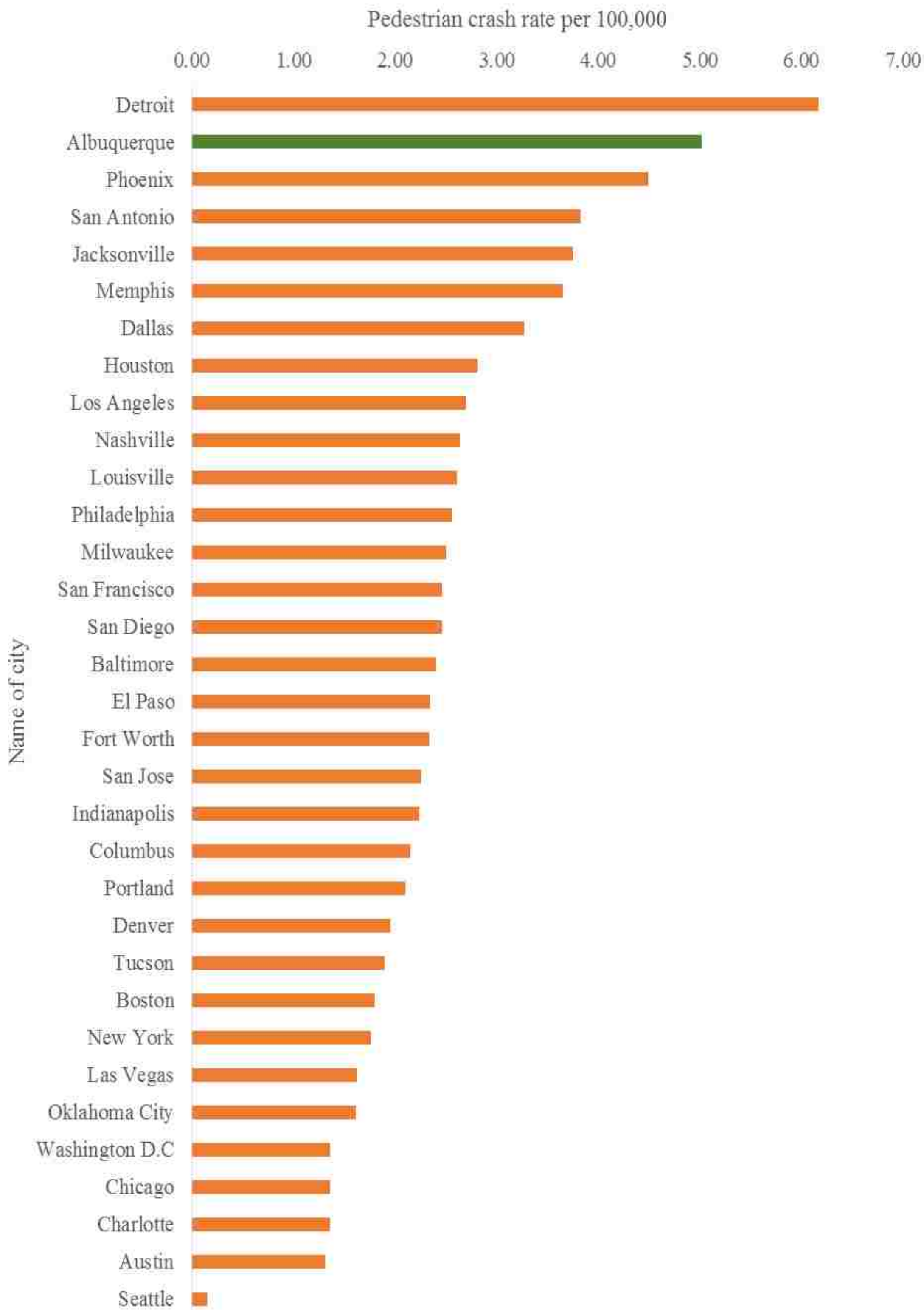


Figure 4: Cities with highest pedestrian fatalities rates (National Highway Traffic Safety Administration, 2013)



It is now more important than ever to understand the factors that affect pedestrian crash risk because Albuquerque has an extremely high pedestrian fatality rate and walking is increasingly encouraged by transportation planning and public health agencies as a more sustainable and healthy mode of transportation. However, understanding what causes increased pedestrian crash risk and what countermeasures may be effective at mitigating risk is challenging. One of the main challenges is the lack of pedestrian crash risk data. Estimating crash risks at individual locations, such as an intersection, requires information about the number of pedestrian crashes and also pedestrian exposure to vehicle traffic (e.g., the total amount of time spent walking on a street or the number of times that pedestrians cross an intersection). Crash data is readily available, however, exposure data is not routinely collected by municipal governments or planning agencies. Another challenge is understanding how various physical (e.g., street design or weather), personal (e.g., age or physical disability) and behavioral (e.g., alcohol use or speeding) factors affect pedestrian crash risk.

The overall goal of this thesis is better understanding the factors contributing to traffic accidents involving pedestrians in Albuquerque, New Mexico - one of the most unsafe places to walk in the United States. To accomplish this I collected new exposure data and combined them with crash records maintained by the New Mexico Department of Transportation to estimate crash risks for a large number of intersections in Albuquerque. I then used graphical, spatial and statistical analysis methods to comprehensively evaluate a range of physical and personal factors that might contribute to higher pedestrian crash risk. Behavioral factors, while important, require additional survey research to collect these data from pedestrians and vehicle drivers. The research findings can help identify effective countermeasures for improving pedestrian safety.

1.1.Thesis Organization

The remainder of the thesis consists of four chapters. The next chapter reviews prior studies investigating pedestrian involved traffic. Chapter 3 describes the data, models and methods used for estimating pedestrian crash risk and the factors associated with greater pedestrian crash risk. Chapter 4 presents the results using summary statistics, graphical and spatial analysis, and statistical modeling. The final chapter summaries the results and discusses what can be concluded as well as additional research needs.

Chapter 2

LITERATURE REVIEW

A large amount of research has been completed in the field of pedestrian safety. Prior research has investigated high risk groups, crash risk factors, measures to improve safety using a variety of research methods. The following literature review summarizes the current state of knowledge and reviews the various research methods that have been used.

1.1.Risk Groups

This section discusses the three major risk groups most associated with being involved in a pedestrian crash. The following subsections discuss the factors involved in pedestrian crashes related to young, middle aged and older pedestrians.

1.1.1. Young pedestrians

The importance of child and young pedestrian safety was studied by a number of reports (Lee and Abdel-Aty, 2005; Roberts et al., 1995; Sonkin et al., 2006). Sonkin et al., (2006) investigated the relationship between pedestrian fatalities in children aged 0-14 and potential risk factors such as socio economic status of households and car usage levels.. A Poisson regression model was built to obtain a 95% confidence interval with the number of deaths as the dependent variable and total population or total exposure miles as the exposure variable. Data for the number of deaths was obtained from the Office of National Statistics for the time period 1985-2003. Data for the average annual number of miles traveled by children aged 0-14 was obtained from the surveys done by the Department of Transport. The found out that for every mile traveled; there are 30 times more child pedestrian deaths than there are child car deaths. They also found out that though the death rates among children have come down, child pedestrians are more vulnerable because they have to walk more than a child from a car owning family.

A study by Lee and Abdel-Aty, (2005) developed log linear models for their study. Two log linear models were developed to identify the crash factors or a combination of these factors which could potentially explain the occurrence of pedestrian crashes. One model estimated the pedestrian crashes when the driver was at fault and another model estimated pedestrian crashes when the pedestrian was at fault. Their variables included a variable for children under the age 14. Their analysis involved the calculation of odd multipliers. Odd multipliers are the likelihood of a crash to occur relative to a reference. These were calculated to get a better understanding on the impact of the factors on the number of crashes. Positive odd multipliers in a scenario when the pedestrian was at fault indicated higher pedestrian crashes. It was observed that the odd multiplier was high for children when the pedestrian was at fault. This meant that more crashes occurred when the child was at fault in a situation that led to a pedestrian crash.

A third study by Roberts et al., (1995) assessed the environmental risk factors which contributed to the injury of child pedestrians. The analysis was carried out using a conditional logistic regression which estimated the odds ratios and the confidence intervals. The variables included were age and sex of the child pedestrians. The results indicated that the possibility of injury to a child pedestrian was great when the traffic volume was high, almost 14 times greater than the sites with the least traffic volume. Also, high density of curb parking was associated with higher injury risk to child pedestrians.

1.1.2. Middle aged Pedestrians

A study by Lee and Abdel-Aty, (2005) which analyzed vehicle-pedestrian crashes in Florida using a log linear model came up with a conclusion that middle aged pedestrians tend to be involved in the highest number of crashes involving a pedestrian. The log linear model was developed to identify potential factors which could cause a crash between a pedestrian and a vehicle. It was set up as two separate models, one when the pedestrian was at fault and one when the driver was at fault. It was seen that middle aged pedestrians were generally high in number and that could contribute to them being more at being involved in the event of a pedestrian crash. This was reinforced by their finding that though middle aged pedestrians were more likely to be involved in a crash, the probability of being hit was higher for younger pedestrians.

This was confirmed by another study by Ren et al., (2011) which used a one way analysis of variance (ANOVA) method to analyze whether social or demographic factors have an influence on the pedestrian crossing behavior. The data used for the analysis was obtained from videotaping intersections and included crossing speed, pedestrian crossing volumes, crossing times, age and gender The variables used in the demographic factors are age and gender, whereas the variable used in the social factor was whether the pedestrian was crossing in a group or alone. When studying about the age, it was found that people below the age of 60 could be more in violation of traffic rules. It was also seen that pedestrians aged 18 to 39 are more likely to ignore traffic rules because of their confidence in speed, ability and flexibility.

This was however in contrast to another study by Zhuang and Wu, (2012) which says that middle aged pedestrians are actually safer than pedestrians from other age group. Data used in this study included demographic and behavioral data. Age and gender were used for the demographic data whereas wait times, crossing times and crossing speeds were used as variables for behavioral data. The authors used correlation analysis to understand the correlations between the factors and safety indexes followed by a stepwise regression which gave the variables most associated with safety. This contrast may be attributed to the fact that the goodness of fit of their models was low and to their admission of simplifying the coding process.

1.1.3. Older Pedestrians

Older pedestrians are pedestrians who are generally regarded to be above the age of 65. A few reports analyzed the relation between age and pedestrian crash risk with respect to people from this age group (Avineri et al., 2012; Dommes et al., 2014; Kim et al., 2008). A study by Kim et al., (2008) studied the effect of age to the frequency of fatal pedestrian crashes. They used two types of models, Multinomial Logit model (MNL) and a Heteroskedastic Logit model (HET). It was seen in both the models that the share of pedestrians fatally injured grows with age despite smaller number of observations for older pedestrians. This shows that the risk of being involved is higher for the elderly. Older pedestrians tend to have slower speeds than people from other age groups and this they say is an important factor behind the high crash risk.

This was further reinstated by another study by Avineri et al., (2012) which analyzed the crossing times of people from different age groups by observational techniques and analysis using a camera. They found that the crossing times for older pedestrians was the highest among all the age groups and this contributed to higher number of people from this age group being hit. This, they say was true to walking on the sidewalk as well as crossing an intersection.

These observations were in line with the analysis of another study by Dommes et al., (2014) which used a Multivariate Analysis of Variance (MANOVA) instead of an Independent analysis of variance (ANOVA) because they found that their dependent variables had a moderately high correlation among them. Some of the variables were crossing times, looking times and number of looks. The study found that older aged pedestrians made choices which could potentially lead to a collision such as tight fits while crossing and poor judgement of an oncoming vehicle's speed. Another interesting observation is that older pedestrians were unable to decide on safe choices for crossing like optimum safety margin and critical gap for crossing an intersection. This could lead to more people being involved in collisions.

1.2. Factors influencing a crash

This section discusses the different factors which affect pedestrian crashes. These factors were chosen based on the importance they exert on vehicular and pedestrian crashes. The sub sections discussed in detail are the influence of alcohol, lightning, failure to yield and vehicle speed. The different reasons discussed below were also chosen given their importance to this study which focuses on pedestrian crashes in Albuquerque. The thesis focuses on the characteristics involved in the occurrence of a pedestrian crash relating to a range of factors and this section studies on some of them in detail.

1.2.1. Influence of alcohol

One of the most primary causes for pedestrian vehicle crashes is alcohol. There is strong evidence that alcohol leads to pedestrian crashes if either the pedestrian or the driver is intoxicated. Some studies (LaScala et al., 2001; Öström and Eriksson, 2001; Oxley et al., 2006; Prijon and Ermenc, 2009) have been done exclusively on this particular issue to find out the correlation between alcohol and pedestrian crashes based on a number of factors like age, alcohol levels and gender. A study done in Sweden by Öström and Eriksson, (2001) analyzed police and hospital records to determine the number of pedestrians killed. Autopsy reports were used to gather information on alcohol concentration in the blood for 70 percent of the fatalities of which 22 percent of the fatalities tested positive for alcohol with a Blood Alcohol Concentration (BAC) of 1.5 g/l (range 0.1 g/l to 3.5 g/l). Chi squared test and Fishers exact test were performed to conduct the analysis. They found that males were found to test more for alcohol than females and the highest number of cases was found to lie in the age group 15-24. This led to a conclusion that alcohol concentration was far more prevalent in younger pedestrians of this age group compared to any other age group.

Another similar study by Prijon and Ermenc, (2009), though without any statistical analysis shows that out of the 125 pedestrian fatalities studied, 42 percent of the fatalities were found to be alcohol positive with a blood alcohol concentration of 2.087 g/kg (range from 0.65 g/kg to 3.97 g/kg). The study dealt more on the epidemiological side and less on the correlation of alcohol to pedestrian crashes. A crucial observation they found out was that in the first 6 hours of being hit, 92 percent of the people who were alcohol positive died in contrast to 69 percent of the people who were alcohol negative.

A different approach was used in the study by LaScala et al., (2001) done in the United States which used the approach of a Geostatistical analysis. The variables used in the model included various socio-demographic information like age, education, marital status, ethnicity, income and employment status. Spatial analysis models were used to determine the effects of these variables on pedestrians who were under the influence of alcohol and other who were not under the influence of alcohol. To determine if the pedestrian was under the influence of alcohol or not, police reports were studied for these particular crashes and necessary information was obtained from the assessment of the police officer writing the report. The significance of the study was that it included neighborhood alcohol availability and the influence of neighborhood characteristics on pedestrian injuries. They found that both types of crashes (with and without alcohol) were largely dependent on a wide variety of factors like environmental, social and demographical. They also found that a higher number of pedestrian crashes involving alcohol was correlated to greater densities of bars.

To study the effect of alcohol impairment in road crossing behavior, a study by Oxley et al., (2006) used analysis of variance (ANOVA). Two groups of people were chosen for their analysis and one group was administered alcohol up to a blood alcohol concentration in the range of 0.07-0.1%. They were then asked to walk for a distance of 5.6m and then shown pictures of traffic scenarios for a survey. The variables used for this method were walking times and decision times. Other variables like alcohol group, time gap and vehicle speed were analyzed using a hierarchical logistic regression modeling. They found out that alcohol interfered in the road crossing behavior as pedestrians were unable to make proper judgements on the safe gap to cross a road. Another interesting observation made by the authors is that among people with alcohol concentration, those with less blood alcohol concentration (0.01-0.07%) were likely to be cautious than people with higher blood alcohol concentration levels (greater than 0.08%). They also say that a person with high BAC is more likely to take a risk while crossing a road than a person who is sober or with less blood alcohol concentration.

1.2.2. Vehicle speed

Another major factor to be considered when evaluating pedestrian crash risk is vehicle speed. Some studies (Kong and Yang, 2010; Rosén and Sander, 2009; Schneider et al., 2010; Ukkusuri et al., 2012) studied the effect of vehicle speed along with a number of other factors in establishing a link with vehicle pedestrian crashes. A study by Kong and Yang, (2010) applied logistic regression analysis to the data sets to study the association between pedestrian casualty and impact speed. The logistic analysis was divided into two parts, single and multiple. A single logistic regression was done to model pedestrian fatalities with respect to impact speed. For the multiple regression, age was included. Risk curves were derived based on normalized weight curves which showed that risk rapidly increases with impact speed. It was also seen that pedestrian age was not correlated to fatality but was correlated to injuries.

Another study by Schneider et al., (2010) which sought to find the association between roadway characteristics and pedestrian crashes used a negative binomial regression method. The variables used in this analysis focused on physical characteristics of the intersection, demographics of pedestrians and roadway design characteristics. It was found that decrease in the volume of the roadway tends to increase the number of crashes. This conclusion was derived from the observation that higher vehicle volume meant higher traffic capacity and in turn, lesser speeds and lesser traffic crashes. They also point out that because most of the highways studied in their research were relatively less congested, crashes tend to increase with the increase in traffic volumes.

The use of negative binomial models was seen in another study by Ukkusuri et al., (2012) which studied the effects of land use and roadway design on the frequency of pedestrian accidents. Different models were created to suit for specific purposes. One model dealt with road classification, the second for road widths and a third for number of lanes on a road. Various variables were used including number of fatal crashes, severe crashes, race and education statistics, land use characteristics, roadway widths, transit share and number of transit stops. They found that pedestrian crashes were greater in industrial, commercial or open land use areas where as a higher share of residential land use resulted in fewer numbers of crashes. This was attributed to lower speed limits in residential areas and higher speed limits in industrial areas. It was also seen that roads with larger width could be seen as ones associated with higher pedestrian crash risk. Roads with larger widths are often associated with higher speeds and that contributes towards the increased risk. Also, it was seen that higher number of lanes increased the number of crashes because a road with high number of lanes is bound to have higher speeds.

Another study by Rosén and Sander, (2009) analyzed the risk of a pedestrian fatality with respect to car speed. They used logistic regression models using variables like pedestrian age, height, weight and impact speed when hit by the car. It was found that pedestrian age and impact speed were highly significant to a pedestrian’s fatality. It was also seen that the fatality risk was very strongly dependent on the impact speed with the risk twice as high when the speed was changed from 40 km/h to 50 km/h.

1.2.3. Lighting

Lighting can be very important when analyzing pedestrian crash risks. It was seen in some studies (Siddiqui et al., 2006; Sullivan and Flannagan, 2007; Wanvik, 2009) that lighting definitely had an effect when pedestrian safety was concerned. An ordered probit model was developed in one study by Siddiqui et al., (2006) with the injury severity as the dependent variable. The light conditions on the roads along with other control variables such as environmental, vehicle, road, pedestrian and driver attributes were used in the analysis. Three control variables for the intersections pertaining to lightning were used; daylight, dark with street lightning and dark without street lightning. It was found that a pedestrian sustaining a fatal injury depended more on the light conditions than the location. Another interesting observation is that the effect of street lighting is smaller than the effect of daylight. The odds of reduction of a fatal injury are considerably higher for daylight than a scenario involving a street light. Also, for both daylight and street lighting scenarios, the greatest reduction was found to be at intersections than mid-blocks.

Another way the effect of lighting was analyzed was by using odds ratio in another study by Wanvik, (2009). The data for this research was obtained from the Institute of Road Network, Holland which contained all the crashes pertaining to vehicular crashes. The data was then filtered to show two types of datasets for daylight crashes and crashes occurring when it is dark. By sampling a large number of crashes over a large amount of time and by dividing the crashes into two groups based on the lighting conditions of the road the accident occurred, the authors calculated odds ratio, which is the ratio of crashes occurring on lit roads for both scenarios to the crashes occurring on unlit roads for both scenarios. In rural areas, a number of other factors have been considered. Lighting showed a reduction of pedestrian accidents by 72 percent, motorcycle accidents by 25 percent and vehicle accidents by 50 percent.

Another study by Sullivan and Flannagan, (2007) used a dark to light ratio to determine the safety of improved lighting in pedestrian crash scenarios. For the analysis, data was obtained from the Fatality Analysis Reporting System (FARS) and the North Carolina Department of Transportation. The data sets were then categorized into crashes which occurred during daylight and crashes that occurred during darkness. Three scenarios were chosen to perform the analysis. The scenarios they chose were curve lighting, motorway lighting and cornering lighting. It was found that on a curved roadway, the dark/light ration tended to increase more than 1 which indicated that darkness on a curved road was more dangerous than when there is light. For the motorway scenario, it was noted that the crash risk in darkness is very highly predicted by speed. Higher speeds indicated higher crashes on an unlit motorway than on a lit motorway. For cornering lighting, it was seen that the crash risk was less for turning vehicles and also less for pedestrians at intersections. Less speeds for turning vehicles, comparatively more lighting at intersections are said to be the reasons behind the lower crash risks.

1.2.4. Failure to yield

Failure to yield by drivers at intersections was found to be another major reason for pedestrian crashes. A study by Lee and Abdel-Aty, (2005) developed log linear models to study the effects of different variables and conditions on pedestrian crash risk in Florida. The data used in these models was obtained from Florida Traffic Crash Records Database maintained by the Florida Department of Highway Safety. Two models were developed for two different scenarios, the fault of the person driving the vehicle and the fault of the pedestrian. In the model where the driver was at fault, it was found that vehicle drivers tend to drive more carefully at traffic signals than when they approach stop signs or yield signs. In the model where the pedestrian was at fault, it was seen that more pedestrian crashes occurred at intersections with control facilities like stop signs and yield signs. This meant that the number of pedestrian crashes reduced when traffic signals were installed at intersections.

Another study by Ulfarsson et al., (2010) aims to analyze the fault in a pedestrian vehicle crash based on different factors. A multinomial logit model was used to determine three cases of a fault in the event of a pedestrian vehicle crash. The three cases were that the pedestrian was at fault, the driver was at fault and both were at fault. The variables used in the model were age, gender ethnicity, traffic control characteristics and roadway characteristics. It was seen that in the event of a crash near a yield sign, there is a large probability that the driver was at fault or both the driver and the pedestrian were at fault. It was also noted that a driver failing to yield and a pedestrian failing to yield are perfectly correlated with fault determination.

To understand the pedestrian and driver behaviors with respect to right of way for pedestrians, a study by Hatfield et al., (2007) used a binary logistic regression model with variables like area, age and gender along with survey data about road crossing behavior. It was concluded that there was some confusion as to the rules of pedestrian right of way at intersections and for some roadway characteristics, it was seen that many respondents did not know if the pedestrian or the driver had the right of way. It was seen that in such confusion about the right of way, many pedestrians walked when across the street when they should not have.

1.3. Measures to Improve Safety

Several studies have suggested measures to improve the safety of pedestrians from a vehicular crash. One study by Lee and Abdel-Aty, (2005) which analyzed pedestrian crash risk based on different log linear models for different variables suggests that there are several countermeasures for pedestrian crashes. The analysis from the models suggests that pedestrian crash risk when the driver or the pedestrian was under the influence of alcohol was high and similar to crash risk of drinking and driving. Therefore intensive awareness programs on the problems of drinking and walking at night should be implemented. The analysis also suggests that more pedestrian vehicle crashes occur when there are less traffic signal and also during reduced vision due to adverse weather conditions. The authors suggest that this can be avoided by installing more traffic signals, particularly at rural areas and increasing street lightning so as to increase the vision during conditions of poor vision.

While studying the safety effects of marked versus unmarked crosswalks at uncontrolled locations, a study by Zegeer et al., (2001) came up with some measures to improve safety. Street crossings, they say should be routinely reviewed to see if any changes are needed to make it safe. Some changes which can be made include marking a crosswalk and installing crosswalk improvements which will reduce vehicle speeds, reduce crossing distances or increasing yield times. Other measures suggested by the authors include the installation of traffic calming measures like raised crossing and narrowing of streets, providing improved lightning, planning crosswalk and intersection design in such a way that it is easy for pedestrians to understand the design better and the usage of pedestrian warning signs in addition to marked crosswalks. Some ways to improve crosswalk and intersection design include removal of parking at an uncontrolled intersection, advanced stop line for vehicles and access management to the intersection. Also, they advocate better land use planning which would greatly help in reducing exposure of pedestrians to elements that could potentially lead to a crash involving a vehicle. Some ways to achieve this are by using busy arteries as boundaries for institutions and by not separating pedestrians with places that are pedestrian frequented.

The improvements suggested in the previous study were also mentioned in another study by Gårder, (2004) done to analyze the effect of speed and the characteristics of the location on the pedestrian crash risk. Their analysis leads to a finding that roadway width, speed and the intersection features all had an effect on the pedestrian crash risk. Higher speeds, wide roadway widths and unmarked crosswalks all led to higher crash risks. They therefore suggest that speeds be reduced, roads made narrower and installing refuge islands as some potential countermeasures to reduce pedestrian crash risk.

Another important issue to be considered is the safety of pedestrians who also use transit. This analysis done by Hess et al., (2004) studies the relation between pedestrian crash location on highways and arterials and the presence of people alighting from public transit systems. The study finds that there is significance between high bus usage along highways and pedestrian vehicle collisions. It was also found that the roads with high volumes of bus ridership had higher pedestrian crashes. It was therefore suggested that transit stops which have high ridership along major arterials should be moved or improvements should be made for the safety of the people using them. Transit stops could be located away from the major arterials which would shield people from walking across the road immediately after disembarking. They also say that agencies should not focus only on the safety of the transit vehicle but also on the people who use it along such high density roads. It also points out that there is a need to invest in safety mechanisms such as improving pedestrian facilities, to promote safe transit and better land use policies which would promote multi modal use of property along those roads which are deemed to be unsafe for pedestrians.

A study by Sullivan and Flannagan, (2007) studied the effect lightning had on pedestrian safety using dark/light ratios. In their analysis, it was found that there is a huge potential to increase the safety of motorways from pedestrian crashes when lightning is provided. They also recognize that speed plays a major part in determining the pedestrian crash risk and lightning should be in conjunction with the roadway design features that would reduce speeds and therefore minimize pedestrian crash risk.

Enforcement is another very important measure advocated so as to decrease the pedestrian crash risk. A study by Van Houten and Malenfant, (2004) analyzed the effects of a two week intensive enforcement program on yielding to pedestrians. The enforcement was carried out using help from police enforcement officers in the form of warnings and citations. They point out that the enforcement program increased yielding to pedestrians by 27 percent on one corridor of the road while it increased yielding to pedestrians by 33 percent on the other corridor and this continued even after the enforcement was reduced substantially. An interesting point they note is that this enforcement helped in spreading the awareness as yielding to pedestrians increased at intersections where there was no enforcement. It is also noted that the increase in engineering features of the sidewalk and the crosswalk will support the police enforcement.

Education is crucial when it comes to increasing pedestrian safety. A study by Dommes et al., (2012) studied the effectiveness of a training program among older pedestrians. A street crossing simulation device was used to train older pedestrians and also to evaluate their street crossing behavior. Street crossing simulation was done on older pedestrians before training, after training and six months after training. This training program included both behavioral and educational aspects. It was found that it improved judgements by older pedestrians, thus improving their overall safety. The explanation to their improved judgement could be that the participants took advantage of the educational feedback from the training program and that they made good use of the visual feedback obtained from the simulation. This hands-on approach could have enabled the participants to adapt their actions to the visual scenario. But it was also found that their reception to a car coming at high speeds could not be improved which is crucial considering how important speed is in the event of a pedestrian vehicle crash. For this, they suggest that the best measures are speed reduction techniques like street narrowing and speed ramps.

1.4. Research Methods

Different research methods were used for different purposes. The methods were varied because of the difference in scope, funds and the needs of the researchers. Following are some of the important areas where different methods were employed in the research.

Data and data collection is very important and good data forms the backbone of any research. A study by Pulugurtha et al., (2007) obtained crash data for a five year period from the Nevada Department of Transportation to conduct their analysis. The crash data was for the Las Vegas metropolitan area and they used GIS to geocode the crash data and then created a crash concentration map. Then according to the shape and size of the area, the zones of pedestrian crash density were identified. This method, they say helps to quantify the concentration of crashes. Another study by Poch and Mannering, (1996) whose objective was to find out the frequency of pedestrian related crashes at intersections, specifically selected intersections which were going to have some kind of operational improvements. This was done so that they could study the before and after scenarios of the improvements. Crash data to perform the analysis were obtained from the city and vehicle volumes were obtained from the annual traffic volume data. It was observed that there was a decrease in approach turn accidents when left turn restriction on approach was placed. Another observation was that intersections where signal control was placed had a decrease in pedestrian crashes.

Another study by Schneider et al., (2010) aimed to find as to what characteristics of a road are likely to cause crashes. Crash data were obtained from the California Highway Patrol Statewide Integrated Traffic Records System database. Pedestrian volumes at intersections were obtained by extrapolating manual counts of two hour time periods. The intersections selected for this study encompassed all kinds of intersections with different design and neighborhood characteristics. The intersections were spread throughout the county and specific intersection data such as lane characteristics, signals and medians were obtained by field observations. The authors point out to a limitation of using extrapolated counts that they are vulnerable to variations caused due to different factors such as weather, demographic changes and land use policies. It was suggested that multiple counts over multiple periods of the day would generate more accurate data.

The study by Schneider et al., (2010) uses pedestrian volumes as one measure of pedestrian exposure to crash risk. This method could be justified for the analysis of pedestrian crashes at intersections but other measures can also be tested to measure pedestrian exposure to crash risk. Some of them are crossing distances, crossing time and wait time. Exposure data is very important when crash risk is analyzed. It was mentioned that a single crash can make a significant difference in a study where there are intersections with few crashes. It is important to collect data at more intersections so that the variables used in any analysis would be significant in explaining the reasons for the occurrence of a pedestrian crash. Another study by Lee and Abdel-Aty, (2005) which analyzed various traffic and environmental conditions responsible for the occurrence of a pedestrian crash does not estimate the risk of each driver and pedestrian in the form of crash rates. The reason given is that it is difficult to estimate exposure factors.

There were different approaches in the way the data was analyzed as well. A study by Ukkusuri et al., (2012), count data regression models were used to investigate the link between crashes and the built environment. They debated the use of Poisson and negative binomial regressions but settled on negative binomial regression given its relative advantages over Poisson regression. Poisson regression was easier to use but it's assumption that the mean and variance are equal was a limitation. On the other hand, a negative binomial model had the ability to account for over dispersion and its model calibration was simple. The models used in this process were modelled based on the total collision counts and counts for fatal collisions. Another study by Schneider et al., (2010) tried using a Poisson model because crashes are count data, but a binomial regression model was used because the number of crashes per intersection did not meet the requirement that the mean be roughly equal to the variance. It was pretty clear that most researchers preferred using a negative binomial regression model. This was understandable given that the data used in research of pedestrian safety is mostly count data. A study by Poch and Mannering, (1996) which analyzed intersection accident frequencies used negative binomial regression for the analysis. It was said that the use of a negative binomial model is best suited for discrete, non-negative events without the limitations of a Poisson model. This was explained by pointing out that in a Poisson model, the mean is constrained to be equal to the mean which might not actually be true for crash data where the variance is likely to be significantly greater than the mean. If a Poisson model was used in this scenario, the variances of the estimated coefficients tend to be underestimated and the coefficients themselves may be biased.

A study by Lee and Abdel-Aty, (2005) used log linear models to identify the groups of drivers and pedestrians and all other characteristics that are correlated to pedestrian crashes. These models identify the factors or the combination of factors which contribute to the occurrence of pedestrian crashes. They also carried out a survey of household travel to collect individual walking trip data. From this, they derived a logical expression of pedestrian exposure to crash risk.

1.5. Conclusion

A lot of research has been conducted in the field of pedestrian safety. One issue which needs to be addressed is that while a number of areas have been thoroughly studied, there are a few areas which have been understudied or not properly understood. Some areas which need to be studied additionally are crash causation and accurately estimating the overall problem of pedestrian casualties based on exposure measures. Lack of exposure data such as crossing times, crossing distances and waiting times is another critical challenge. Better exposure data will help us understand the causes of pedestrian crashes far better than any other research method. It is crucial to understand exposure data because that will give us an insight into the actual reasons as to why crashes occur and could potentially lead to better countermeasures to reduce pedestrian crashes. Police reports provide the best source for pedestrian safety research by including data like neighborhood characteristics, pedestrian and driver variables and intersection design but they often lack critical information pertaining to exposure variables at different locations.

The literature reviewed has helped in understanding the problem of pedestrian safety in Albuquerque. As one of the city with the highest number of pedestrian crash rates in the country, it is important to understand the reasons and causes for pedestrian crashes in the city. Studies which dealt with roadway characteristics and intersection design have helped to understand the scenario in Albuquerque and to possibly look for more variables related to the design of the intersections which could explain pedestrian crashes.

The literature review helped understand the different age groups involved in pedestrian crashes and that younger and older pedestrians were more at risk of being involved in a fatal pedestrian crash though middle aged pedestrians were seen to be more involved in crashes. The different factors which can lead to a pedestrian crash such as influence of alcohol, poor lightning, failure to yield and vehicle speed have been studied and this has helped in deciding on what data needed to be collected as part of the different variables to be used in the analysis of pedestrian crashes in Albuquerque.

Finally, different methods used by different researchers have been looked at, which gave an idea on the advantages and disadvantages of specific analysis methods. It was seen that a majority of researchers preferred the use of a negative binomial regression model for statistical analysis because of its advantages over a Poisson regression. Both, Poisson regression and negative binomial regression though best suited for count data, the assumption that the mean and variance are equal in a Poisson regression could lead to bias and underestimation of coefficients. This could be eliminated with the use of a negative binomial regression.

Chapter 3

DATA AND METHODOLOGY

This chapter describes how data were collected and how they were evaluated to identify factors associated with pedestrian involved traffic accidents in Albuquerque, NM. The main data collection tasks were manually collecting pedestrian counts at study intersections, collecting information about the physical roadway and sidewalk infrastructure near each intersection, and generating other potential explanatory variables through a spatial analysis of census data around each intersection. These data were then used in graphical, spatial and a statistical analysis to identify factors associated with pedestrian crash risk.

1.1.Crash data

Vehicular crash records for New Mexico were obtained from the New Mexico Department of Transportation (NMDOT) for the years 2010-2013. The crash records contain information for all types of vehicle involved accidents reported to police in the state of New Mexico. Each record contains the information shown in Table 1.

Table 1: Crash record data from NMDOT

Field
Report number
Month, Date, Year
Month of crash occurrence
Date of crash
Year of crash
Time of crash reported
Day of crash
Main street

Intersecting street
Crash classification
Reason for crash
Pedestrian involvement
Weather conditions
Light conditions
Grade of accident site location
Latitude coordinate
Longitude coordinate

The data files were inspected manually and merged together to create one dataset for all crashes. The data was then filtered to only include pedestrian related crashes in Albuquerque. These pedestrian crash data were then used for the remainder of the analysis in the thesis.

A geographic information system (ESRI's ArcGIS software) was then used to create a map displaying the location of each pedestrian crash (Figure 5). A pedestrian crash density map was also created to analyze areas with the highest pedestrian crash frequency (Figure 6). This was achieved by using the ArcGIS point density tool to create a map of pedestrian related crash density per square mile. The pedestrian crash density map was used to help select intersections with a wide range of crash frequencies in an effort to include intersections that likely had a wide range of crash risks. Pedestrian counts were then completed at the selected study intersections.

Figure 5: Pedestrian crashes in Albuquerque, 2010-2013 (NMDOT)

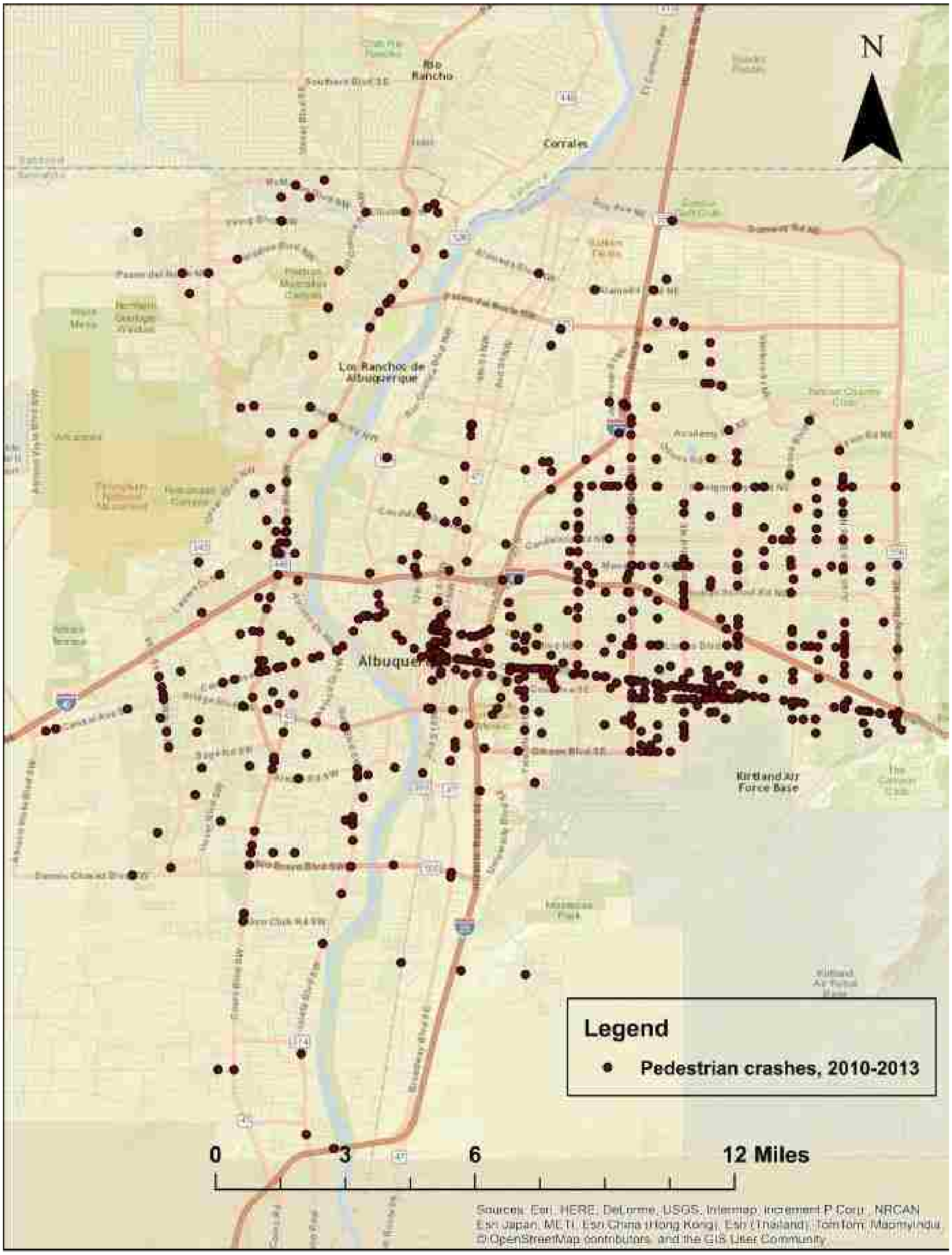
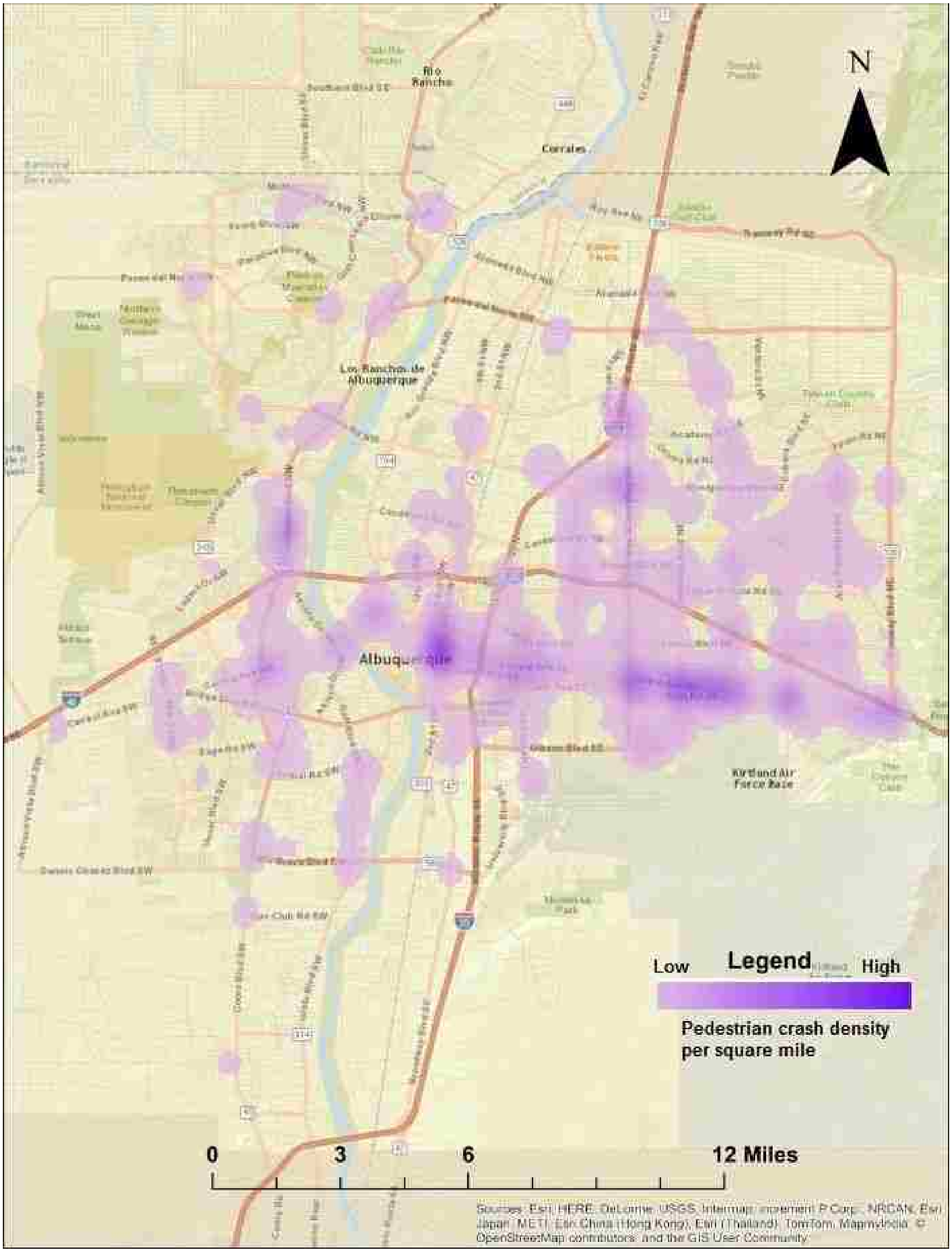


Figure 6: Pedestrian crash density, 2010-2013 (NMDOT)

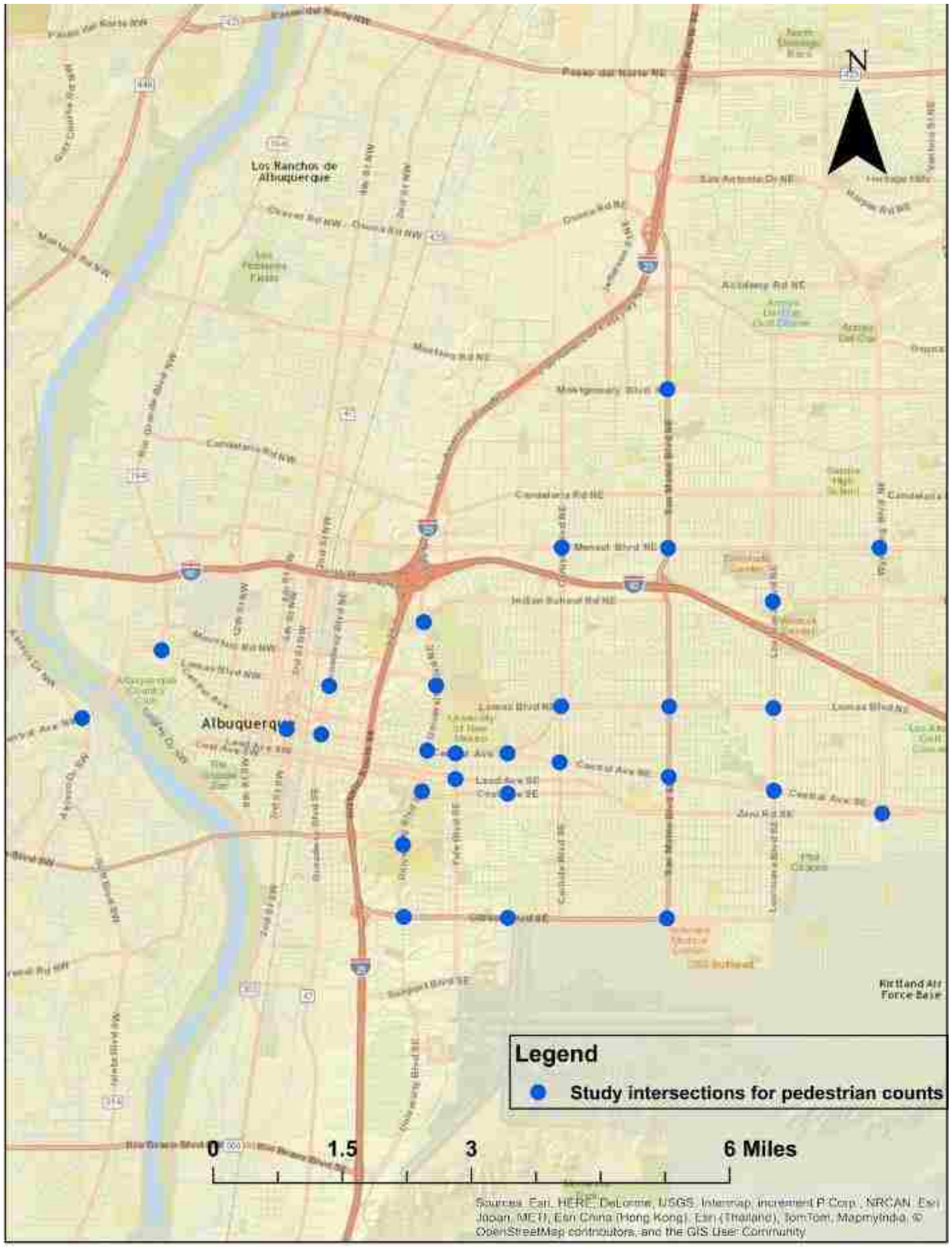


1.2. Count Data

Pedestrian count data were obtained from two sources which gave rise to two datasets. One dataset contained count data collected manually by me and with help from others at thirty intersections around Albuquerque while the other dataset contained count data obtained from the Mid Region Council of Governments (MRCOG).

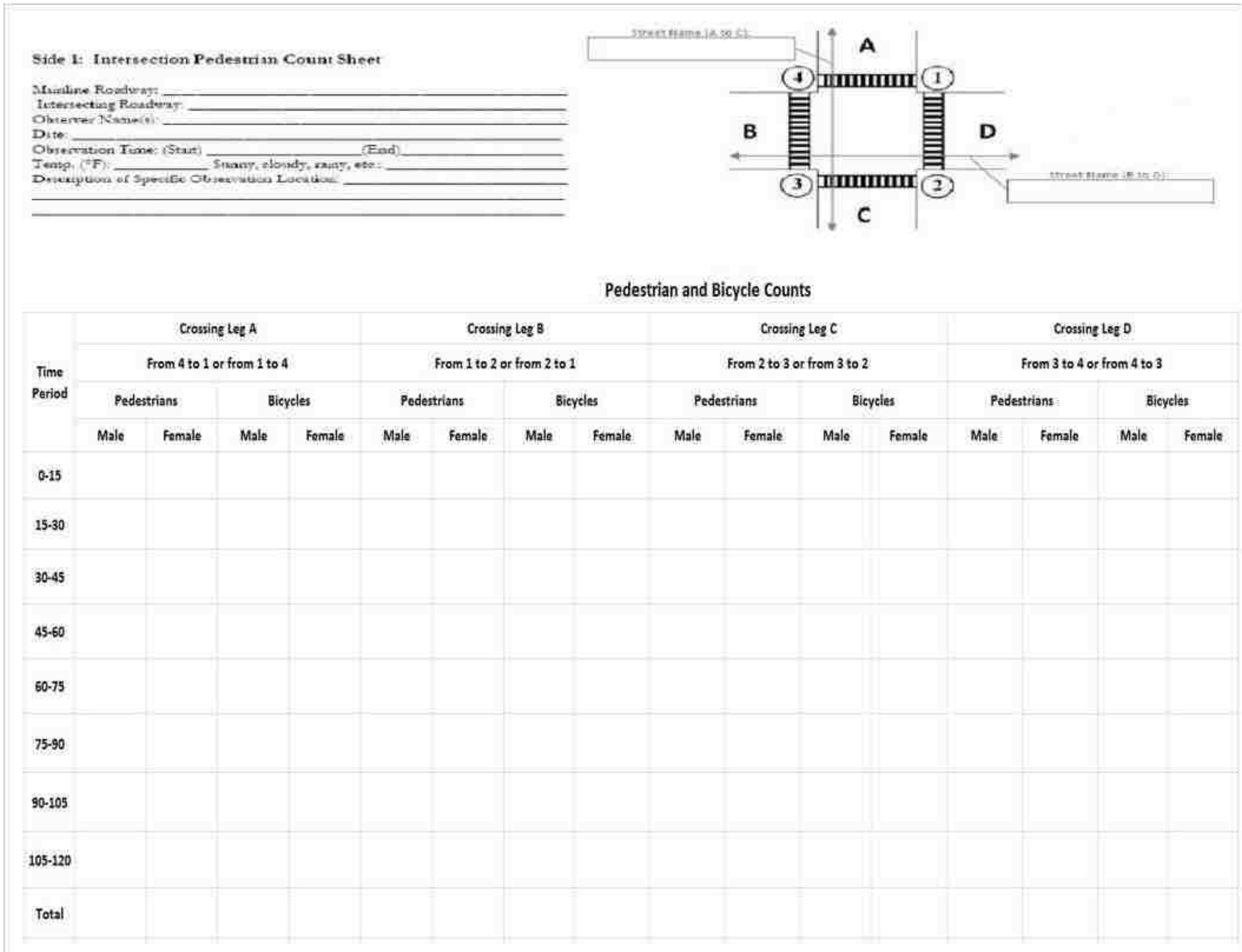
The pedestrian crash density map (Figure 6) was used to identify areas with a wide range of pedestrian crash frequency. It was seen that Downtown, East Central and the intersection of San Mateo Boulevard and Montgomery Boulevard were areas of frequent pedestrian crashes. The South valley and the North East heights had fewer pedestrian related vehicle crashes. A total of 30 intersections were identified with varying crash frequencies. The intent was to select intersections that would have a wide range of crash risk, which could then be used to investigate factors that affect pedestrian crash risk. Including intersections with a wide range of risk was intended to help capture important explanatory factors. Of the thirty intersections selected, three intersections were located in the Downtown area, nine locations were located in the vicinity of the University of New Mexico (UNM) and others were spread around the city with a majority of them on the eastern part of the city where most crashes appeared to be concentrated (Figure 7).

Figure 7: Study locations for manual counts



Pedestrian counts were collected manually by observing the number of pedestrians crossing each intersection at different times of the day and week. Multiple, repeat, counts were made at each intersection for the same time period to capture daily fluctuations in pedestrian activity. The average of these repeated counts were used in the later analysis steps.

Figure 8: Sample count form used for pedestrian counts



Side 1: Intersection Pedestrian Count Sheet

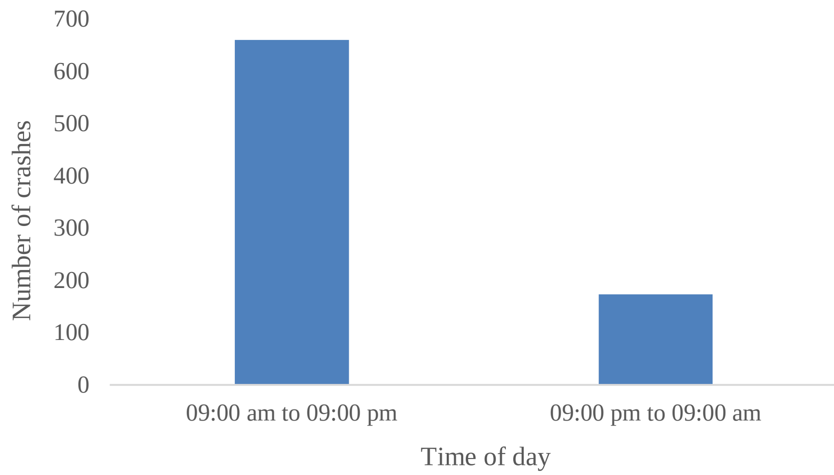
Mainline Roadway: ______
Intersecting Roadway: ______
Observer Name(s): ______
Date: ______
Observation Time: (Start) ______ (End) ______
Temp. (°F): ______ Sunny, cloudy, rainy, etc.: ______
Description of Specific Observation Location: ______

Pedestrian and Bicycle Counts

Time Period	Crossing Leg A				Crossing Leg B				Crossing Leg C				Crossing Leg D			
	From 4 to 1 or from 1 to 4				From 1 to 2 or from 2 to 1				From 2 to 3 or from 3 to 2				From 3 to 4 or from 4 to 3			
	Pedestrians		Bicycles		Pedestrians		Bicycles		Pedestrians		Bicycles		Pedestrians		Bicycles	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
0-15																
15-30																
30-45																
45-60																
60-75																
75-90																
90-105																
105-120																
Total																

Counts were collected using the paper form shown in Figure 8. Counts were made for a 30 minute period over three consecutive weekdays for each intersection. The 30 minute time period was different for different intersections and was spread out throughout the day between the hours of 9:00 am and 9:00 pm. Counts were made during this time period because it was observed that most crashes have occurred in Albuquerque during this 12 hour period. High crime rates around some study intersections and limited resources were also factors in limiting the hours when counts were made. Figure 9 shows pedestrian crash statistics for Albuquerque based on their time of occurrence.

Figure 9: Pedestrian crash statistics based on time of occurrence (NMDOT, 2010-2013)



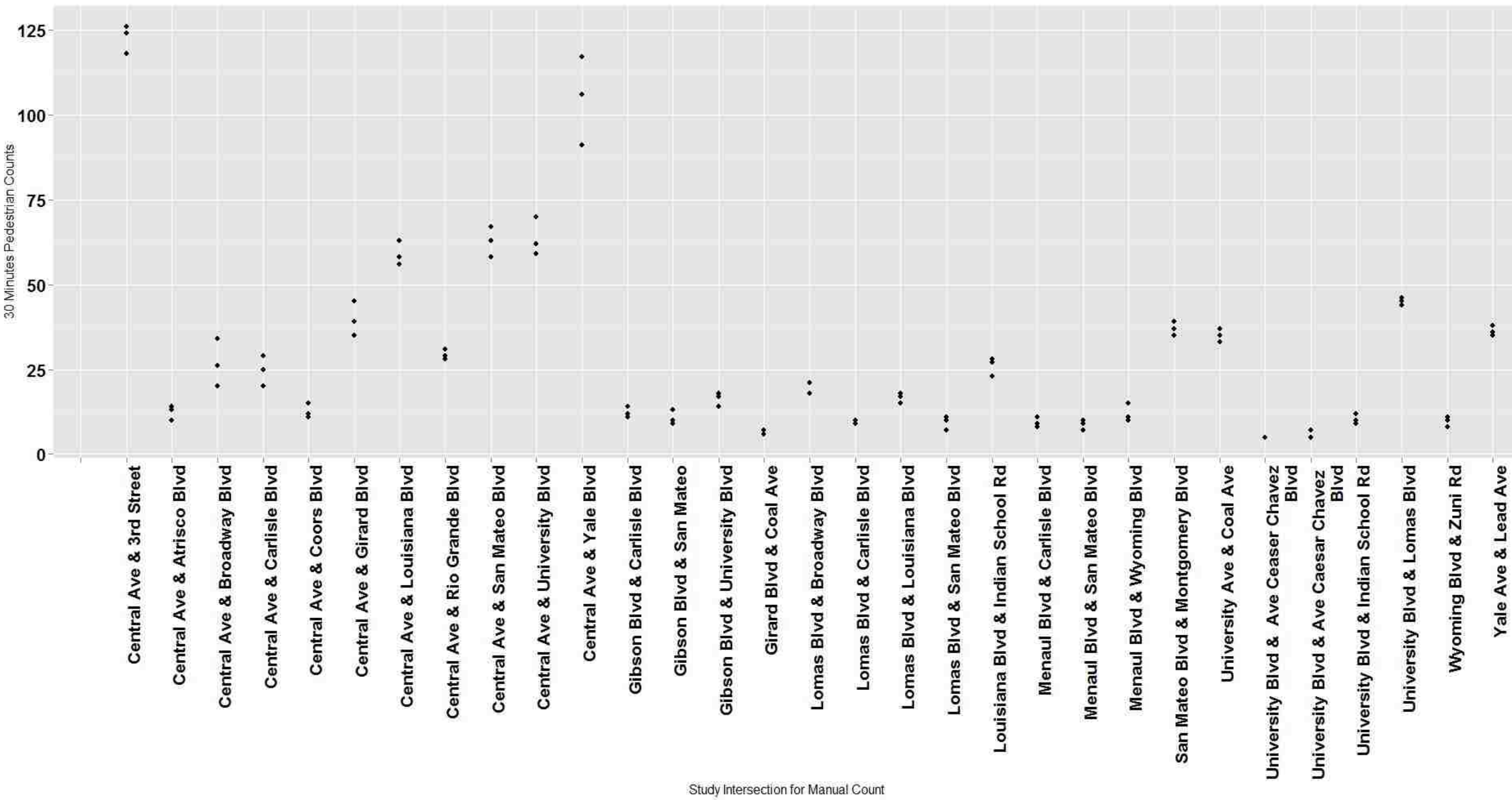
Skateboarders, physically disabled persons on a wheelchair, a person being carried and strollers were all counted as pedestrians. Any person crossing multiple legs of the intersection was counted multiple times. To have comprehensive data, any pedestrian crossing the street within 100 feet of the intersection was also counted as it was observed that pedestrians also crossed the street close to an intersection without actually crossing at the intersection. Table 2 identifies the information obtained from manual pedestrian counts.

Figure 10 shows the 30 minute counts obtained over a three day period at the study intersections. It can be seen from the figure that pedestrian counts at most intersections were consistent without any major day to day variation. One intersection, Central and Yale, had a relatively higher variation as compared to other intersections. Based on analysis of these data it was determined that the three repeat counts were sufficient for estimating average pedestrian volumes at the study intersections.

Table 2: Pedestrian count data variables for UNM counts

Field	Comments
Mainline roadway	Major arterial
Intersecting roadway	Minor arterial
Date	
Time	
Temperature	
Pedestrian counts	30 minute counts over two 15 minute intervals (male and female)

Figure 10: Pedestrian count data at study intersections



Counts spanning the entire 12 hour study time period were also collected from two control locations. These control location counts were then used to estimate 12 hour counts from each of the 30 minute pedestrian counts completed at the study intersections shown in Figure 10. While it would have been ideal to collect counts at all intersections over the entire 12 hour time period, this was not practical under the project's resource constraints. The two control locations were located near the University of New Mexico and in downtown Albuquerque. At these two control locations, counts were taken for 12 continuous hours from 9:00 am to 9:00 pm and repeated on three separate days (Table 3).

The locations established as control locations were the intersection of University Boulevard and Central Avenue, and Broadway and Central Avenue. All intersections close to the university, intersections frequented by students due to presence of university parking and university facilities were extrapolated based on the volumes obtained at Central Ave. and University Blvd. while all other intersections were extrapolated based on Central Ave and Broadway. Figures 11 and Figure 12 show the trends observed at both control locations.

The temporal trends observed for both control locations generally meet expectations. Pedestrian volumes peak in the late afternoon at the end of the work and school day as people begin their commute home and are lower during the middle of the day when people are at work or school. Our study period occurred after the morning peak. The peak pedestrian volume occurs earlier in the afternoon downtown than at UNM. The wider range of business types in the downtown area, with a potentially wider range of working hours, may contribute to this difference.

The 30 minute counts were extrapolated using equation Eq-1. The number of pedestrians crossing a study intersection for a specific hour was estimated by multiplying the pedestrian volume at the control intersection for the desired hour by the pedestrian count obtained at the study intersection and then dividing by the pedestrian volume obtained at the control intersection for the hour corresponding when the study intersection counts were made. The estimated hourly counts were then summed to obtain 12 hour volumes at each study intersection (Eq-2).;

$$PDS_t = \frac{PDC_t \cdot PDS_{t0}}{PDC_{t0}} \qquad \text{Eq-1}$$

$$PDS_{tot} = \sum_t PDS_t \qquad \text{Eq-2}$$

Where;

PDS_t = Estimated pedestrian count at study intersection for desired time period t.
PDS_{t0} = Pedestrian count for time period t0
PDC_t = Pedestrian count at control location for time period t
PDC_{t0} = Pedestrian count at control location for time period t0

Table 3: Pedestrian repeat count trends at control locations

	Central and Broadway			Central and University		
Time	Count1	Count2	Count3	Count1	Count2	Count3
9:00 AM	38	42	41	66	65	62
10:00 AM	45	49	51	52	54	61
11:00 AM	48	48	48	56	56	56
12:00 PM	36	41	43	56	61	64
1:00 PM	43	50	51	60	63	68
2:00 PM	44	44	45	72	71	72
3:00 PM	70	75	73	64	66	73
4:00 PM	66	66	59	89	93	93
5:00 PM	61	64	63	100	93	96
6:00 PM	56	56	56	68	68	68

7:00 PM	48	50	57	49	55	56
8:00 PM	42	46	43	56	54	58
9:00 PM	41	43	49	49	48	46

Figure 11: Pedestrian count trends at Central Avenue and University Blvd

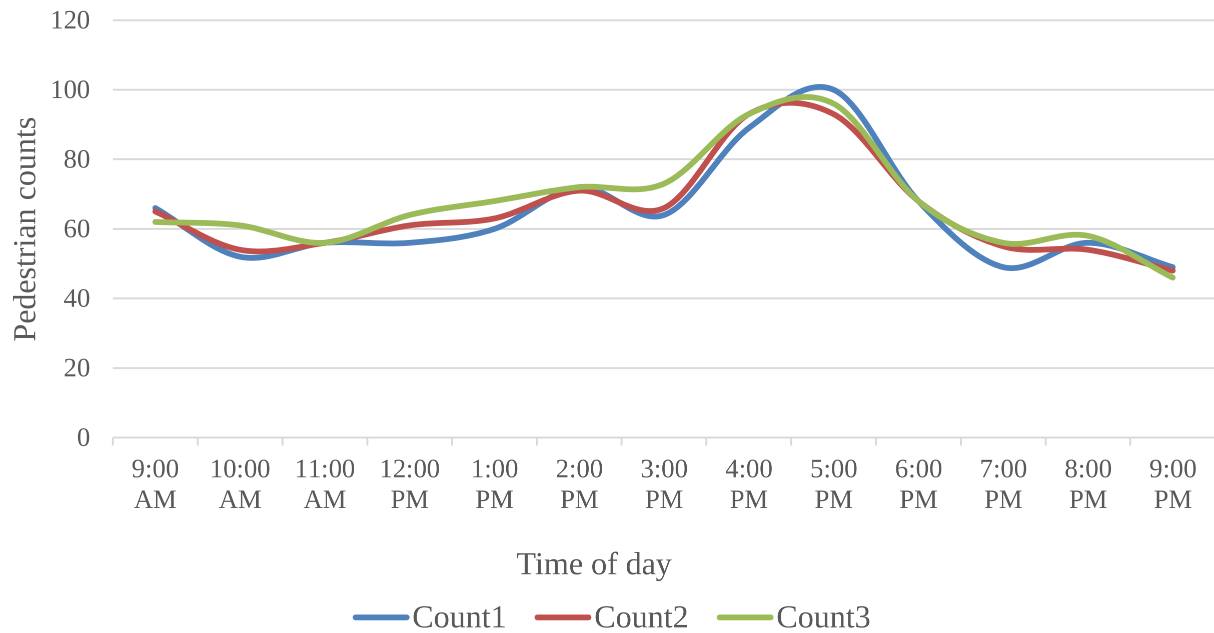


Figure 12: Pedestrian count trends at Central Avenue and Broadway Blvd

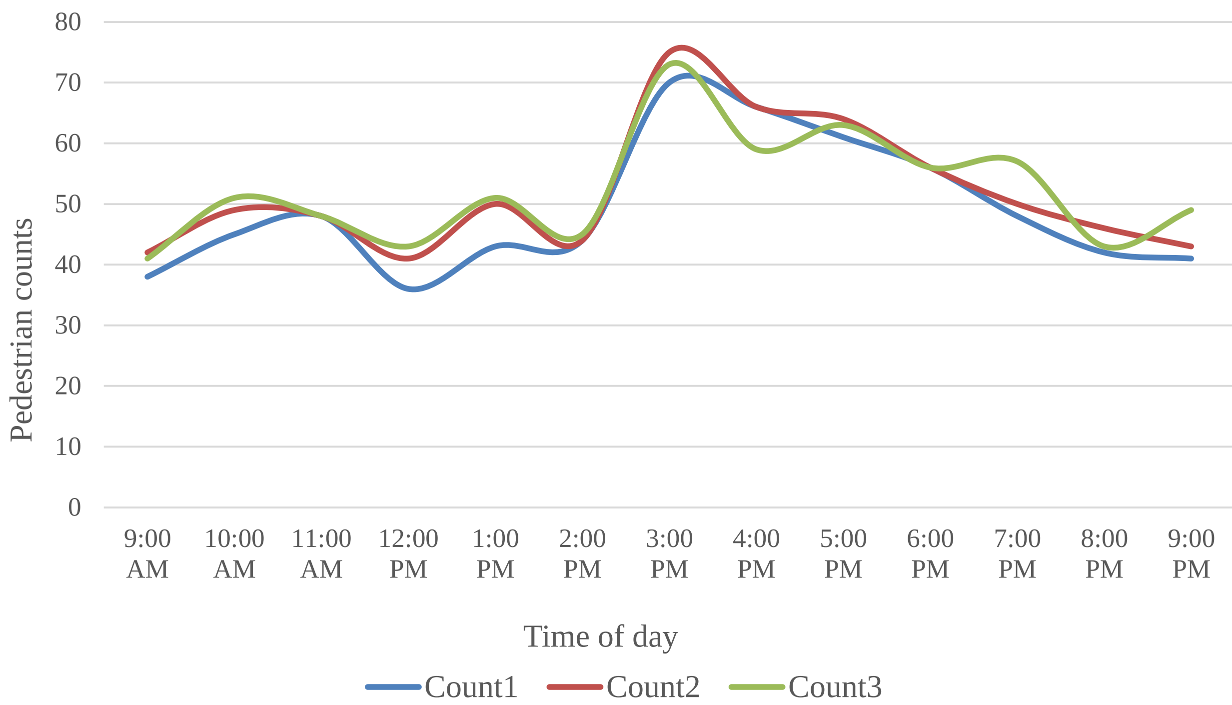


Table 4 provides the estimated 12-hour pedestrian volumes for each of the study intersections. The intersection with the highest pedestrian crossings was Central Avenue and 3rd street and other intersections with high pedestrian crossings were Central Avenue and Yale Blvd, and Central Avenue and San Mateo Blvd. The intersection with the least pedestrian crossings was Girard Blvd and Coal Avenue while other low pedestrian volume intersections were Lomas Blvd and San Mateo Blvd, and Menaul Blvd and San Mateo Blvd. The intersections with the highest pedestrian volumes were located in areas where it was expected to have high pedestrian crossings such as Downtown and the University of New Mexico. Other intersections where high pedestrian volumes were observed were located along Central Avenue, one of the most frequented and used arterials in the city. Locations where low pedestrian volumes were observed included areas along major arterials with high speed limits (San Mateo Blvd, Louisiana Blvd and

Wyoming Blvd) and locations where the land use varied from university infrastructure (University Blvd, Cesar Chavez) to single family housing (Girard Blvd, Coal Avenue).

Table 4: Estimated 12 hour pedestrian volumes at study intersections

S.no	Intersection	Pedestrian volume
1	Lomas & Carlisle	225
2	Central & Carlisle	560
3	Central & San Mateo	1,745
4	University & Lomas	808
5	University & Cesar Chavez	183
6	Central & Louisiana	1,352
7	San Mateo & Montgomery	1,046
8	Louisiana & Indian School	664
9	Central & Broadway	802
10	Central & University	1,065
11	Central & Girard	1,128
12	Central & Yale	2,744
13	Central & 3rd	3,622
14	Lomas & Broadway	567
15	Wyoming & Zuni	282
16	University & Coal	618
17	Girard and Coal	117
18	Yale and Lead	612
19	Central and Coors	280
20	Central and Atrisco	228
21	Central and Rio Grande	581
22	Menaul and Carlisle	204
23	Lomas and San Mateo	166
24	Menaul and San Mateo	156
25	University and Indian School	188
26	Lomas and Louisiana	332
27	Menaul and Wyoming	208
28	Gibson and University	342
29	Gibson and San Mateo	187
30	Gibson and Girard	218

Pedestrian count data were also obtained from the Mid Region Council of Governments , MRCOG (2002-2008).These data include counts of daily pedestrian crossings for 586 intersections in the Albuquerque metropolitan area over a period of seven years from 2002 to 2008. Counts were manually done using count forms along pedestrian crossing locations. Table 5 shows the data obtained from these counts.

Table 5: Pedestrian count data variables-MRCOG data

Field	**Comments**
Intersection	
Date	
Month	
Year	
Season	
Ped total	Total pedestrian counts for one day

The manually collected and MRCOG counts are used in separate statistical analysis to investigate factors associated with increased pedestrian crash risk. The main advantage of the counts that were made as part of this project is that they are more recent than MRCOG's counts and therefore align with the time period of our crash data. On the other hand, MRCOG's counts cover a much larger number of intersections, providing more statistical power to explore factors potentially associated with increased pedestrian crash risk.

The counts obtained from MRCOG were spread over a period of six years from 2002-2008 and collected at different times of the year. The counts therefore had to be adjusted so that they correspond to the crash data being studied for 2010-2013. The average population growth of Albuquerque over a period of 10 years (2002-2012) was calculated from US Census population estimates. The average growth rate (1.2%) was then used to adjust pedestrian counts with equation 3.

$$PDS_{popadj} = PDS_{tot} * (1 + r)^t \quad \text{Eq-3}$$

Where,

PDS_{popadj} = Adjusted pedestrian volumes based on poplation growth

PDS_{tot} = Daily pedestrian counts obtained from MRCOG

r = annual population growth rate

t = number of years between the year the count was made and crash data collected

The year adjusted counts were then multiplied with seasonal adjustment factors. Seasonal adjustment factors were obtained for every month from the National Bicycle and Pedestrian Documentation Project (NBPD, 2009) (Table 6). The project involved collecting pedestrian and count data from 310 counts across 93 communities across the country over a period of 5 years from 2004 to 2009 through surveys. Adjustment factors were then estimated based on the location and time of counts collected through the survey. Albuquerque was taken to be a city of very hot summer and mild winter. Pedestrian volumes were adjusted accordingly.

$$PDS_{adj} = \frac{PDS_{popadj,k}/MF_k}{12} \quad \text{Eq-4}$$

Where,

PDS_{adj} = Average annual daily pedestrian count

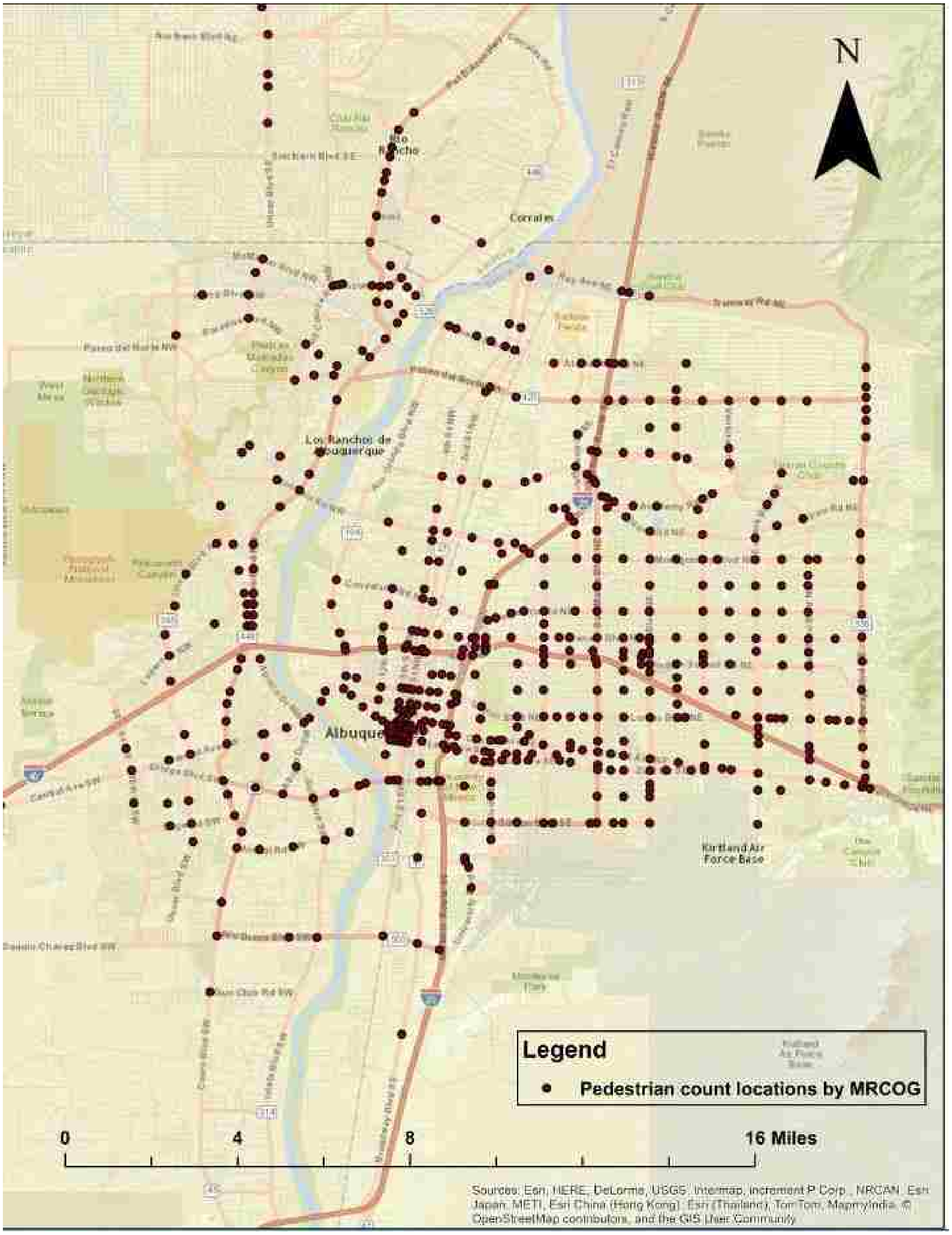
$PDS_{popadj,k}$ = Daily pedestrian count for the month k

MF_k = Percentage of annual pedestrian volume occurring during month k (Table 6)

Table 6: Climate adjustment factors

	Climate Region		
Month	Long winter short summer	Moderate Climate	Very hot summer Mild winter
Jan	3%	7%	10%
Feb	3%	7%	12%
Mar	7%	8%	10%
Apr	11%	8%	9%
May	11%	8%	8%
Jun	12%	8%	8%
Jul	13%	12%	7%
Aug	14%	16%	7%
Sep	11%	8%	6%
Oct	6%	6%	7%
Nov	6%	6%	8%
Dec	3%	6%	8%

Figure 13: Pedestrian count locations for data obtained from MRCOG



1.3. Data for explanatory variables

Different socio-economic, demographic and physical factors were studied as part of the statistical analysis to evaluate their potential association with different levels of crash risk. 12 hour pedestrian volumes for the counts done by UNM students were obtained from the extrapolated hourly volumes as discussed in the previous section. Daily vehicle volumes were obtained for all intersections from the Mid Regional Council of Governments, MRCOG 2009. Pedestrians frequently come in contact with vehicular traffic, which is why this variable was seen as important to include in the study. Average Median income and demographic data such as age of the population and percentage of minority population were obtained from the American Community Survey (ACS) conducted by the United States Census Bureau. It was hypothesized that income and the percentage of minorities could be indicators of poverty levels which could have an impact on pedestrian crash risk. Higher transit use, alcohol and drug abuse in more disadvantaged areas were hypothesized to have a potential an impact on pedestrian crash risk. Intersection characteristics such as the presence of right turn lanes, presence of yield lanes and the presence of medians were obtained by looking at the intersections in Google Maps whereas the average driveway distance, which is the total length of all driveways within 100m of an intersection was obtained by measuring the length of driveways within 100 meters for each intersection. This was achieved by using ArcGIS. Intersection characteristics could indicate a relation between the way an intersection is designed and their role in ensuring the safety of pedestrians. Right turn lanes and yield lanes could lead to a conflict of right of way whereas the presence of large driveway distances could lead to the pedestrians in direct conflict with turning vehicles. Shown below in Table 7 are the descriptive statistics for the explanatory variables used in the analysis of UNM data and in Table 8 are the descriptive statistics of the explanatory variables used in the analysis of MRCOG data.

Table 7: Descriptive statistics for variables used for UNM counts data analysis

Variable	Mean	Median	Standard Deviation	Range
Daily Vehicle Volume	77,567	76,425	29,764	23,200 - 155,100
Daily Pedestrian Volume	707.7	451	793.4	117 - 3,622
Demographic characteristics (within 0.25 mile of intersection)				
Average Median Income	40,736	36,847	18,349	19,392 - 93,801
% population under 25	34.22	31.8	7.78	22.96 - 55.28
% population over 60	16.17	14.55	5.9	6.68 - 28.10
% of nonwhite population	33.5	33.31	8.33	21.07 - 48.67
Intersection Characteristics				
Presence of right turn only lanes	Yes = 1, No = 0			
Presence of medians	Yes = 1, No = 0			
Presence of yield lanes	Yes = 1, No = 0			
Total driveway distance (100 m from the intersection)	57.72	61.31	31.41	0 - 113.96

Table 8: Descriptive statistics for MRCOG counts data analysis

Variable	Mean	Median	Standard Deviation	Range
Daily Vehicle Volume	126,530	93,683	127,983	13,988 - 750,722
Daily Pedestrian Volume	255	97	573	8 - 5,437
Demographic characteristics (within 0.25 mile of intersection)				
Average Median Income	35,687	37,048	14,512	3,850 - 68,077
% population under 18	25	24.07	3.99	11.75 - 42
% population under 25	33.77	33.47	4.94	15.08 - 63.26
% population over 65	13.48	10.98	7.5	4.87 - 82.03
% of nonwhite population	57.87	54.92	18.27	19.45 - 96.9
Intersection Characteristics				
Total driveway distance (100 m from the intersection)	336.3	323.5	182.71	27 – 876.6
Presence of right turn only lanes	Yes = 1, No = 0			
Presence of yield lanes	Yes = 1, No = 0			
Presence of medians	Yes = 1, No = 0			

1.3.1. Estimating crash risk

Pedestrian crash risk is estimated for each study intersection as the number of pedestrian crashes divided by the total number of pedestrian crossings for one year.

For the analysis involving pedestrian counts obtained by manual data collection methods, the number of crashes for each intersection was determined from the crash data obtained from the New Mexico Department of Transportation (NMDOT). Because the pedestrian counts were for a 12-hour time period, 09:00 a.m. to 09:00 p.m., only crashes which have occurred during this time period have been considered. Also, as the counts were taken only on weekdays, only weekday crashes were considered. The annual average number of crashes for the time period 2010-2013 was computed for all intersections. The daily pedestrian volumes for each intersection, obtained by extrapolating hourly volumes from the control intersections was multiplied with the number of weekdays and the number of weeks to get annual weekday pedestrian volumes. Then, the average number of pedestrian crashes per year was divided with the pedestrian volume to obtain pedestrian crash risks.

For pedestrian count data obtained from the Mid Region Council of Governments, crash risks were compiled using a similar approach. First, pedestrian crash data was filtered to depict all crashes with their corresponding intersections. This crash data was intersected with the intersection data where pedestrian counts have been taken and at least one crash had occurred. This narrowed the number of intersections studied to 151 intersections. The pedestrian volumes obtained by MRCOG were weekday pedestrian volumes at the intersections. These volumes were multiplied by the number of weekdays and the number of weeks to obtain annual weekday pedestrian volumes. The average number of pedestrian crashes which have occurred on weekdays was calculated divided with the annual pedestrian volumes to obtain pedestrian crash risks at these intersections.

1.3.2. Statistical analysis

To understand factors that may affect pedestrian crash risk, a statistical analysis was performed using R software. A negative binomial regression model was used to investigate potential associations between intersection level crash risk and the explanatory variables discussed above. A negative binomial model was chosen because this is generally accepted as the best method for evaluating discrete, non-negative events that may be over dispersed Unlike the Poisson regression model which is also commonly used with discrete count data, the negative binomial model does assumes that the variance and mean are equal, making the model more flexible.

A variety of model specifications were tested to explore the effects that each of the variables in Table 7 and Table 8 had on pedestrian crash risk. The number of pedestrian crashes was the dependent variable in each model and pedestrian volume was modeled as an offset (exposure variable) for the dependent variable. This allowed us to study the association of the independent variables with crash risk.

To determine if the model included in the study had the best fit, first, all variables were included in the model. After this was tested and checked for goodness of fit using a Chi-squared and a Breusch Pagan test, it was seen that some of the variables were insignificant, determined at the 10% confidence level, which could be a result of correlation between the variables in addition to these variables having no association with crash risk. To reduce the potential for multicollinearity, pairs of variables with a correlation coefficient greater than 0.6 were not included together as this indicates a high amount of correlation and therefore higher potential for problems due to multicollinearity. The variable that improved the overall fit was included and the model was fit again. This led to different models which were checked for goodness of fit and compared to the original model for the best fit. The model with the best fit was included in the study. Tables 9 and 10 show the correlation matrices used for both datasets.

Table 9: Correlation matrix of p values for variables used in UNM counts

Variable	Vvol	Income	Age25	Age60	Minority	Drdist
Vvol		0.1348	0.6919	0.0237	0.6652	0.1298
Income	0.1348		0.0276	0.5806	0.3174	0.3568
Age25	0.6919	0.0276		0.0031	0.0161	0.1612

Age60	0.0237	0.5806	0.0031		0.1466	0.0197
Minority	0.6652	0.3174	0.0161	0.1466		0.0694
Drdist	0.1298	0.3568	0.1612	0.0197	0.0694	

Table 10: Correlation matrix of p values for variables used in MRCOG counts

Variable	Age25	Age65	Minority	Income	Vvol	Drdist
Age25		0	0.01	0	0.5238	0.0216
Age65	0		0.007	0.0007	0.4089	0.1796
Minority	0.01	0.007		0	0.8715	0.3495
Income	0	0.0007	0		0.0029	0.1608
Vvol	0.5238	0.4089	0.8715	0.0029		0.3464
Drdist	0.0216	0.1796	0.3495	0.1608	0.3464	

Chapter 4

RESULTS

The first section in this chapter presents pedestrian crash risk estimates using two different data sources. 30 intersections in the city were studied, where pedestrians were counted manually. We refer to this as ‘UNM Counts’. In addition, the dataset from Mid Region Council of Governments (MRCOG) provides pedestrian counts for 151 intersections in the city, which we refer to as ‘MRCOG counts’. The results were evaluated graphically using scatter plots and maps. The second section in the chapter presents the results of the statistical analysis.

1.1.Pedestrian crash risk

When pedestrian crash risk estimates for intersections that included in both the UNM counts and MRCOG counts were compared, the following observations were made:

- Crash risks are high along Central and San Mateo Blvd, San Mateo and Lomas Blvd and San Mateo and Montgomery Blvd in both the datasets.
- Louisiana Blvd, which is another major arterial intersection, has relatively less risk at Central and Louisiana and Louisiana and Lomas Blvd for UNM counts data when compared to MRCOG counts.
- The magnitude of change for crash risks varied considerably among the datasets. For example, even though the intersections near University as well as Downtown had the lowest crash risks, the risk was comparatively higher in magnitude for MRCOG counts than for UNM counts

The magnitude in estimated crash risks likely varied because of the different time periods and years when pedestrian volumes were collected and the various ways in which they were adjusted to be compatible with the crash data. The uncertainty in our risk estimated should result in caution when interpreting the results. Intersection specific risk estimates are uncertain, and depend on which data set was used. However, the trends between the two data sets are generally the same and so the overall trends between crash risk and potential explanatory factors are expected by be more consistent and reliable than individual intersection specific data points.

Pedestrian crash risks for the thirty intersections where manual counts were taken are reported in Table 11 as the number of crashes per 10 million crossings per year at or near an intersection. Figure 13 shows the relation between pedestrian crashes and pedestrian crash risk whereas figure 14 shows the spatial display of the relation between pedestrian crash risk and the number of pedestrian crashes.

The results indicate that a higher number of crashes at an intersection do not necessarily mean that these intersections are the most dangerous. The intersection with the highest pedestrian crash risk (Central and Atrisco) does not have the highest number of pedestrian crashes (San Mateo and Montgomery). This is interesting as it goes against the presumption that an intersection with the highest number of pedestrian crashes is generally regarded as the most dangerous intersection for pedestrian usage. Furthermore, the results show that intersections with relatively low pedestrian volumes also tend to have relatively high pedestrian crash risks, while intersections with relatively high pedestrian volumes tend to have relatively low pedestrian crash risks. This shows that safety may depend on the number of pedestrians using an intersection or “safety in numbers”.

The spatial relation between pedestrian crashes and pedestrian crash risk shows that intersections away from downtown and the university have relatively high crash risk as compared to intersections in downtown or near the university. It is also observed that major arterials such as Lomas Blvd, Menaul Blvd, San Mateo Blvd and Louisiana Blvd have higher crash risks. Some intersections (Central and Coors, Girard and Coal) have similar high crash risks though the number of crashes is low.

Table 11: Intersection crash risk estimates for UNM counts

S.no	Mainline Roadway	Intersecting Roadway	Weekday Ped volume	Weekday Ped crashes[a]	Weekday Ped crash risk[b]
1	Lomas	Carlisle	225	1	43
2	Central	Carlisle	560	0	0
3	Central	San Mateo	1,745	6	33
4	Lomas	University	808	0	0
5	University	Av Caesar Chavez	183	0	0
6	Central	Louisiana	1,352	8	57
7	San Mateo	Montgomery	1,046	10	92
8	Louisiana	Indian School	664	3	43
9	Central	Broadway	802	0	0
10	Central	University	1,065	2	18
11	Central	Girard	1,128	0	0
12	Central	Yale	2,744	2	7
13	Central	3rd	3,622	3	8
14	Lomas	Broadway	567	1	17
15	Wyoming	Zuni	282	3	102
16	University	Coal	618	2	31
17	Girard	Coal	117	1	82
18	Yale	Lead	612	0	0
19	Central	Coors	280	2	69
20	Central	Atrisco	228	5	211
21	Central	Rio Grande	581	3	50
22	Menaul	Carlisle	204	0	0
23	Lomas	San Mateo	166	2	116
24	Menaul	San Mateo	156	1	62
25	University	Indian School	188	1	51
26	Lomas	Louisiana	332	2	58
27	Menaul	Wyoming	208	3	139
28	Gibson	University	342	0	0
29	Gibson	San Mateo	187	1	51
30	Gibson	Girard	218	0	0

[a]Total crashes for years 2010-2013

[b]Crashes per 10 million crossings

Figure 14: Relationship between pedestrian crashes and pedestrian crash risk for UNM counts

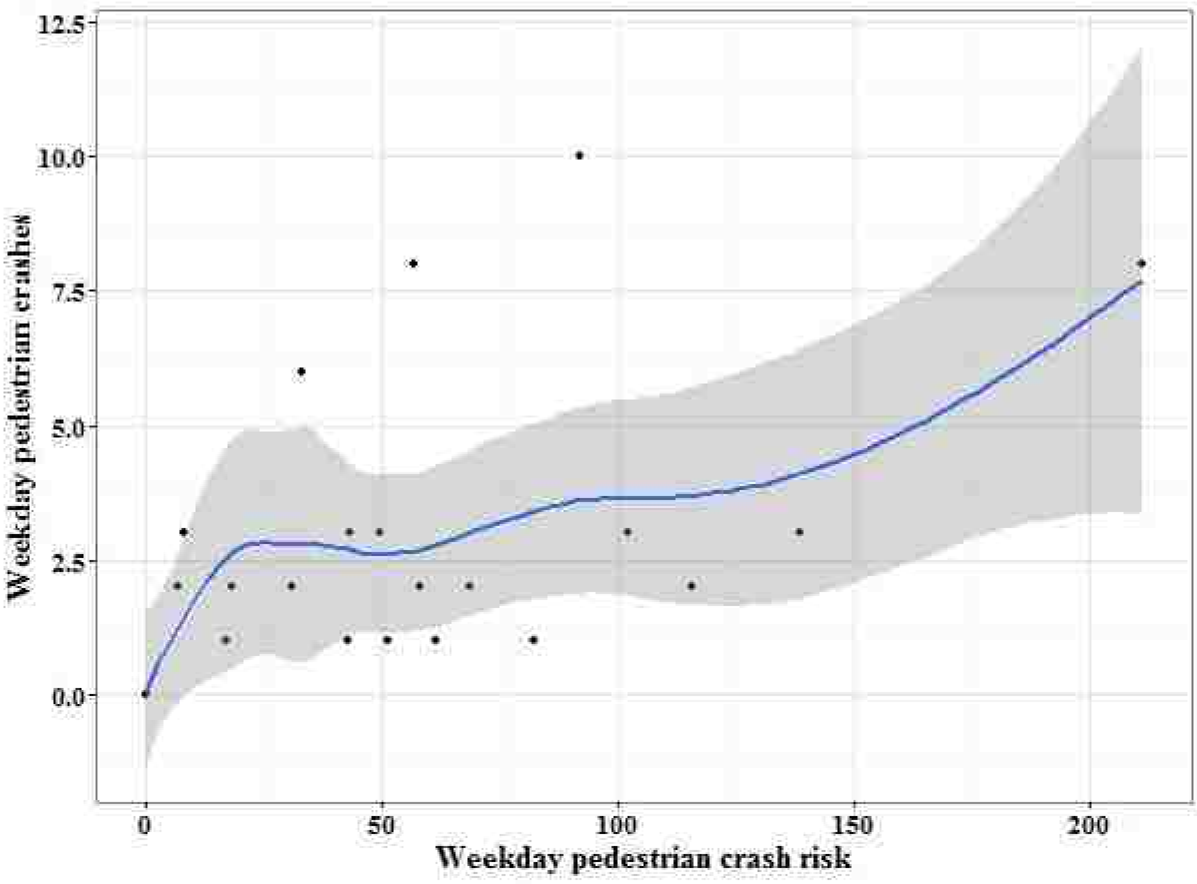
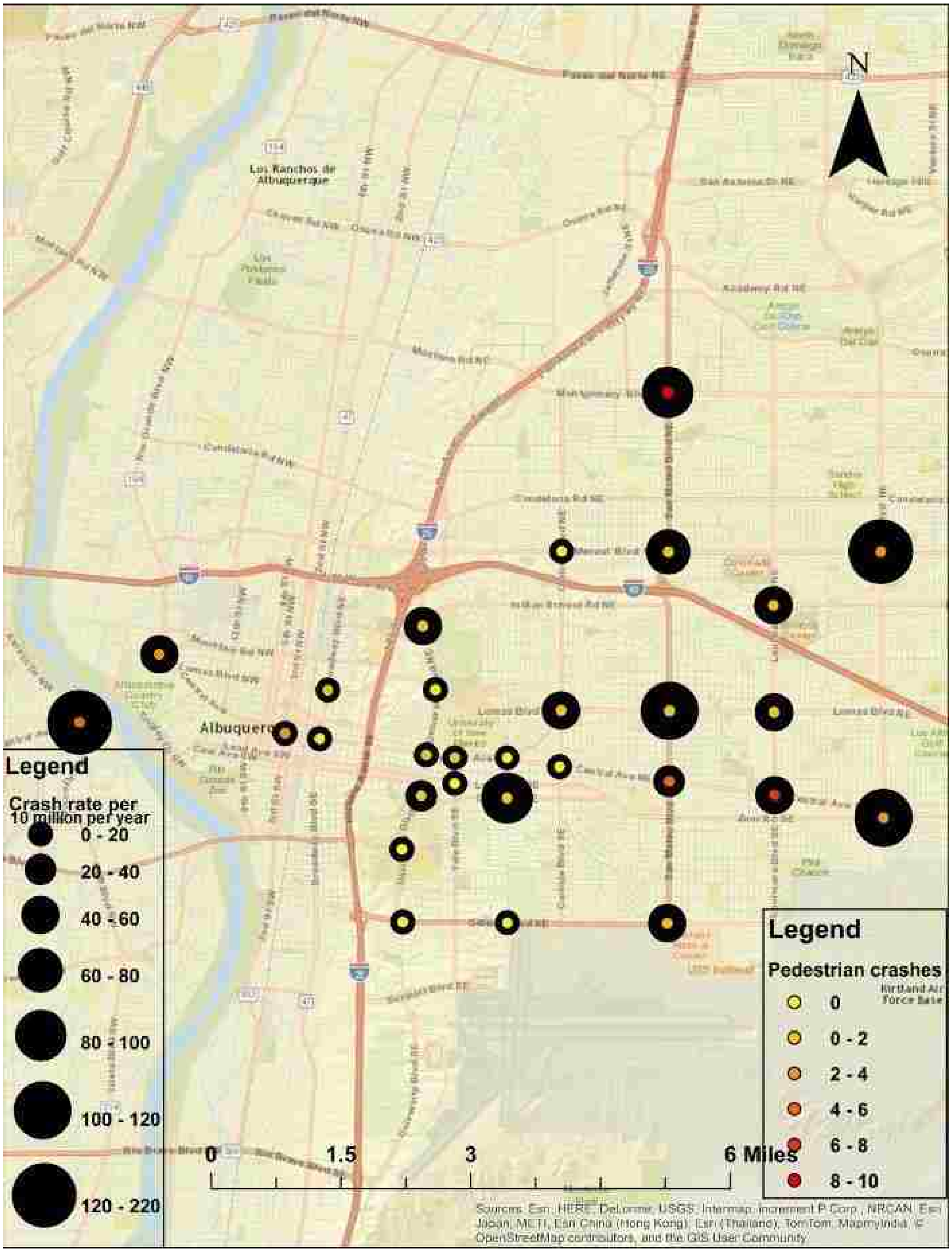


Figure 15: Relationship between pedestrian crashes and pedestrian crash risk for UNM counts



Pedestrian crash risks for the intersections where counts were obtained from MRCOG are also computed. Figure 16 below shows the relation between pedestrian crash risks and pedestrian crashes for these intersections. Figure 17 shows the spatial relation between pedestrian crash risk and the number of pedestrian crashes.

The results for pedestrian crash risk again show that intersections with the highest number of pedestrian crashes do not have the highest pedestrian crash risks. Most intersections near the university and downtown have low pedestrian crash risks. This may be due to higher pedestrian volumes near these intersections which are located in the highest density and most walkable parts of the city. These higher volumes might lead to a safety in numbers effect which would be seen as to decrease risk. Intersections on the west side of the river have relatively high pedestrian crash risks even though the number of crashes is low. Higher pedestrian crash risks are also seen on the east end of Central Avenue and on busy arterials such as Louisiana Blvd and San Mateo Blvd. Higher speed limits on east central and on major arterials such as San Mateo Blvd and Louisiana Blvd can be one of the reasons as well as lower pedestrian volumes. One study by Gårder, 2004 shows that the risk of a pedestrian being hit was higher in locations where the speed limits were high.

Figure 16: Relationship between pedestrian crashes and pedestrian crash risk for MRCOG counts

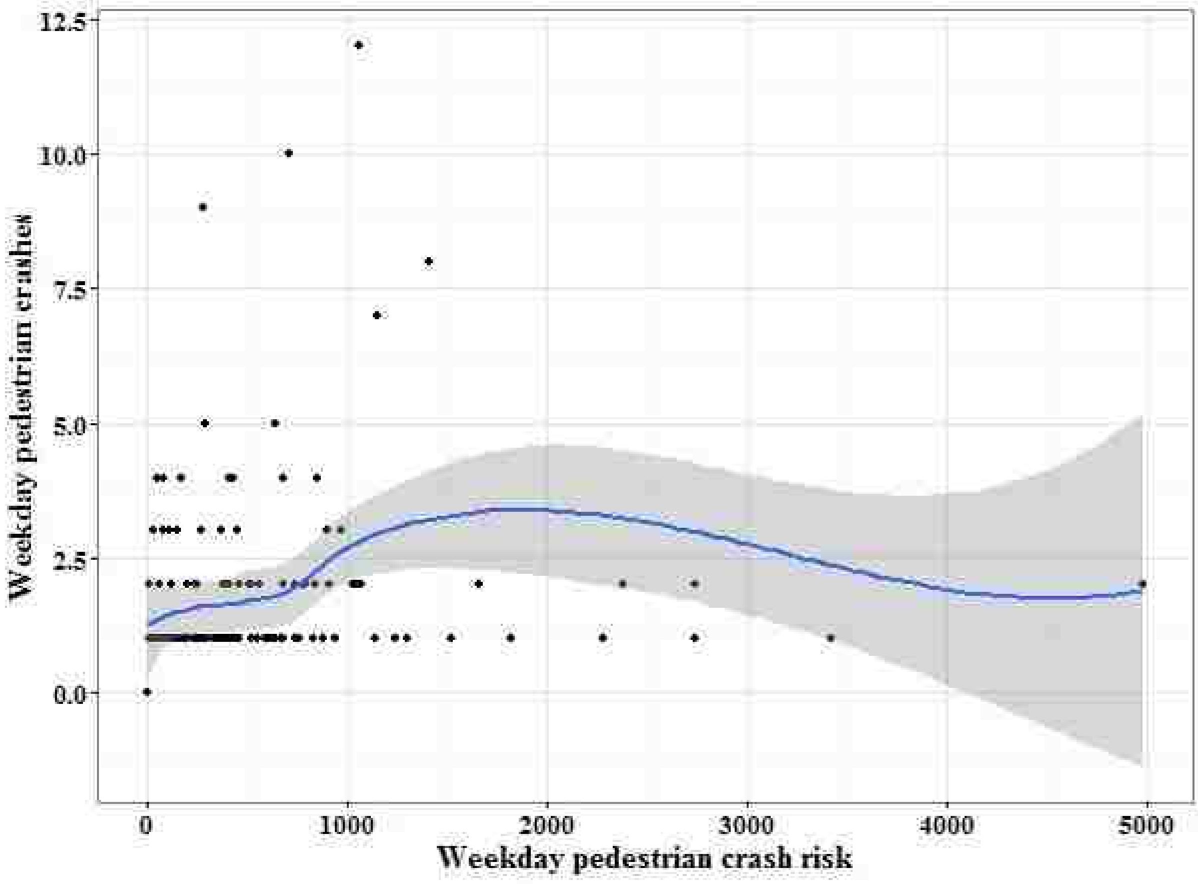
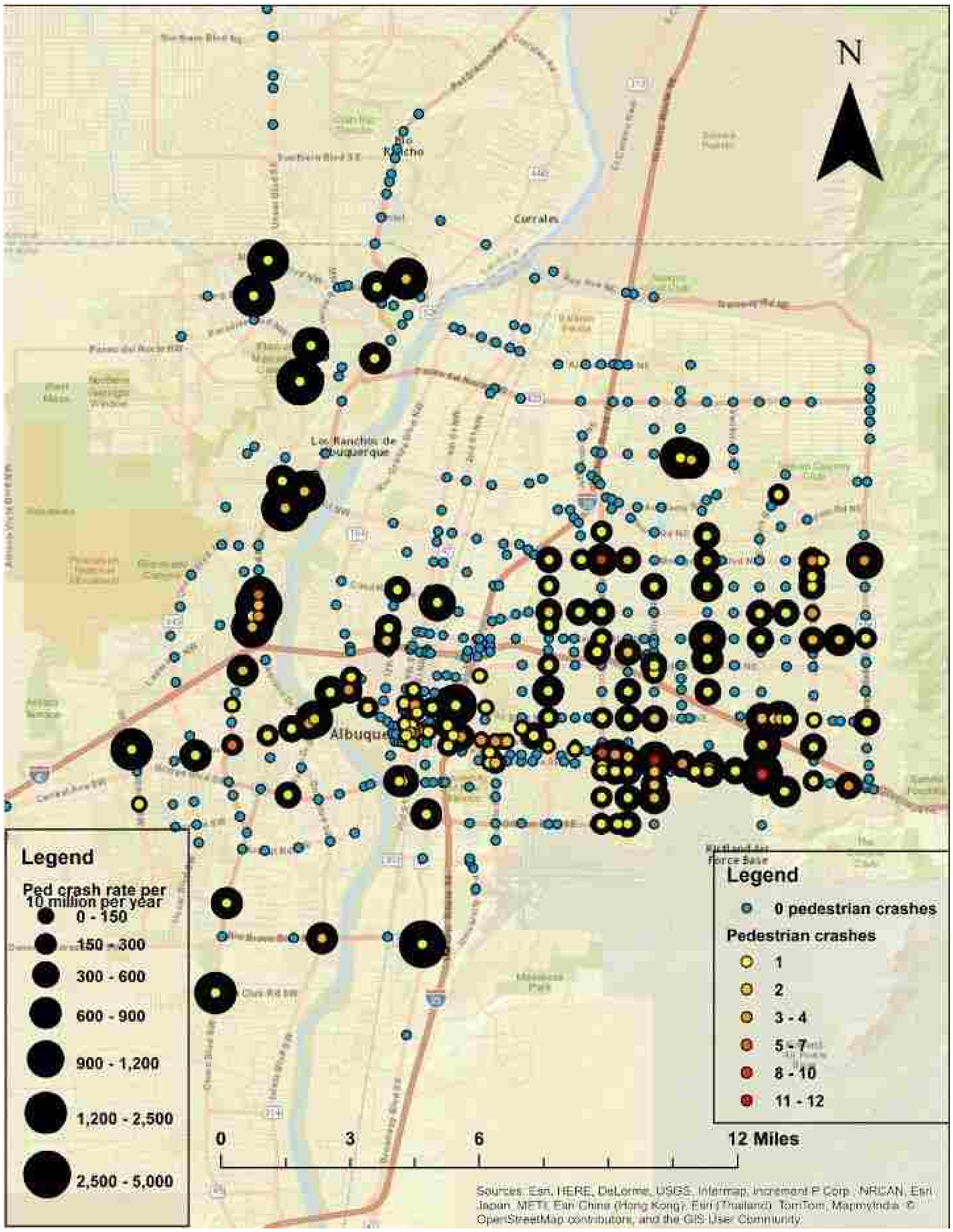


Figure 17: Relationship between pedestrian crash risk and pedestrian crashes for MRCOG counts



1.1. Graphical and spatial analysis of explanatory variables

This section shows the different variables used in the negative binomial regression as part of a graphical and spatial analysis with respect to weekday pedestrian crash risks for the intersections. Each figure in the analysis has a graphical component and a spatial component. Two subsections differentiate the analysis into variables used in the analysis of UNM counts and the variables used in the analysis of counts obtained from MRCOG.

1.1.1. Analysis of variables for intersections with UNM counts

Figure 18 shows the relationship between weekday pedestrian crash risk and average daily vehicle volume for intersections with UNM counts. It can be observed from the plot that there is an association between pedestrian crash risk and vehicle volumes. Pedestrian crash risk increases with an increase in vehicle volume.

From the map, it is observed that the intersections with the lowest pedestrian crash risks have low vehicle volumes. Locations near the university and downtown have relatively low vehicle volumes and also lower crash risks. Less exposure to vehicle traffic may account for the reduced risk. Lower volume roads may also have other attributes that lower risk such as lower speed limits, better pedestrian infrastructure, and higher pedestrian volumes. Intersections away from the city core such as those on San Mateo Blvd, Menaul Blvd and west and east Central Avenue have higher vehicular volumes and comparatively higher crash risks. These locations have higher speed limits as they are father from areas of dense population.

Figure 19 shows the relationship between weekday pedestrian crash risk and the percentage of the population under the age 25. It is seen that the overall trend shows a decrease in risk with an increase in the percentage of population below 25. It is observed from the map that locations with the highest percentage of population below 25 are all located near the university and in downtown. The decrease in risk due to an increase in the percentage of population below 25 years seems to be attributable to the large number of people who probably walk to the university and to work downtown, an example of a safety in numbers effect.

Figure 20 shows the relation between pedestrian crash risk and the total driveway distance within 100m of an intersection. It is observed that an increase in the total driveway distance tends to increase pedestrian crash risk. The majority of the intersections on major arterials have the highest total driveway distances. These are intersections with a heavy presence of strip malls and commercial activities. The relation between crash risk and driveway distance may be due to increased pedestrian exposure to vehicle traffic using these driveways or from vehicles turning out of these driveways and into an intersection.

Figure 18: Relationship between weekday pedestrian crash risk and average weekday vehicle volume (UNM counts)

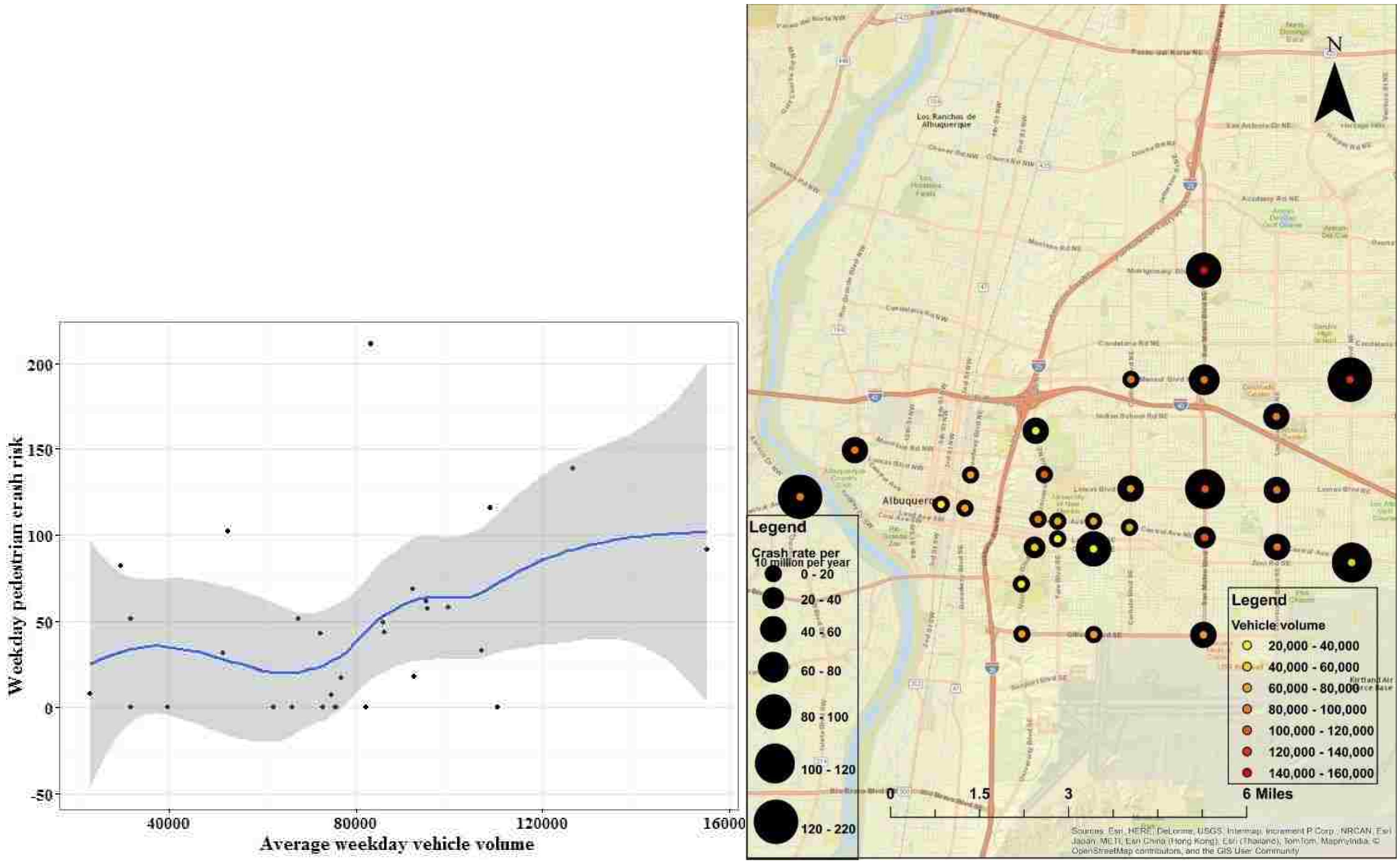
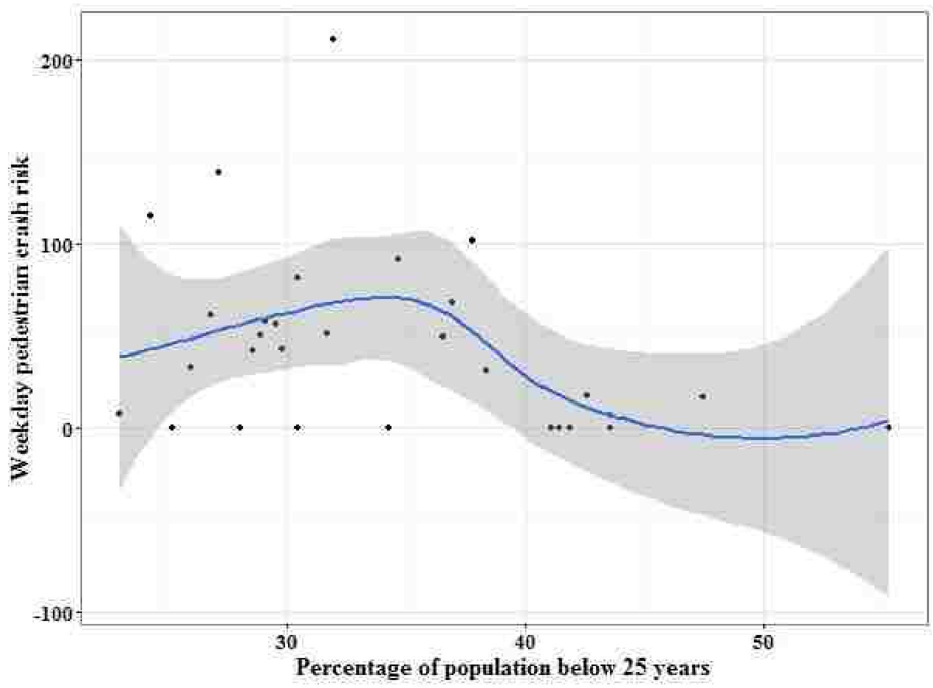


Figure 19: Relationship between weekday pedestrian crash risk and percentage of population under 25 years of age (UNM counts)



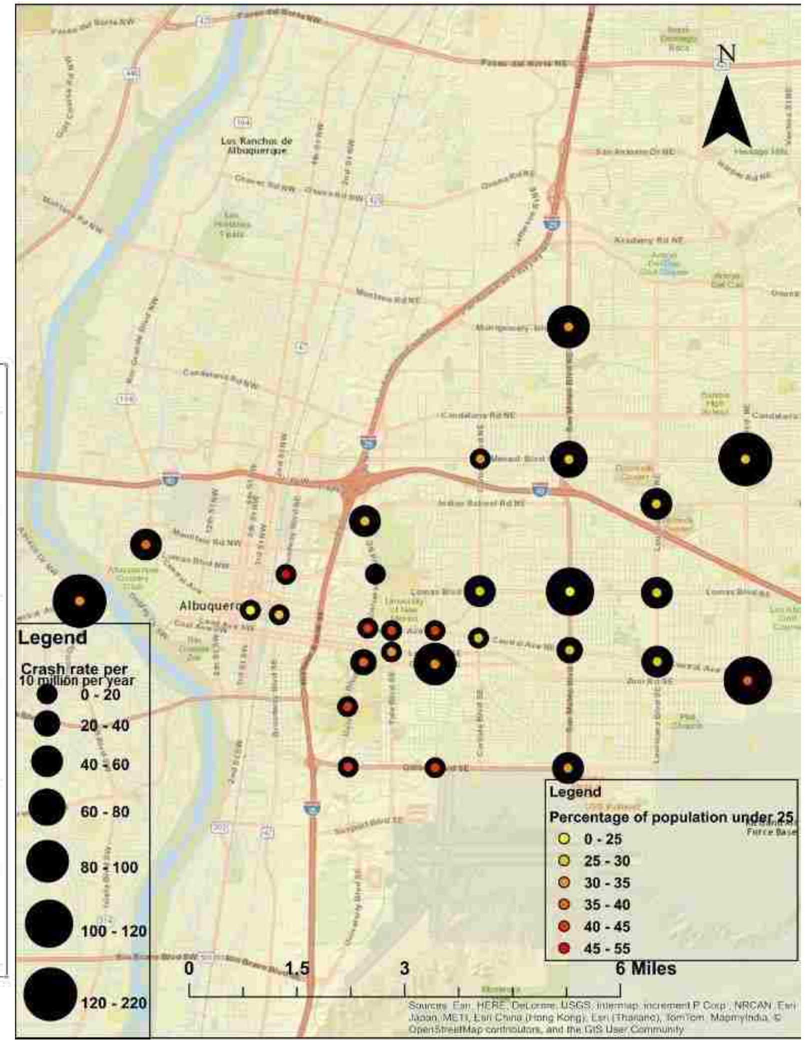
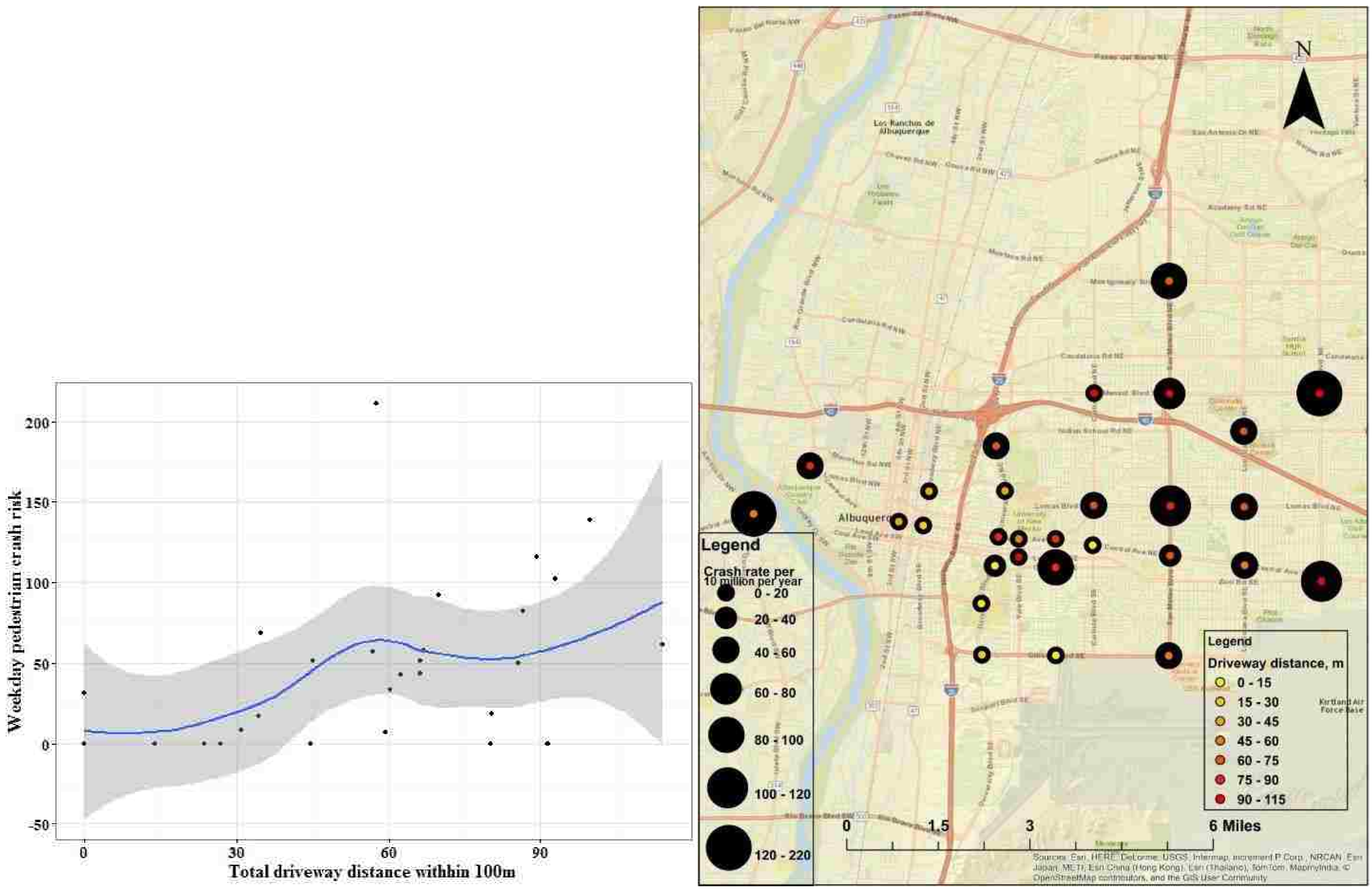


Figure 20: Relationship between weekday pedestrian crash risk and total driveway distance within 100m (UNM counts)



1.1.2. Analysis of variables for intersections with MRCOG counts

Figure 21 shows the relation between weekday pedestrian crash risk and average daily vehicle volume for intersections with MRCOG counts. It can be observed that an increase in traffic volume is associated with an increased crash risk. Intersections with the highest traffic volumes are along Coors Blvd, a 4 lane arterial with high speed limits. Some of the highest crash risk intersections are also along Coors Blvd. Some of the lowest traffic volumes are observed in downtown, near the university and in intersections near Nob Hill. These are also locations with some of the least pedestrian crash risk. Speeds along these lower volume roads are also lower compared to other major arterials.

The relation between weekday pedestrian crash risk and average annual income is shown in figure 22. The general trend shows a decrease in crash risk with an increase in income. Some of the highest crash risks were on the west side and the South Valley, locations with some of the lowest annual incomes. Locations near the university and in the eastern part of the city had relatively lower crash risks and are also areas with higher income levels. The relation between income levels and pedestrian crash risk is likely an indicator that other factors associated with poverty likely contribute to increased risk.

Figure 23 shows the relation between weekday pedestrian crash risk and the percentage of minorities. Similar to the relation between crash risk and income levels, it is once again seen that intersections on the west side and in the South valley which have some of the highest crash risks are also areas with some of the highest minority populations. Areas along East Central are also seen to have comparatively high levels of minority population and crash risks. Areas with large minority populations also tend to have lower incomes and, therefore, the association between minority populations and crash risk is likely an indicator that other factors associated with poverty likely contribute to increased risk.

Figure 21: Relationship between weekday pedestrian crash risk and average weekday vehicle volume (MRCOG counts)

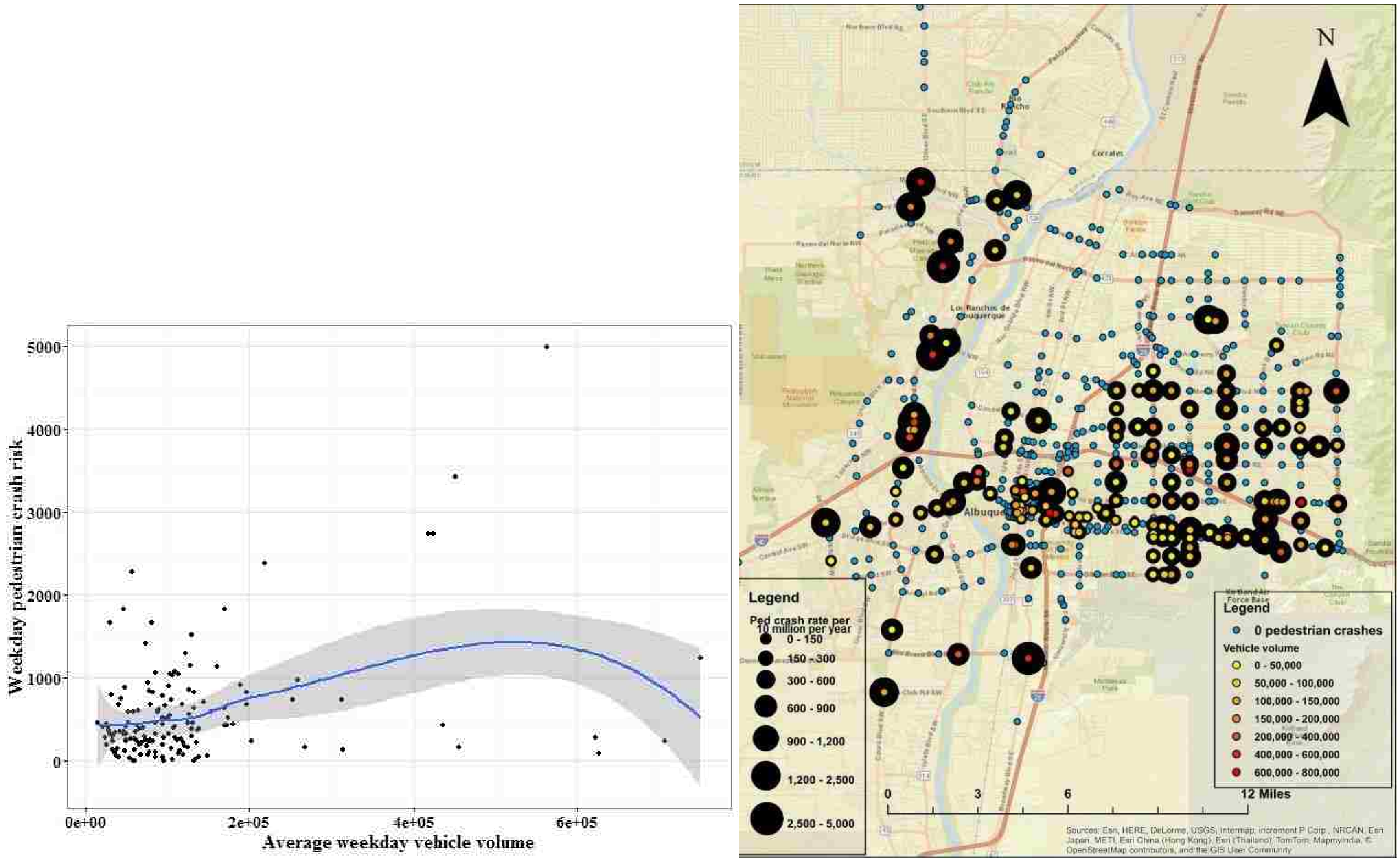


Figure 22: Relationship between weekday pedestrian crash risk and average annual income (MRCOG counts)

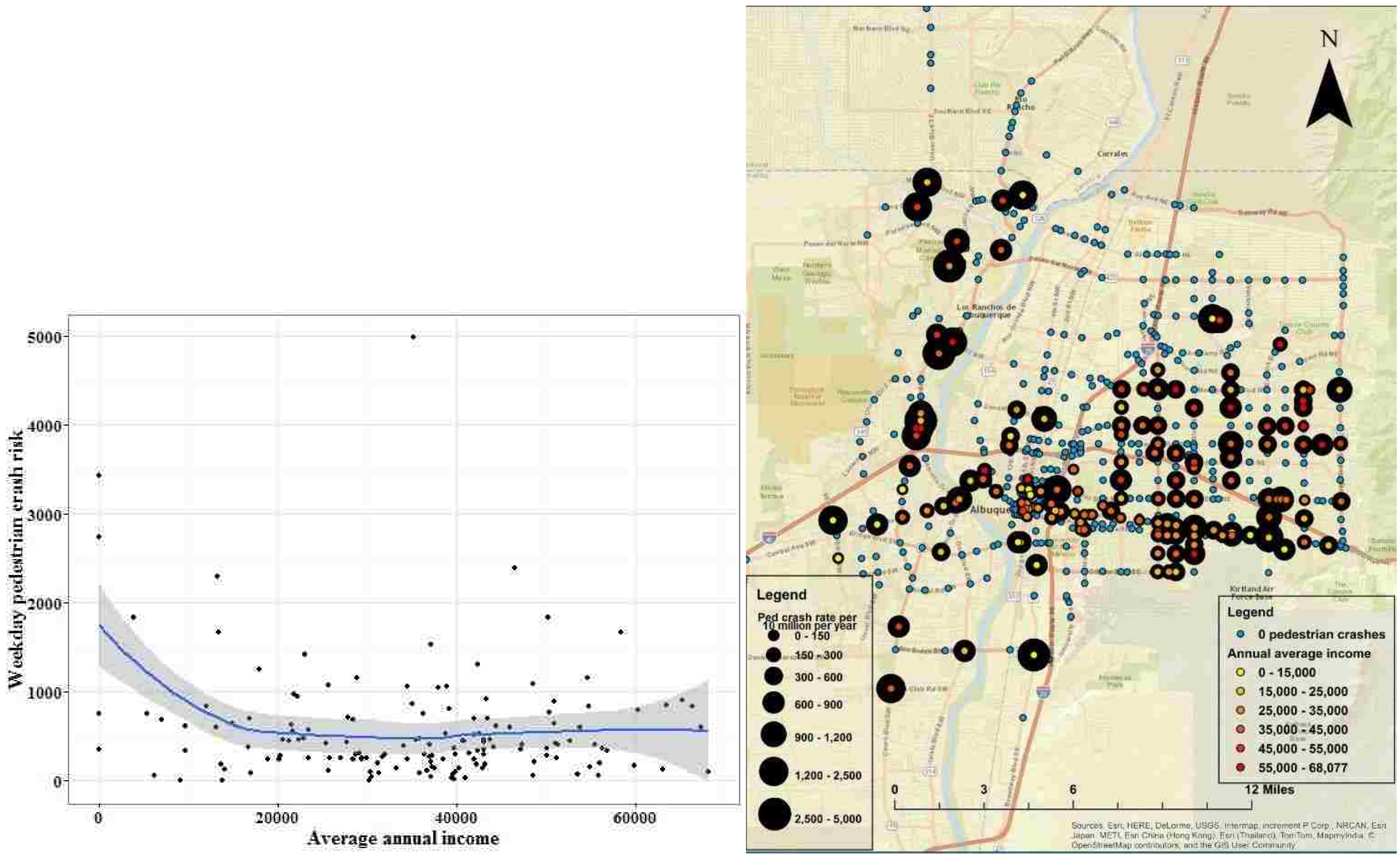
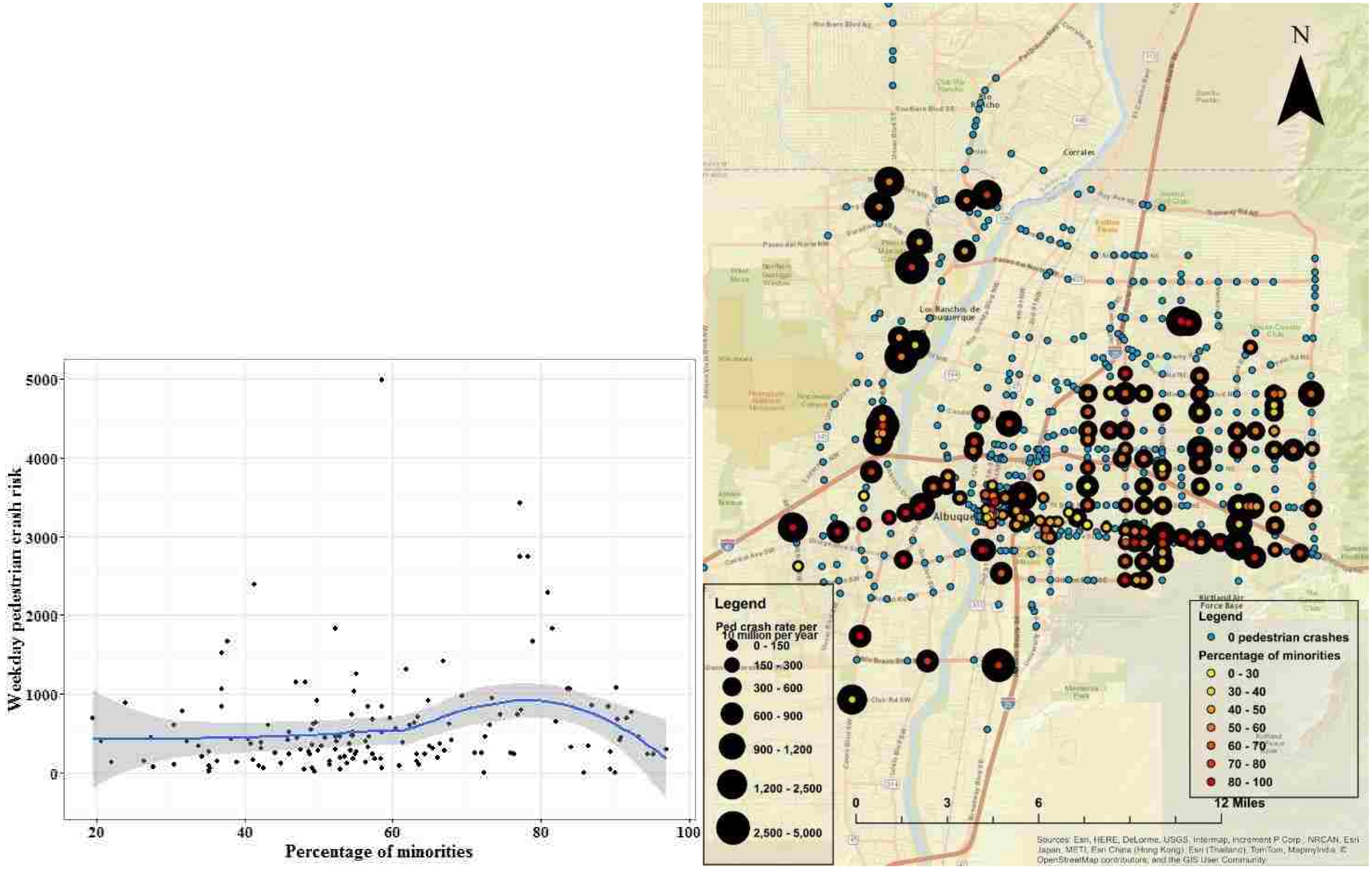


Figure 23: Relationship between weekday pedestrian crash risk and percentage of minorities (MRCOG counts)



1.2. Statistical Regression Analysis

The following section discusses the regression analysis results. The section is divided into two sections to discuss findings from the analysis of both sets of data; manual count data and count data obtained from MRCOG.

1.2.1 Analysis of pedestrian crash risk for UNM data

Table 12 shows the results of the initial model fit using all of the available explanatory variables. It can be seen that only three variables are statistically significant at the 90% confidence level ($p < 0.1$) among all the variables considered in the analysis. The three variables are the average driveway distance within 100 meters of the intersection, percentage of minorities and the presence of right turn only lanes. It was expected that the average vehicle volume would be significant given the importance vehicle volume plays in studying pedestrian safety as crashes occur only when a vehicle is present. It was also seen that the age variables were not significant which was not expected since prior studies(Dommes et al., 2012; Kim et al., 2008) found that older pedestrians were more prone to being involved in a crash than younger pedestrians.

Table 12: Regression analysis with all input variables for UNM counts

Model Variable	Estimate	SE[j]	Z-test	P-value	Confidence level
Constant	$8.17*e^{+00}$	$1.65*e^{+00}$	4.939	0.000	***
Vvol[a]	$1.09*e^{-05}$	$7.19*e^{-06}$	1.509	0.131	
Age25[b]	$-5.77*e^{-02}$	$4.69*e^{-02}$	1.232	0.218	
Age60[c]	$1.95*e^{-02}$	$4.73*e^{-02}$	0.412	0.680	
Inc[d]	$-1.74*e^{-05}$	$1.55*e^{-05}$	1.128	0.260	
Minority[e]	$7.32*e^{-02}$	$2.94*e^{-02}$	2.492	0.013	**
Drdist[f]	$1.91*e^{-02}$	$7.91*e^{-03}$	2.408	0.016	**
Rightyes[g]	$7.47*e^{-01}$	$3.98*e^{-01}$	1.874	0.061	*
Yieldyes[h]	$7.26*e^{-01}$	$5.66*e^{-01}$	1.284	0.199	
Medianyes[i]	$-4.61*e^{-01}$	$5.38*e^{-01}$	0.856	0.391	

VVol[a] = Average daily vehicle volume
Age25[b] = Percentage of population below the age 25

Age60[c] = Percentage of population above the age 60
Inc[d] = Average annual income
Minority[e] = Percentage of nonwhite population
DrDist[f] = Total driveway distance within 100 m of the intersection
Rightyes[g] = Presence of right turn only lanes
Yieldyes[h] = intersections with yield lanes
Medianyes[i] = intersections with yield lanes
SE[j] = Standard Error
*** >=99% confidence level, ** >=95%, and *>=90%

Null deviance: 66.624 on 29 degrees of freedom
Residual deviance: 28.731 on 20 degrees of freedom

R-squared = 1 – (residual deviance/null deviance)
= 1 - (28.73/66.62)
= 0.57

Two tests were run to test for goodness of fit and the presence of heteroscedasticity. Presence of heteroscedasticity can lead to invalidation of tests of significance and result in biased estimates. A chi-square test was run to conduct a goodness of fit test along with the quasi R-squared value calculated for each model run. The p value was calculated for the chi squared test and the significance level was set at 0.05. To check for heteroscedasticity, a Breusch-Pagan test was conducted. A p value from the Breusch-Pagan test greater than 0.05 meant that the model did not suffer from heteroscedasticity and the variables used were homoscedastic.

Chi-squared p-value = 0.093

B-P test p-value = 0.14

The model passed both the tests which meant that the variables used in the model were homoscedastic and was consistent with the distribution.

Table 13 shows the results of a reduced model created by incrementally removing the most insignificant variables. It has five explanatory variables that are statistically significant at the 90% confidence level ($p < 0.1$).

Table 13: Regression analysis results for UNM counts

Model variable	Estimate	SE	Z-test	P-value	Confidence interval
Constant	$-6.35*e^{+00}$	$1.17*e^{+00}$	-5.43	0.000	***
Age25	$-6.22*e^{-02}$	$3.16*e^{-02}$	-1.97	0.049	**
Inc	$-2.81*e^{-05}$	$1.39*e^{-05}$	-2.03	0.043	**
Minority	$5.26*e^{-02}$	$2.48*e^{-02}$	2.12	0.034	**
Drdist	$2.49*e^{-02}$	$6.94*e^{-03}$	3.59	0.000	***
Rightyes	$9.66*e^{-01}$	$3.84*e^{-01}$	2.52	0.011	**

Null deviance: 59.595 on 29 degrees of freedom
Residual deviance: 30.310 on 24 degrees of freedom

R-squared = 1 – (residual deviance/null deviance)
= 1 - (35.21/84.12)
= 0.58

Chi squared p-value = 0.175

B-P test p-value = 0.58

A 1% increase in the percentage of population below 25 years was associated with reducing crash risk by a factor of 0.94. One reason can be that many pedestrians in this age group are college students who are concentrated near the university and its surroundings which might lead to a safety in numbers effect. A larger number of signalized pedestrian crossings at intersections near the university may also explain the lower crash risks.

The income variable indicates that a 1% increase in the average income of the population living near the intersection is associated with reducing crash risk by a factor of 0.99. The income variable is likely associated with other, unobserved, risk factors associated with poverty such as higher levels of alcohol and drug abuse and transit use (running across the street to catch the bus may be a significant risk factor).

An increase in the average driveway distance by of all the driveways within 100 meters of an intersection by 1 meter was associated with increasing crash risk by a factor of 1.02. More driveways and a greater total length of driveways are associated with greater pedestrian exposure to vehicle traffic, particularly turning movements that are especially dangerous.

The percentage of minorities living near the intersection was found to be positively associated with pedestrian crash risk. An increase in crash risk by a factor of 1.05 was observed with a 1% increase in the minority population living near that intersection. The minority variable was highly correlated to the daily vehicle volume variable and its inclusion led to the best fit. The minority variable may be capturing the effect of high traffic volume and also lower incomes.

The final significant variable is the presence of right turn only lanes. Intersections with right turn only lanes were seen to have 2.6 times higher pedestrian crash risk than intersections without right turn only lanes. This was also a finding of a study by Schneider et al., (2010) where a positive association was found between crash risk and right turn only lanes.

Both the chi squared p-value and the B-P test's p-value were greater than the model when all the variables were included in the model. This meant that the reduced model fit better than the model with all variables and did not suffer from heteroscedasticity as well. A higher quasi R-squared value also showed that the model fit better than the previous model.

1.2.2. Analysis of pedestrian crash risk for MRCOG counts

It can be seen from the regression results in Table 15 that three the variables used in the analysis are statistically significant at the 90% confidence level ($p < 0.1$). The three variables are the percentage of the population under the age 25, the percentage of minorities and the presence of right turn only lanes. Average daily vehicle volume was again insignificant along with the total driveway distance within 100m. These were variables assumed to have a major effect but were not significant in the model.

A Chi square test run on this model gave a significant p value which meant that the variables in the model fit the distribution. The model also passed the Breusch-Pagan test for heteroscedasticity.

Table 14: Regression analysis with all input variables for MRCOG counts

Model Variable	Estimate	Std. Error	z value	Pr(>|z|)	Confidence interval
Constant	$6.47*e^{-01}$	$1.15*e^{+00}$	0.561	0.5747	
Vvol	$-3.81*e^{-07}$	$7.02*e^{-07}$	-0.544	0.5866	
Age25	$-5.35*e^{-02}$	$2.32*e^{-02}$	-2.296	0.0217	**
Age65	$-1.37*e^{-02}$	$1.55*e^{-02}$	-0.877	0.3804	
Minority	$1.25*e^{-02}$	$5.89*e^{-03}$	2.127	0.0334	**
Income	$-1.07*e^{-06}$	$7.59*e^{-06}$	0.141	0.8878	
Rightyes	$3.48*e^{-01}$	$1.83*e^{-01}$	1.9	0.0575	*
Yieldyes	$2.07*e^{-01}$	$2.21*e^{-01}$	0.936	0.3492	
Mediansyes	$3.57*e^{-01}$	$2.15*e^{-01}$	1.658	0.0974	*
Drdist	$-2.25*e^{-04}$	$4.48*e^{-04}$	-0.503	0.6149	

Null deviance: 129.78 on 150 degrees of freedom
Residual deviance: 107.09 on 141 degrees of freedom
R square = 1- (Residual deviance/Null Deviance)
= 1-(107.09/129.78)
= 0.17

Chi square p-value = 0.98

B-P test p-value = 0.52

The regression model results obtained after removing insignificant variables are shown in Table 15. There are three variables which are significant. The three significant variables are the percentage of population above 65, the percentage of minorities and the presence of right turn only lanes. The significance of two variables, percentage of minorities and the presence of right turn only lanes was seen in the regression analysis of UNM counts as well.

Table 15: Regression analysis results for MRCOG counts

Model Variable	Estimate	Std. Error	Z-value	P-value	Confidence interval
Constant	0.1577	0.603	0.261	0.793	
Age25	-0.04	0.174	-2.302	0.021	**
Minority	0.013	0.004	2.842	0.004	***
Rightyes	0.434	0.167	2.593	0.009	***

Null deviance: 125.06 on 150 degrees of freedom
Residual deviance: 108.06 on 147 degrees of freedom

R square = 1- (Residual deviance/Null Deviance)
= 1- (129.41/172.05)
= 0.14

Chi square p-value = 0.99

B-P test p-value = 0.17

The percentage of population below the age of 25 was seen to be associated with respect to pedestrian crash risk. An increase of 1% in the percentage of population below 25 years of age was associated with reducing crash risk by a factor of 0.96.

Another variable, the percentage of minorities living near the intersection was also positively associated with pedestrian crash risk. An increase of 1% in the percentage of minorities living near the intersection was associated with a 1.01 times greater crash risk. It would have been interesting to see the results when vehicle volume was seen along with the percentage of minorities but they were highly correlated (p=0.87) and only one could be used in the model. Using the percentage of minorities gave the model with the best fit.

It was also observed that intersections that have a right only turn lane are also associated with a higher crash risk. Intersections with right turn only lanes were seen to have 1.54 times higher pedestrian crash risk than intersections without right turn only lanes. This could be a result of drivers not looking out for pedestrians while turning. Right turn only lanes also put pedestrians in direct conflict with vehicles when they are crossing.

The Chi square p-value for this model was higher than the p-value for the model when all the variables were included indicating that this model had the best fit among both the models. A B-P test p-value greater than 0.05 meant that the model did not suffer from heteroscedasticity.

Chapter 5

SUMMARY AND CONCLUSIONS

The objective of the thesis was estimating crash risk for different intersections in Albuquerque and to then identify factors associated with increased risk. A graphical and statistical analysis of potential physical, demographic and socio-economic variables was completed.

Crash rates

It was observed that intersections with more crashes did not always have the highest crash risk associated with them. This is important as most pedestrian crash statistics only report the number of pedestrian crashes and these statistics are usually used to identify dangerous intersections. However, more crashes may be partly the result of more pedestrian traffic, rather than the presence of a particular risk factor. Some combination of crash volume and crash risk should be used to prioritize investments in safety countermeasures.

Another set of data which involved pedestrian counts obtained from the Mid Region Council of governments (MRCOG) was also used to calculate pedestrian crash rates. It was seen that crash rates were markedly low in areas of high pedestrian volumes such as downtown and the University of New Mexico. There is a potential safety in numbers effect as drivers may be more aware of pedestrians in these areas and therefore more careful. It was also seen that areas on the west side of the city had a low frequency of crashes and high crash rate. Possible explanatory factors are a lack of safety in numbers, unobserved factors associated with low income communities, and roadways with higher speed limits and more traffic lanes.

Statistical Analysis

For the analysis involving manual counts collected at thirty study intersections, the percentage of population below 25 years, average annual income, percentage of minorities, presence of right turn only lanes and total driveway distance were the variables seen to be most significant among all the variables. Variables with a p-value greater than 0.1 from the regression were taken to be significant. In the analysis involving counts obtained from MRCOG, three variables were significant. The variables are the percentage of people above 65, percentage of minorities and the presence of right turn only lanes. The variables which were significant in both the analyses were the percentage of minorities and the presence of right turn only lanes.

It can be seen that the variables explain some of the reasons as to what causes a pedestrian to be involved in a crash. The negative coefficient estimate of the income variable showed that areas with lower incomes posed greater risk to pedestrians. The percentage of minorities had a positive association with crash risk. An increase in this percentage increased pedestrian crash risk. As both these variables are significant in the same model, when looked together it can be assumed that there is an association between increasing crash risk and disadvantaged communities. This was the finding of a study by Cottrill and Thakuriah, (2010) where it was observed that the incidence of pedestrian-vehicle crashes was higher in areas of low income and high minority populations. One reason for the association of income and minority percentages with crash risk may be due to higher rates of alcohol and drug abuse (factors known to pose significant crash risk). However, there may be other unobserved factors that explain these associations with increased crash risk. For example, low income and minority communities may have poorer quality pedestrian infrastructure, may be located in areas with higher volume and higher speed roadways, and may be at greater risk of crashes while attempting to catch a bus.

Two age variables were significant, the percentage of population below 25 years and the percentage of population above 65. The percentage of population below 25 had a negative association with pedestrian crash rate, while the percentage of population above 65 had a positive association with crash risk. The finding that older people were more at risk of being involved in a pedestrian crash was also the finding by two other studies (Avineri et al., 2012; Kim et al., 2008). Younger average age was likely capturing the population of college students living near the university which may be a lower risk due to safety in numbers, lower traffic speeds and volumes, and better pedestrian infrastructure. Older populations are likely at increased risk due to slower response times (drivers and pedestrians) and the greater time needed to cross roadways

Increase in the driveway distance was found to be associated with increased crash risk. Schneider et al., (2010) study in California also found a positive association between driveways and pedestrian crash risk. An increased number of driveways increased pedestrian exposure to vehicle traffic, and therefore it is not surprising that pedestrian crash risk would also increase.

Another variable related to intersection design that was associated with increased pedestrian crash risk is the presence of right turn only lanes. The statistical analysis of UNM and MRCOG counts showed that intersections with right turn only lanes had 1.9 to 2.6 times greater crash risk. This was also a finding made by Schneider et al., (2010). The reasons as to why right turn only lanes increase pedestrian crash risk may be the increased complexity in understanding the traffic flow pattern through the intersection, and drivers and pedestrians that do not understand the right of way. Other exposure variables might be involved when an intersection design variable is significant in the regression. Exposure variables such as crossing distances and crossing times are crucial when analyzing pedestrian crash risk. However, these variables were not collected or evaluated in this study.

A few measures can be suggested to improve pedestrian safety based on findings in the study. Slow response and slower crossing times among older people may increase crash risk. A training program in street crossing as suggested by Dommes et al., (2012) could be designed to help older pedestrians understand the different scenarios of a crash and to develop methods which would increase response times and decrease crash risk. Signal timing could also be investigated and adjusted to allow longer pedestrian crossing times in places with larger populations of older residents. It was also found that more driveways were associated with increased risk. Driveways along major arterials could be removed or reduced in number and parallel parking introduced which would make it safer for pedestrians to walk on the sidewalk and also accommodate parking and access to businesses. The provision for parallel parking would also act like a buffer between moving traffic and pedestrians and could also provide some traffic calming by narrowing the roadway. Right turn lanes appear to be particularly dangerous. Further research is required to understand how to mitigate their risk to pedestrians.

1.1.Generalization of results

The analyses conducted in this research uses crash data from the New Mexico Department of Transportation (NMDOT) and count data both manually collect and obtained from the Mid Region Council of Governments (MRCOG). The analysis only focused on intersections in Albuquerque, New Mexico. The analysis also did not consider every possible risk factor. While the results generally agree with findings from prior studies, they may not be entirely generalizable to other locations. For example, lower income and minority populations were associated with higher crash risks. Income and minority status are not directly responsible for crash risk, they indicate associations with some unknown and unobserved factor which may be particular to Albuquerque or not.

Limitations

The study suffers from a few limitations. The project had no funding budget and therefore was completed with limited resources. This led to some concessions made on the number of intersections studied and the way information was collected. A total of 30 intersections were studied as part of the study for UNM counts which does not take into consideration a large number of other intersections and resulted in a relatively small sample size. The small sample sized limited the statistical inferences that could be made in the regression modeling. Another limitation of the study is the lack of other exposure variables like walking distances and walking times. These variables could better explain the variation in crash rates and allow us to evaluate crashes occurring away from intersections too.

Another limitation was the demographic variables based on census data. These were estimated based on a buffer drawn around each intersection. This may not necessarily explain the characteristics of the pedestrians or drivers using particular study intersections as they may be from another neighborhood. Furthermore, it was not possible to collect detailed behavioral data such as alcohol and drug use by pedestrians and drivers, illegal or dangerous crossing behaviors by pedestrians, and dangerous driving behavior.

1.2. Future Research

An extension of this study should consider a larger number of intersections to increase the statistical power of the analysis.. An extension should also consider more potential explanatory factors which are likely to influence pedestrian crash risk. The present study accounted for some intersection characteristics but it was not possible to include given the study's resource constraints a comprehensive set of variables related to an intersection. Pedestrian crash risk could be directly related to a number of engineering aspects of the intersection such as traffic signal timing and congestion levels which were not included in this study. Another area of increasing the scope of the study is to include pedestrian and driver behavior variables which would control for differences in these variables. A survey among pedestrians and drivers while collecting count data could lead to more information on behaviors while crossing an intersection and driving through an intersection. For example, it is well established that drunk driving is very dangerous. While we know that many pedestrian crashes involved pedestrians who have consumed alcohol, we have no information on what percentage of pedestrians are intoxicated and therefore if intoxicated pedestrians are more likely to be involved in crashes.

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National Pedestrian and Bike Documentation Project, NPBD 2009

APPENDIX

OBJECTID	Intersection	Month	Year	Season	pedvol
	adjpedvol	crashrate	crashes	age25	age65
	minority	income	vvol	right	yield
	medians	drdist			
1	AMERICAS	PKWY/WINROCK	&	LOUISIANA	BLVD.
	January	2003	Winter	97	95
	282.45	1	29.02	17.15	54.29
	43066.52174	622363	yes	yes	yes
	404.51				
2	AVALON RD. & 98TH ST.		May	2003	Spring
	12	15	2283.11	1	45.13
	4.87	80.92	13200	55575	no
	no	yes	155.41		
3	AVENIDA CESAR CHAVEZ & 3RD ST.			November	2007
	Fall	40	50	684.93	1
	33.47	10.38	91.66	16837.5	196682
	yes	no	yes	440.92	
4	AVENIDA CESAR CHAVEZ & 4TH ST.			October	2007
	Fall	33	46	830.22	1
	33.47	10.38	89.07	12070.58824	196682
	yes	no	yes	444.53	
5	BLAKE RD. & COORS BLVD.		May	2008	Spring
	36	45	761.04	1	42.4
	7.36	92.16	50275.33333	43338	yes
	no	yes	280.09		
6	BRIDGE BLVD. & ATRISCO DR.		February	2005	Winter
	60	49	456.62	1	36.94
	12.34	93.13	22353.84615	51623	yes
	no	yes	359.31		
7	CAMPUS BLVD. & GIRARD BLVD.			December	2006
	Winter	202	250	135.63	1
	63.26	22.74	26.46	40304.7619	31860
	yes	yes	yes	325.47	
8	CAMPUS BLVD. & MONTE VISTA BLVD.			July	2004
	Summer	69	98	397.06	1
	41.42	8.88	20.66	37000	69964
	yes	no	no	240.17	
9	CANDELARIA RD. & 12TH ST.		August	2007	
	Summer	66	93	415.11	1
	30.8	15.16	67.94	25381.66667	26360
	no	no	yes	381.47	
10	CANDELARIA RD. & 2ND ST.		October	2004	Fall
	29	40	944.73	1	30.8

	15.16	73.4	22256.19048	75676	yes
	yes	yes	353.46		
11	CANDELARIA RD. & ADAMS		February	2003	Winter
	73	60	375.3	1	29.02
	17.15	61.31	44190.21739	27946	no
	no	no	242.59		
12	CANDELARIA RD. & CARLISLE BLVD.			December	2004
	Winter	107	132	512.1	2
	29.58	16.52	58.55	41907.36842	100087
	no	no	no	439.82	
13	CANDELARIA RD. & EUBANK BLVD.			May	2003
	Spring	69	85	397.06	1
	28.51	18.29	52.43	47305.55556	106742
	no	no	yes	620.35	
14	CANDELARIA RD. & JUAN TABO BLVD.			May	2006
	Spring	2032	2516	53.93	4
	29.22	17.6	42.56	55901.11765	84804
	no	no	yes	565.06	
15	CANDELARIA RD. & MORRIS ST.			October	2003
	Fall	82	115	334.11	1
	28.59	18.21	50.34	47218.47368	29569
	no	no	yes	638.49	
16	CANDELARIA RD. & SAN MATEO BLVD.			May	2004
	Spring	46	57	595.59	1
	29.02	17.15	62.25	45982.6087	153373
	yes	no	yes	446.99	
17	CENTRAL AVE. & 1ST ST.		November	2002	Fall
	552	683	148.9	3	33.47
	10.38	36.2	37224.39024	103604	no
	yes	no	165.97		
18	CENTRAL AVE. & 2ND ST.		January	2003	Winter
	1128	1106	24.29	1	33.47
	10.38	35.24	39500	106005	no
	no	no	180.46		
19	CENTRAL AVE. & 3RD ST.		April	2007	Spring
	1277	1405	85.82	4	33.47
	10.38	35.24	39848.75	112831	no
	no	no	194.77		
20	CENTRAL AVE. & 47TH ST.		October	2004	Fall
	63	89	434.88	1	36.94
	12.34	90.76	21240.90909	61737	yes
	no	yes	381.54		
21	CENTRAL AVE. & ALVARADO DR.			March	2007
	Spring	161	159	680.68	4
	34.81	10.68	57.32	28482.75862	39668
	no	no	yes	400.04	

22	CENTRAL AVE. & ATRISCO DR.			February	2008
	Winter	128	106	856.16	4
	36.94	12.34	86.92	35079.31034	126645
	yes	no	yes	278.77	
23	CENTRAL AVE. & BROADWAY BLVD.			June	2003
	Summer	254	314	107.86	1
	33.47	10.38	44.93	25673.25	84569
	no	no	yes	146.76	
24	CENTRAL AVE. & CARLISLE BLVD.			January	2006
	Winter	389	382	70.43	1
	37.45	9.96	27.63	35880	66388
	no	no	yes	454.74	
25	CENTRAL AVE. & CEDAR ST.		August	2006	
	Summer	255	361	429.76	4
	40.47	9.06	40.47	27668.09524	436921
	yes	no	yes	153.89	
26	CENTRAL AVE. & COORS BLVD.			April	2008
	Spring	469	516	292.08	5
	42.89	6.91	96.9	36450	70910
	no	yes	yes	364.49	
27	CENTRAL AVE. & CORNELL DR.			February	2008
	Winter	5437	4488	10.08	2
	41.42	8.88	49.46	39714.28571	59443
	yes	no	yes	135.29	
28	CENTRAL AVE. & DORADO DR.			December	2005
	Winter	184	228	446.69	3
	33.03	13.69	72.48	20500	25222
	no	no	yes	517.94	
29	CENTRAL AVE. & EUBANK BLVD.			November	2007
	Fall	155	192	1414.05	8
	33.03	13.69	66.81	23030	73133
	yes	yes	yes	589.29	
30	CENTRAL AVE. & I-25 EAST FRONTAGE RD.			December	2002
	Winter	116	144	236.18	1
	37.63	9.59	48.87	18868.18182	708266
	no	no	no	128.35	
31	CENTRAL AVE. & JUAN TABO BLVD.			March	2007
	Spring	119	117	230.23	1
	33.03	13.69	57.28	38411	134673
	yes	no	yes	425.55	
32	CENTRAL AVE. & LAGUNA BLVD.			January	2005
	Winter	95	93	288.39	1
	30.89	14.98	47.54	39800	23814
	no	no	yes	231.99	
33	CENTRAL AVE. & LOUISIANA BLVD.			December	2002
	Winter	310	384	1060.54	12

	34.81	10.68	83.86	25731.57895	85096
	yes	no	yes	352.63	
34	CENTRAL AVE. & MOON ST.		August	2008	
	Summer	84	119	326.16	1
	33.03	13.69	84.11	9640.625	45444
	no	no	no	392.19	
35	CENTRAL AVE. & NEW YORK AVE.			March	2006
	Spring	44	43	622.67	1
	30.27	16.08	62.86	21540	89313
	no	no	yes	241.52	
36	CENTRAL AVE. & PENNSYLVANIA AVE.			August	2006
	Summer	264	374	415.11	4
	34.81	10.68	90.73	25422.30769	48576
	no	no	yes	447.86	
37	CENTRAL AVE. & RIO GRANDE BLVD.			March	2006
	Spring	252	250	434.88	4
	30.27	16.08	50.79	40780.89286	172014
	yes	yes	yes	373.26	
38	CENTRAL AVE. & SAN MATEO BLVD.			February	2008
	Winter	866	715	284.73	9
	34.81	10.68	52.31	32008.33333	108025
	yes	no	yes	694.7	
39	CENTRAL AVE. & SAN PEDRO DR.			June	2008
	Summer	221	274	247.94	2
	34.81	10.68	71.11	25829.16667	71940
	no	no	yes	423.54	
40	CENTRAL AVE. & STANFORD DR.			March	2002
	Spring	971	962	56.43	2
	41.42	8.88	49.15	39577.77778	37192
	no	no	yes	107.46	
41	CENTRAL AVE. & SUNSET RD.		September	2004	Fall
	52	86	1053.74	2	35.75
	13.01	83.68	34428.57143	112202	yes
	no	yes	130.83		
42	CENTRAL AVE. & UNIVERSITY BLVD.			August	2004
	Summer	995	1408	82.6	3
	41.42	8.88	41.88	31314.73684	75461
	no	no	yes	284.44	
43	CENTRAL AVE. & UNSER BLVD.			June	2007
	Summer	41	51	668.23	1
	45.13	4.87	90.39	7045.454545	96489
	no	yes	yes	259.45	
44	CENTRAL AVE. & WASHINGTON ST.			October	2004
	Fall	213	301	128.63	1
	34.81	10.68	39	37470.27027	47804
	no	no	yes	427.11	

45	CENTRAL AVE. & WYOMING BLVD.			March	2003
	Spring	214	212	640.12	5
	34.03	11.99	82.09	14900.86957	132810
	no	no	yes	876.63	
46	CENTRAL AVE. & YALE BLVD.		November	2007	Fall
	2483	3074	33.1	3	41.42
	8.88	47.96	37154	53042	yes
	no	yes	169.75		
47	CENTRAL AVE. & YUCCA DR.		July	2008	
	Summer	118	167	232.18	1
	39.09	10.37	94.44	28400	62205
	yes	no	yes	202.42	
48	CLAREMONT AVE. & CARLISLE BLVD.			May	2006
	Spring	103	127	265.99	1
	29.44	16.68	55.11	50017.64706	58484
	no	no	no	526.72	
49	COAL AVE. & 2ND ST.		January	2005	Winter
	658	645	41.64	1	33.47
	10.38	52.87	30523.07692	92990	no
	no	no	298.14		
50	COAL AVE. & BUENA VISTA DR.			March	2005
	Spring	268	266	102.23	1
	41.42	8.88	51.52	36660	76573
	yes	no	no	409.91	
51	COAL AVE. & YALE BLVD.		October	2007	Fall
	273	387	200.71	2	41.42
	8.88	53.43	37077.27273	64828	yes
	no	no	428.72		
52	COMANCHE RD. & CARLISLE BLVD.			February	2006
	Winter	115	95	238.24	1
	29.86	16.21	64.36	23476.47059	81572
	yes	yes	yes	249.51	
53	COMANCHE RD. & JUAN TABO BLVD.			December	2005
	Winter	83	103	330.09	1
	27.29	19.46	33.68	56797.91667	84849
	no	no	yes	345.42	
54	COMANCHE RD. & LOUISIANA BLVD.			November	2004
	Fall	46	57	595.59	1
	29.02	17.15	43.09	53800	57068
	no	no	yes	187.16	
55	COMANCHE RD. & WYOMING BLVD.			July	2003
	Summer	33	46	830.22	1
	28.34	18.05	36.85	66243.47826	132764
	no	no	yes	393.6	
56	CONSTITUTION AVE. & CARLISLE BLVD.			October	2003
	Fall	31	44	883.78	1

	35.22	13.01	23.95	50946.15385	46997
	yes	no	yes	433.91	
57	CONSTITUTION AVE. & SAN PEDRO DR.			June	2004
	Summer	76	94	360.49	1
	29.02	17.15	40.78	50062	41403
	no	no	no	333.43	
58	CONSTITUTION AVE. & WYOMING BLVD.			April	2007
	Spring	65	71	421.5	1
	29.57	16.97	38.2	43090	107893
	yes	no	yes	547.33	
60	COPPER AVE. & 5TH ST.		August	2007	
	Summer	1772	2507	15.46	1
	33.47	10.38	35.24	40895	133101
	no	no	no	185.13	
61	COPPER AVE. & EUBANK BLVD.			May	2007
	Spring	52	65	1053.74	2
	33.47	10.38	36.83	38939.02439	102879
	yes	no	yes	178.9	
62	COPPER AVE. & JUAN TABO BLVD.			November	2005
	Fall	59	73	464.36	1
	33.03	13.69	54.5	22927.27273	125177
	yes	no	yes	275.77	
63	CUTLER AVE. & SAN MATEO BLVD.			June	2005
	Summer	61	76	449.14	1
	33.03	13.69	52.19	42989.58333	179434
	yes	no	yes	141.7	
64	DELLYNE AVE. & COORS BLVD.			October	2003
	Fall	11	15	4981.32	2
	29.02	17.15	58.47	35175.38462	562451
	yes	no	yes	163.17	
65	ELLISON DR. & CIBOLA LOOP RD.			July	2003
	Summer	33	46	830.22	1
	35.29	8.56	58.56	54727.27273	81113
	yes	no	yes	73.7	
66	GIBSON BLVD. & BROADWAY BLVD.			August	2005
	Summer	45	64	608.83	1
	36.38	8.85	67.68	9644.444444	86918
	yes	yes	yes	164.2	
67	GIBSON BLVD. & SAN MATEO BLVD.			April	2008
	Spring	118	130	232.18	1
	33.47	10.38	95.22	20090.90909	32304
	yes	yes	yes	399.44	
68	GIBSON BLVD. & SAN PEDRO DR.			September	2003
	Fall	50	82	547.95	1
	39.73	8.62	48.89	21602.13333	102854
	yes	no	yes	253.34	

69	GIBSON BLVD. & VALENCIA DR.			November	2007
	Fall	97	120	282.45	1
	34.81	10.68	49.98	28683.7	94329
	yes	no	yes	561.34	
70	GOLD AVE. & 2ND ST.		July	2004	
	Summer	710	1004	115.76	3
	34.81	10.68	53.88	14042.84615	114000
	no	no	no	472.04	
71	GOLD AVE. & 3RD ST.		March	2005	Spring
	308	305	266.86	3	33.47
	10.38	35.24	37205	115871	no
	no	no	186.91		
72	GUN CLUB RD. & COORS BLVD.			August	2004
	Summer	18	25	1522.07	1
	33.47	10.38	36.94	37047.61905	129813
	yes	no	no	235.37	
73	HANOVER RD. & COORS BLVD.			October	2006
	Fall	69	98	794.12	2
	39.67	9.85	77.41	39116.94444	30775
	yes	no	no	308.42	
74	HARPER RD. & BARSTOW ST.		February	2003	Winter
	51	42	1074.4	2	38.43
	10.98	90.24	48564	108972	no
	no	no	136.66		
75	HIGHLAND AVE. & SAN MATEO BLVD.			July	2004
	Summer	437	619	125.39	2
	28.39	18.64	21.99	63040	35667
	no	no	yes	96.64	
76	INDIAN SCHOOL RD. & 12TH ST.			August	2007
	Summer	120	170	456.62	2
	34.81	10.68	56.84	35393	85196
	yes	no	yes	693.8	
77	INDIAN SCHOOL RD. & CARLISLE BLVD.			March	2008
	Spring	115	114	238.24	1
	31.75	13.45	76.38	26992.30769	201957
	yes	no	yes	359.92	
78	INDIAN SCHOOL RD. & LOUISIANA BLVD.			January	2003
	Winter	63	62	434.88	1
	36.6	12.09	27.4	52705.55556	169669
	yes	yes	yes	600.47	
79	INDIAN SCHOOL RD. & UNIVERSITY BLVD.			March	2004
	Spring	204	202	134.3	1
	29.02	17.15	56.35	42884.79167	313611
	no	no	yes	465.38	
80	IRVING BLVD. & COORS BLVD.			June	2007
	Summer	45	56	608.83	1

	15.08	82.03	49.26	44400	64307
	yes	no	yes	373.39	
81	IRVING BLVD. & LYON BLVD.		May	2003	Spring
	15	19	1826.48	1	36.38
	8.85	52.2	50180	169015	yes
	yes	yes	216.22		
82	JUAN TABO BLVD. & EUBANK BLVD.			August	2008
	Summer	151	214	181.44	1
	36.38	8.85	52.85	56017.30769	73824
	yes	yes	yes	117.3	
83	JUAN TABO PLACE & JUAN TABO BLVD.			October	2005
	Fall	46	65	595.59	1
	27.29	19.46	30.43	67272.72727	52384
	yes	no	yes	77.5	
84	KATHRYN AVE. & LOUISIANA BLVD.			October	2003
	Fall	70	99	782.78	2
	27.29	19.46	31.64	60204.54545	94106
	no	no	no	313.32	
85	KATHRYN AVE. & SAN MATEO BLVD.			September	2005
	Fall	144	237	190.26	1
	34.81	10.68	66.06	31197.22222	24415
	no	yes	yes	177.87	
86	KATHRYN AVE. & SAN PEDRO DR.			October	2006
	Fall	76	107	360.49	1
	34.81	10.68	54.1	39720	45122
	yes	no	no	418.89	
87	LEAD AVE. & BUENA VISTA DR.			May	2007
	Spring	202	250	135.63	1
	34.81	10.68	63.29	33302.96296	58974
	no	no	no	443.42	
88	LEAD AVE. & I-25 WEST FRONTAGE RD.			September	2003
	Fall	118	194	232.18	1
	41.42	8.88	45.99	34481.25	78285
	no	no	no	465.43	
89	LOMAS BLVD. & 3RD ST.		March	2007	Spring
	637	631	172.04	4	36.05
	9.89	54.54	13637.5	455691	yes
	no	yes	72.31		
90	LOMAS BLVD. & 6TH ST.		May	2002	Spring
	328	406	83.53	1	33.47
	10.38	60.9	16927.27273	118306	yes
	no	yes	266.4		
91	LOMAS BLVD. & BROADWAY BLVD.			June	2004
	Summer	120	149	228.31	1
	33.47	10.38	54.92	29346.34146	118301
	yes	no	yes	234	

92	LOMAS BLVD. & CARLISLE BLVD.			May	2003
	Spring	100	124	273.97	1
	33.47	10.38	67.02	20304	55214
	yes	no	yes	378.89	
93	LOMAS BLVD. & EUBANK BLVD.			May	2003
	Spring	80	99	684.93	2
	37.31	10.94	19.45	43506.45161	77763
	yes	no	yes	506.02	
94	LOMAS BLVD. & HOTEL AVE.		March	2006	Spring
	53	52	516.93	1	31.13
	15.67	54.53	42453.94737	174414	yes
	no	yes	373.53		
95	LOMAS BLVD. & I-25 W. RAMPS			June	2003
	Summer	21	26	1304.63	1
	30.78	16.04	61.82	42300	121895
	no	no	no	490.34	
96	LOMAS BLVD. & JUAN TABO BLVD.			October	2005
	Fall	283	400	96.81	1
	34.23	10.24	63.6	30401.90476	627312
	no	no	yes	44.21	
97	LOMAS BLVD. & LOUISIANA BLVD.			December	2007
	Winter	106	131	516.93	2
	31.39	15.4	45.94	38790.90909	92829
	no	no	yes	715.63	
98	LOMAS BLVD. & MORRIS ST.		September	2003	Fall
	53	87	1033.86	2	30.85
	15.11	54.69	37928.42105	105120	no
	no	yes	364.26		
99	LOMAS BLVD. & SAN MATEO BLVD.			June	2006
	Summer	156	193	175.62	1
	31.03	15.78	58.3	42266.66667	120623
	yes	no	yes	466.52	
100	LOMAS BLVD. & SAN PEDRO DR.			October	2003
	Fall	90	127	304.41	1
	31.91	13.92	42.23	41386.91176	129338
	yes	no	yes	719.17	
101	LOMAS BLVD. & TOMASITA ST.			January	2004
	Winter	106	104	258.46	1
	32.02	13.8	48.65	36896.2963	111533
	no	no	yes	323.46	
102	LOMAS BLVD. & TRAMWAY BLVD.			April	2003
	Spring	84	93	326.16	1
	31.07	15.74	56.62	42361.53846	100628
	yes	no	yes	259.65	
103	LOMAS BLVD. & UNIVERSITY BLVD.			August	2004
	Summer	187	264	146.51	1

	31.85	14.92	51.4	54844.34783	38863
	no	yes	yes	96.34	
105	MARTIN LUTHER KING JR & ELM ST.			February	2005
	Winter	62	51	441.89	1
	26.72	54.63	47.07	40687.5	93683
	no	no	yes	221.14	
106	MCLEOD RD. & SAN MATEO BLVD.			October	2004
	Fall	106	150	258.46	1
	39.12	10.35	89.41	31683.46667	48203
	yes	no	yes	86.5	
107	MCMAHON BLVD. & UNSER BLVD.			February	2006
	Winter	22	18	1245.33	1
	35.62	9.97	55.13	17911.89189	750772
	yes	no	yes	155.74	
108	MENAUL BLVD. & 12TH ST.		September	2005	Fall
	46	76	595.59	1	30.97
	16.75	73.12	13100	87612	no
	no	no	496.85		
109	MENAUL BLVD. & CHELWOOD PARK BLVD.			July	2007
	Summer	65	92	842.99	2
	36.38	8.85	56.61	63418.33333	76567
	no	no	yes	62.69	
110	MENAUL BLVD. & EUBANK BLVD.			November	2002
	Fall	81	100	338.24	1
	30.84	15.09	64.96	43086.66667	34873
	no	no	yes	301.45	
111	MENAUL BLVD. & JUAN TABO BLVD.			October	2004
	Fall	134	189	408.91	2
	30.03	16.82	45.9	51065.38462	20515
	no	no	yes	355.76	
112	MENAUL BLVD. & SAN MATEO BLVD.			May	2005
	Spring	163	202	168.08	1
	30.03	16.82	57.52	43133.33333	124308
	yes	no	yes	518.01	
113	MENAUL BLVD. & TRAMWAY BLVD.			March	2003
	Spring	110	109	249.07	1
	30.03	16.82	44.09	51179.25	79143
	yes	yes	yes	545.51	
114	MENAUL BLVD. & WYOMING BLVD.			July	2004
	Summer	60	84	913.24	2
	29.02	17.15	64.76	43341.08696	188771
	no	yes	yes	424.68	
115	MONTANO & COORS BLVD.		November	2006	Fall
	33	41	1660.44	2	30.03
	16.82	37.73	58264.28571	28661	yes
	no	yes	31.75		

116	MONTANO & TAYLOR RANCH RD.			July	2007
	Summer	43	61	637.15	1
	29.28	17.06	49.64	50932.6087	169683
	yes	no	yes	518.16	
117	MONTGOMERY BLVD. & CAIRO			September	2004
	Fall	474	783	57.8	1
	35.29	8.56	58.49	53450	149161
	no	no	yes	140.75	
118	MONTGOMERY BLVD. & CARLISLE BLVD.			October	2007
	Fall	70	99	391.39	1
	35.29	8.56	56.34	51272.72727	64695
	yes	no	yes	142.25	
119	MONTGOMERY BLVD. & JEFFERSON ST.			January	2008
	Winter	138	135	198.53	1
	27.29	19.46	34.27	48680.55556	93691
	yes	no	yes	299.92	
120	MONTGOMERY BLVD. & JUAN TABO BLVD.			March	2008
	Spring	224	222	366.93	3
	30.29	16.14	66.36	16692.30769	136291
	yes	no	yes	654.52	
121	MONTGOMERY BLVD. & SAN MATEO BLVD.			October	2007
	Fall	387	547	707.94	10
	29.77	16.99	63.36	27919.23077	144159
	yes	no	yes	403.23	
122	MONTGOMERY BLVD. & SAN PEDRO DR.			October	2004
	Fall	140	198	391.39	2
	27.29	19.46	32.26	55386.53846	129015
	yes	no	yes	414.21	
123	MONTGOMERY BLVD. & TRAMWAY BLVD.			December	2005
	Winter	85	105	966.96	3
	29.51	17.05	69.32	21762.5	259435
	yes	no	yes	779.23	
124	MONTGOMERY BLVD. & WYOMING BLVD.			August	2004
	Summer	98	139	559.13	2
	29.93	16.96	60.41	23486.66667	126413
	no	no	yes	479.05	
125	MOUNTAIN RD. & 4TH ST.		October	2007	Fall
	297	420	92.25	1	27.29
	19.46	30.47	68076.66667	35976	no
	no	no	79.08		
126	MOUNTAIN RD. & RIO GRANDE BLVD.			January	2008
	Winter	168	165	163.08	1
	29.12	18.01	41.06	59845.45455	267841
	yes	yes	yes	810.86	
127	N.M. 528 & ELLISON		January	2008	Winter
	33	32	1660.44	2	33.47

	10.38	78.89	13351.28205	79641	no
	yes	yes	221.65		
128	NORTHEASTERN BLVD. & WYOMING BLVD.			July	2004
	Summer	40	57	684.93	1
	30.27	16.08	59.65	41990	116896
	yes	no	yes	232.97	
129	OSUNA RD. & WYOMING BLVD.			August	2003
	Summer	59	83	464.36	1
	34.64	10.23	54.67	35840	130144
	yes	no	yes	127.63	
130	OURAY RD. & ATRISCO DR.		August	2006	
	Summer	23	32	2382.37	2
	29.3	17.06	41.22	46522.22222	219258
	yes	no	no	258.41	
131	PARADISE BLVD. & GOLF COURSE DR.			October	2005
	Fall	24	35	1141.55	1
	29.02	18.18	48.19	54617.05882	160460
	yes	no	no	291.84	
132	PASEO DEL NORTE & GOLF COURSE DR.			January	2005
	Winter	10	10	2739.73	1
	35.29	8.56	78.2	0	417884
	yes	no	yes	228.37	
133	QUAIL RD. & ATRISCO DR.		May	2007	Spring
	78	97	351.25	1	36.38
	8.85	49.14	56303.57143	61234	yes
	no	yes	83.66		
134	QUAIL RD. & COORS BLVD.		November	2003	Fall
	91	112	903.21	3	35.83
	8.7	49.78	65152.08333	100251	yes
	no	yes	95.79		
135	REDLANDS RD. & COORS BLVD.			September	2003
	Fall	20	33	2739.73	2
	35.29	8.56	77.19	0	424626
	yes	no	yes	245.64	
136	RIO BRAVO BLVD. & BROADWAY BLVD.			August	2007
	Summer	8	12	3424.66	1
	35.29	8.56	77.12	0	451656
	yes	yes	yes	291.41	
137	RIO BRAVO BLVD. & ISLETA BLVD.			May	2008
	Spring	74	92	740.47	2
	35.29	8.56	76.88	0	312801
	yes	yes	yes	384.85	
138	ROMA AVE. & 2ND ST.		June	2007	
	Summer	627	777	43.7	1
	36.94	12.34	89.35	6250	39867
	no	no	no	56.38	

139	SAN ANTONIO/HARPER & WYOMING BLVD.			February	2003
	Winter	15	12	1826.48	1
	36.94	12.34	81.6	3850	45455
	yes	no	yes	312.36	
140	SEQUOIA RD. & COORS BLVD.		October	2006	Fall
	167	237	1148.39	7	33.47
	10.38	46.96	28814.28571	127959	yes
	yes	yes	219.77		
141	SILVER AVE. & 4TH ST.		May	2004	Spring
	500	620	54.79	1	30.15
	17.35	35.35	48483.33333	137594	no
	no	no	280.9		
142	SOUTHERN AVE. & ELIZABETH ST.			January	2005
	Winter	37	36	740.47	1
	35.29	8.56	74.58	5411.764706	252266
	yes	no	yes	417.34	
144	TRUMBULL AVE. & LOUISIANA BLVD.			November	2006
	Fall	143	177	383.18	2
	33.47	10.38	42.18	34134.14634	138143
	no	no	no	269.97	
145	UPTOWN BLVD. & SAN PEDRO DR.			September	2007
	Fall	120	199	456.62	2
	33.03	13.69	52.94	43678.82353	13988
	yes	no	yes	27	
146	ZUNI RD. & ALVARADO DR.		August	2003	
	Summer	82	115	334.11	1
	45.13	4.87	86.42	0	48513
	no	no	no	128.35	
147	ZUNI RD. & LOUISIANA BLVD.		March	2006	Spring
	224	222	244.62	2	34.81
	10.68	71.98	29899.6	48564	no
	no	no	372.97		
148	ZUNI RD. & SAN MATEO BLVD.			May	2008
	Spring	119	147	230.23	1
	29.02	17.15	63.19	41903.42105	67444
	no	no	yes	183.58	
149	ZUNI RD. & SAN PEDRO DR.		August	2005	
	Summer	90	127	304.41	1
	34.81	10.68	65.37	29113.63636	33021
	no	no	no	571.98	
150	ZUNI RD. & UTAH ST.		November	2005	Fall
	113	140	242.45	1	34.81
	10.68	75.9	29352.4	76075	yes
	no	no	445.23		
151	ZUNI RD. & WYOMING BLVD.		September	2005	Fall
	37	61	740.47	1	34.81

	10.68	54.44	36249.52381	103753	no
	no	no	643.37		
59	COPPER AVE. & 3RD ST.		January	2007	Winter
	2339	2294	0	0	34.81
	10.68	72.34	30275.41667	95405	no
	no	no	716.22		
104	LOS VOLCANOS & COORS BLVD.			December	2002
	Winter	38	47	0	0
	34.81	10.68	90.05	13789.23077	57218
	yes	no	no	436.32	
143	TOWER RD. & 98ST.		November	2003	Fall
	14	18	0	0	34.01
	12.02	85.76	9136.666667	132552	yes
	yes	yes	821.46		

S.no	intersection	vvol	wdpvol	wdprate	inc
	age25	age60	nonwhite	right	median
	yield	drdist	wdpcrash		
1	Lomas & Carlisle	72600	225	42.7	
	57355.4	28.54	8.96	22.5	yes
	yes	no	62.32	1	
2	Central & Carlisle		62400	560	0
	52282	28.06	16.7	27.3	yes
	yes	no	13.78	0	
3	Central & San Mateo		107100	1745	33.1
	27359	25.96	22.35	33.84	no
	yes	no	60.31	6	
4	University & Lomas		110300	808	0
	93801.3	55.28	15.85	36.63	yes
	yes	no	44.71	0	
5	University & Cesar Chavez		39900	183	0
	25901	41.91	10.13	44.72	yes
	yes	no	0	0	
6	Central & Louisiana		95300	1352	56.9
	20232	29.57	22.99	46.46	yes
	yes	no	56.93	8	
7	San Mateo & Montgomery		155100	1046	91.9
	33533.3	34.67	15.01	32.21	yes
	yes	no	70	10	
8	Louisiana & Indian School		86300	664	43.4
	27388.6	29.83	28.1	21.43	no
	yes	yes	66.31	3	
9	Central & Broadway		66300	802	0
	31559.5	25.19	14.1	36.82	no
	yes	no	23.66	0	

10	Central & University		92600	1065	18.1
	60646	42.64	9.24	38.32	no
	yes	no	80.33	2	
11	Central & Girard	75700	1128	0	85949
	43.62	10.49	33.31	yes	yes
	no	80.14	0		
12	Central & Yale	74800	2744	7	
	66671.8	43.62	10.49	33.31	yes
	yes	no	59.51	2	
13	Central & 3rd	23200	3622	8	31000
	22.96	12.7	24.44	no	no
	no	30.85	3		
14	Lomas & Broadway		76900	567	17
	25007.5	47.49	13.24	38.4	yes
	yes	no	34.48	1	
15	Wyoming & Zuni	52800	282	102.3	
	19392.3	37.77	12.05	48.67	no
	yes	no	92.87	3	
16	University & Coal		51740	618	31.1
	20073	38.4	6.68	31.2	yes
	yes	yes	0	2	
17	Girard and Coal	29700	117	82.2	30042
	30.45	13.1	27.24	no	no
	no	86.61	1		
18	Yale and Lead	31870	612	0	
	25042.5	30.45	13.1	27.24	no
	no	yes	91.19	0	
19	Central and Coors		92160	280	68.7
	34936	36.98	17.4	43.77	no
	yes	yes	34.73	2	
20	Central and Atrisco		83310	228	210.9
	39822	31.95	19.55	48.12	yes
	yes	no	57.55	8	
21	Central and Rio Grande		86010	581	49.6
	38758.5	36.57	19.71	26.58	yes
	yes	yes	85.54	3	
22	Menaul and Carlisle		82160	204	0
	46694.4	34.32	13.48	28.97	no
	yes	no	91.58	0	
23	Lomas and San Mateo		108750	166	115.8
	42644.5	24.29	24.2	29.88	yes
	yes	no	89.36	2	
24	Menaul and San Mateo		95050	156	61.6
	49862.7	26.78	24.51	25.3	yes
	yes	no	113.96	1	

25	University and Indian School		32010	188	51.1
	39649	28.92	23.47	21.07	no
	no	no	66.23	1	
26	Lomas and Louisiana		99760	332	57.9
	39275.3	29.09	22.15	38.78	no
	no	no	66.97	2	
27	Menaul and Wyoming		126440	208	138.7
	51176.7	27.13	26.31	21.24	yes
	no	no	99.66	3	
28	Gibson and University		75950	342	0
	24813	41.45	10.58	44.72	yes
	yes	no	26.78	0	
29	Gibson and San Mateo		67840	187	51.4
	31126	31.66	18.1	34.4	yes
	yes	yes	45.09	1	
30	Gibson and Girard		72950	218	0
	50087	41.1	10.3	38.05	yes
	yes	no	0	0	