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# A Framework to Predict High Risk Roadways for Pedestrians in Tennessee

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To the Graduate Council:

I am submitting herewith a thesis written by Zane Hunter Pannell entitled "A Framework to Predict High Risk Roadways for Pedestrians in Tennessee." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Civil Engineering.

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# A  Framework to Predict High Risk Roadways for Pedestrians in Tennessee

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## Abstract

Pedestrians and bicyclists are a class of vulnerable road users that are often over-represented in incapacitating injury or fatal crash statistics. Because non-motorized trips are vital to many urban and rural residents for utility or recreation and exercise, it is essential to identify safety deficiencies in our existing transportation infrastructure to address rising injuries and fatalities among this group of road users. As the economy continues to struggle and fuel prices remain high, many cities and rural transportation agencies are seeing large increases in bicycling, walking, and transit ridership. While passenger car fatalities have shown sharp declines in the last decade in Tennessee, pedestrian and bike fatalities have remained relatively constant, about 100 per year (about 8%). Most of these deaths are avoidable. As such it is very important to address bicycle and pedestrian safety and prioritize funding. The goal of this project is to develop a framework to identify pedestrian and bicycle high crash locations for investment prioritization of Highway Safety Improvement Program funds to maximize the reduction in state-wide severe pedestrian and bicycle crashes. The final result combined two statistical models, crash count and injury severity, into one pedestrian harm model to target roadway segments in Tennessee that increase harm for pedestrian incapacitating injuries and fatalities if struck by a vehicle. Factors that influence pedestrian harm are increasing speed limits; number of lanes; total population density; AADT; and Central Business District, commercial, fringe, industrial, residential, and public land use.

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# CHAPTER I INTRODUCTION

The population of Tennessee is increasing with projections indicating that by the year 2030 the number of people living in the state will grow by nearly 33 percent [1]. A press release from the U.S. Census Bureau ranked Tennessee among one of the top 15 fastest growing states [1]. This projected increase in population may lead to congestion on roadways throughout Tennessee. Many residents are interested in walking and bicycling as a mode of transportation and recreation. Walking and bicycling promote livable communities, which are communities that provide safe and convenient transportation for all modes of transportation, and are a high priority for the United States Department of Transportation (DOT) and Obama Administration [2]. Walking and bicycling have several benefits, including healthy lifestyles, low cost, zero emissions, easy and convenient, and relatively zero noise pollution compared to one's personal automobile .Walking and bicycling make up about 1.7% of the work-related trips in Tennessee as of 2000, making them the second most popular forms of travel after driving [1]. Even with this small percentage, pedestrian and bicyclist present conflicts when combing these sustainable modes of transportation with automobiles in our transportation network. However, pedestrians and bicyclists are a class of vulnerable road users that are often over-represented in incapacitating injury or fatal crash statistics. While passenger car fatalities have shown sharp declines in the last decade in Tennessee, pedestrian and bike fatalities have remained relatively constant, about 100 per year (about 8%). Most of these deaths are avoidable. It is very important to address pedestrian and bicycle safety and prioritize funding towards walking and bicycling modes of transportation. The purpose of this framework is to develop a proactive method to identify pedestrian high crash locations along with high injury severity levels, such as incapacitating injury and fatalities, for prioritizing investments from the Highway Safety Improvement Program (HSIP) to maximize the reduction in state-wide severe pedestrian crashes.

In order to develop this framework, the research involved several preliminary tasks. Two literature reviews were conducted; one was to review statistical modeling for pedestrian and bicycle crashes, and the second was to synthesize best-practices in other states on how they are prioritizing pedestrian and bicycle projects with HSIP funds. Study data was gathered including information about roadway geometrics, socio-economic demographics, traffic volumes, and crash information which was used for the statistical data analysis. Statistical data analysis of crash count and injury severity was conducted to identify factors that significantly affect crashes. Results from the statistical data analysis were combined to develop a framework using Microsoft Excel and GIS software to identify harmful road segments to pedestrians.

# CHAPTER II LITERATURE REVIEW

## 2.1 Introduction

A literature review was conducted to understand pedestrian and bicycle safety using statistical modelling and the factors that influence crash county and injury severity. Also, the review consists of what other states are doing to prioritize pedestrian and bicycle projects with HSIP funding.

## 2.2 Review of Statistical Modeling of Pedestrian and Bicyclist Crashes

There have been numerous studies in the past that examine the causes affecting crash counts between pedestrian and vehicles [3-7]. These studies use police recorded crash data with at least three years of data to try and account for randomization of crash locations [3-7]. Using descriptive statistical analysis, Garder [3] used 1,589 police reported pedestrian crashes from 1994-1998 in Maine. Using descriptive statistical analysis, his findings indicate that more pedestrian crashes occur on Saturday, during the afternoon between 4:00 pm and 7:00 pm, 68% of crashes occur during clear weather, 71% of crashes occur on level straight roads, and 65% of crashes occur on roads with no traffic control device or signage. Other studies that have examined pedestrian crash counts use multivariate statistical crash count models such as, the Negative Binomial (NB) Regression Model or Poisson Distribution Model [4-6]. The NB model is used more often because it allows for overdispersion and relaxes the mean-variance constraint, which allows the variance of the variable in question to be greater than the mean. Few studies have joined crash data with census tracts, road geometrics, and traffic counts using GIS software [4-6]. Hashimoto [4] used the NB model with pedestrian crash data from 1999 to 2001 with 1,648 pedestrian crashes in Hillsborough County, Florida, and census data, Average Annual Daily Traffic (AADT) counts, and roadway data from the Florida Geographic Data Library. Hashimoto's findings indicate crash counts increase with commercial and service land use and residential land use, while average household income and residents 65 years and older decrease the number of pedestrian crashes. By examining police recorded crash data with 7,345 pedestrian crashes from 2002 to 2006 and census data in New York City, Ukkusuri [5] found that the likelihood of pedestrian crashes increase in black and Hispanic neighborhoods, on commercial and industrial land use, in school zones, and at intersections with increased number of lanes with using a NB model. Lee and Abdel-Aty [6] used the NB model over the Poisson Distribution Model for 247 crashes at intersections throughout Florida from 1999 to 2002. Their findings indicate that the likelihood of pedestrian crashes increased at intersections with higher average traffic volume and in urban areas, while results show a decrease in pedestrian crashes at intersections during daylight hours. Another study, in Florida looked at 247 pedestrian crashes on state roads in Orange County, Florida from 1999 to 2003 and used log-linear models and found that driver age, number of lanes, median type, pedestrian age, and speed limit are critical factors influencing pedestrian crash count [7]. This study also found that more pedestrian and vehicle crashes occurred around middle and high schools than elementary schools and middle-aged alcohol impaired male drivers are more like to be involved in school-aged children crashes. One interesting study by Miranda-Moreno eta al. [8] proposed a framework on the standard NB model, the Generalized NB model, and the latent class NB model. Their results show that intersections have a small direct effect on pedestrian and vehicles crash counts, but indicate high pedestrian exposure.

There have been a multitude of statistical studies using different discrete outcome models to determine variables that influence injury severity of pedestrian and bicycle to vehicle crashes, such as Mixed Logit Model, heteroskedastic Model, Multinomial Logit (MNL) Model, Mixed Generealized Ordered Logit Model, and Ordered Probit Models [9-17]. The most common modeling approach to injury severity is the MNL model [8]. Like the crash count studies, injury severity studies use police reported crash data.

Three studies in North Carolina used 5,808 reported pedestrian crashes and 2,834 reported bicyclist crashes from 1997 to 2000 to develop different types of injury severity models for pedestrians and bicyclist. By using a Mixed Logit Model one of the studies discovered that darkness without streetlights, trucks, freeways, driver speeding, and driver under the influence of alcohol doubled the average probability of pedestrian fatalities [9]. Mixed Logit Models eliminate possible random variations in the data. Another study using the same crash data used a hetroskedasticity model and found that increasing pedestrian age, male drivers, intoxicated driver, traffic signs, commercial areas, and darkness with or without streetlights increased the probability of pedestrian fatalities [10]. This study also found that increasing driver age, during the PM traffic peak, inclement weather, curved roadway, at a crosswalk, and when walking along a roadway decreased the probability of a fatality. The heteroskedaticity model in this study makes the assumption that the probability of pedestrians past the age of 65 are weaker and more prone to fatalities. The last study in North Carolina used the 2,834 reported bicyclist crashes and used a MNL model with the following injury severity outcomes for bicyclist: fatal, incapacitating, non-incapacitating, and possible or no injury [11]. Findings from this study indicate that factors that increase the likelihood of a fatality are inclement weather, darkness with no street lights, a.m. peak (06:00 to 09:59), head on collisions, vehicle speeds above 30 mph, heavy truck, intoxicated driver, bicyclist age 55 and over, and intoxicated bicyclist. The MNL model allows flexibility and an unbiased approach to observe the maximum likelihood for all variables in the model.

Another study that used a MNL model was in South Korea and examined 48,381 pedestrian and vehicle crashes in 2006 [12]. Crashes with heavy vehicles, intoxicated drivers, male drivers, drivers under the age of 65, pedestrians over the age of 65, female pedestrians, pedestrians hit in the middle of the road, road with high speeds, inclement weather (cloud, rain, and fog), and at night increased the likelihood of fatal and severe injury crashes compared to minor injury related crashes. Harruff et al. [13] undertook a descriptive analysis of 217 pedestrian traffic fatalities in Seattle, Washington using medical records for over a 6 year time period. His finding indicate that male pedestrians are 50% more likely to be involved in a fatal crash than females, 66% of fatalities occurred on city or residential streets, 29% of fatalities occurred on major thoroughfares, 12% of fatalities occurred on single urban highways. The Mixed Generalized Ordered Response Logit Model was developed in a different study to examine injury severity using 3,200 non-motorist crashes from the 2004 General Estimates System database obtained from the National Highway Traffic Safety Administration's National center for Statistics and Analysis [14]. The analysis suggested that higher speed limits and later time-of-day leads to higher injury severity levels, whereas crashes at signalized intersections result with a less severe injury. Multinomial models are used when wanting to find the significance of multiple variables with respect to one variable. Ordered models may be used when you want find the significance of the overall model by listing variables in order with affects from least to greatest, such as no injury to fatality.

Several studies have been conducted on modeling injury severity for bicycle and vehicle crashes. One study in North Carolina used the Ordered Probit Model with 1,025 bicycle crashes on two-lane roadways from 1990 to 1993 and concluded that the variables that significantly increase injury severity for bicyclist are presence of fog, dark unlighted sections, high speed limits, on road sections with an upgrade or downgrade [15]. They also found a decrease in injury severity on roadways with increasing Average Annual Daily Traffic (AADT), street lighting, and an interaction of the shoulder width and speed limit.  While another study in Ohio developed separate standard MNL and Mixed Logit models to independently assess the impacts of various factors on the degree of bicyclist injury severity in Ohio from 10,029 bicycle and vehicle crashes from 2002 to 2008 [16]. The results indicate that the potential for severe bicyclist injuries is highest when the bicyclist is female, the driver of the vehicle is intoxicated, the vehicle is a commercial motor vehicle, the front of the vehicle impacts the side of the bicycle, and the roadway surface is dry. A study in Edmonton, Canada examined 571 bicycle to vehicle crashes at intersections and mid-block along the roadway from 2006 to 2009 [17].  The results of the mixed logit model are female bicyclist are more prone to injury than males bicyclist, older bicyclist are more involved in injuries than younger cyclist at intersections, younger drivers are more prone to hit bicyclist at mid-block, and a decrease in bicyclist collisions at mid-block with parking only one one-side of the street.

In conclusion, five general observations may be made from this literature review. First, the field is seeing a movement toward multivariate analysis and away from the descriptive analysis used in past studies. Second, the most commonly used approach to model crash counts is using the NB or Poisson distribution. Third,  the multinomial and ordered response models have been widely used when the injury severity is represented in  multiple categories, such as property damage only, no visible injury but pain, non-incapacitating injury, incapacitating injury, and fatal injury for multivariate modeling. In injury severity modeling, there are not many studies that have combined census data, road geometric, and traffic counts. Fourth, all earlier studies have used pedestrian and bicycle crash data along with census data, traffic history, and road geometrics to perform crash count statistical analyses but not injury severity analyses. Fifth, there are any studies in the past that have combined crash count and injury severity models into one model.

## 2.3 Synthesis of Funding Best Practices for Bicycle and Pedestrian Projects

On August 10, 2005, Safe, Accountable, Flexible, Efficient Transportation Act: A Legacy for Users (SAFETEA-LU) was established by the Federal Highway Administration (FHWA) to reduce traffic fatalities and injuries on all public roads by improving highway safety infrastructure [18]. Section 1401 of SAFETEA-LU entails the HSIP, which provides funding for states to improve the safety of all public roadways. The reauthorization, Moving Ahead for Progress in the 21$^{st}$ Century (MAP-21), extends the HSIP program. HSIP includes bicyclist and pedestrians as a mode because they are placed at  high risk for fatalities and injuries on or along roadways because of their vulnerable exposure to sever injury. However, allocating HSIP funding to bicycle and pedestrian modes is difficult because comparative safety analysis for these modes are challenging. Although there is a limited amount of information available, this section synthesizes how other states are using HSIP funding for pedestrian and bicycle safety projects by conducting a literature review and phone call survey to other state DOTs.

Virginia was one of the most prominent states for allocating HSIP funds for pedestrian and bicycle projects. For FY2012-2013, Virginia has set aside 10% of HSIP funding from FHWA for the Virginia DOT bicycle and pedestrian program [19]. Virginia DOT decided to use 10% simply because pedestrian and bicycle fatalities account for 10% of traffic related deaths in Virginia [20]. Virginia DOT has listed projects that are eligible for HSIP funding, including but not limited to, are on-street facilities; shared-use paths; treatments for intersections; mid-block crossings; crosswalks, signs, and pavement markings; accessibility features; and traffic calming measures [19]. Several other states mentioned how much funding that they are using for bicycle and pedestrian projects as a policy, but do not list any allocation details in published reports. Connecticut is using 1% of their HSIP funds for bicycle and pedestrian safety [21]. For FY2012, California used 3% of total federal funds (not just HSIP funds) for bicycle and pedestrian projects [22]. This article also stated that 15% of trips made are by bicyclist and pedestrians and make-up 27% of transportation related fatalities in California. Florida has one of the highest pedestrian and bicycle crash rates in the US. From 2006-2012, Florida used 13% of total federal funds towards pedestrian and bicycle projects [23].

A survey questionnaire was conducted to examine what other states are doing for pedestrian and bicycle projects. Nineteen out of 47 state DOTs (includes all states except Tennessee, Hawaii, and Alaska) have been contacted via telephone to get an understanding of how they are spending HSIP and other federal funding for pedestrian and bicycle projects. The four questions that were asked were as followed:

Question 1: Does your state use HSIP funding for pedestrian and bicycle projects?
Question 2: If the answer is yes to "Question 1", what percentage is used for pedestrian and bicycle funding? If the answer is no to "Question 1", skip to "Question 3".
Question 3: What other types of federal funds does your state use for pedestrian and bicycle projects?
Question 4: Does your program invest more funding on infrastructure improvements or educational campaigns?
Table 1 provides a summary of the states, contacts, and the answers to the 4 questions

**Table 1. Survey Questionnaire Responses.**

| State | Contact | Question 1 | Question 2 | Question 3 | Question 4 |
|---|---|---|---|---|---|
| Alabama | Mary Lou Crenshaw | Yes | Unsure | Unsure | Education |
| Arizona | Mark Poppe | Yes | Unsure | Transportation Enhancement and Safe Routes to School (SRTS) | Infrastructure uses HSIP; education and infrastructure uses SRTS |
| Arkansas | Kim Sanders | No | N/A | None | None |
| Colorado | Betsy Jacobsen | Yes | 1% | N/A | Education |
| Idaho | Maureen Gresham | Yes | 3% | N/A | Infrastructure |
| Indiana | Jay Mitchell | Yes | Unsure | N/A | Infrastructure |
| Massachusetts | John Lehman | No | N/A | High Priority, Congestion Mitigation Air Quality (CMAQ), Transportation Enhancement, Federal Transit, Safe Routes to School | Infrastructure receives majority of funding and Education receives a small portion |
| Michigan | Josh DeBruyn | Some years, but not on a routine basis every year | Varies from year to year | MAP-21 | Infrastructure |
| Nebraska | Dave Schoenmaker | No | N/A | Surface Transportation Program-1%, Transportation Enhancement-3%, State Planning and Research funds-1% | Infrastructure receives majority of funding and Education receives a small portion |
| New Hampshire | Larry Keniston | No | N/A | Transportation Enhancement | Infrastructure |
| New York | Eric Ophardt | No | Well under 10%, 1-2% of federal funding is used toward bike/ped | Transportation Enhancement and Safe Routes to School | Infrastructure |

**Table 1. Continued.**

| | | | | | |
|---|---|---|---|---|---|
| North Carolina | Lauren Blackburn | No | N/A | A very small amount from MAP-21 | Infrastructure |
| North Dakota | Bennett Kubishta | No | N/A | Transportation Enhancement and Surface Transportation Program | Infrastructure |
| South Carolina | Tom Dodds | Yes only in 2012 | Unsure | CMAQ | Infrastructure (provide wider paved shoulders, streetscape, sidewalks, ADA curb ramps |
| Texas | Charles Riou | Yes | Unsure | Transportation Enhancement (TE) and Safe Routes to School (SRTS) | Infrastructure uses HSIP and TE; Education uses SRTS |
| Utah | Evelyn Tuddenham | Yes | Unsure | Transportation Enhancement | Infrastructure |
| Vermont | Jon Kaplan | No | N/A | Surface Transportation Program and Transportation Enhancement | Infrastructure |
| Virginia | John Bolecek | Yes | 10% | CMAQ, Surface Transportation Program, Transportation Enhancement, Safe Routes to School | Infrastructure |
| Washington | Ian Macek | Yes | Varies from year to year | Surface Transportation Program, Transportation Enhancement, Safe Routes to School(SRTS) | Majority goes to infrastructure and SRTS goes to education and infrastructure. |

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In conclusion, the few states that said they were using HSIP funding for pedestrian and bicycle projects are using a very small portion of the total HISP funding available for their state. The states that are using HSIP funding pedestrian and bicycle projects are using the funding towards improving transportation infrastructure. Pedestrian and bicycle have to use funding from other sources than HSIP. This addresses the need that states need a fixed methodology for how to appropriate HSIP funding for pedestrian and bicycle projects to improve transportation safety for pedestrians and bicyclists.

# CHAPTER III PROJECT DATA

## 3.1 Crash Data

The data used for this study was pedestrian crash data obtained from Tennessee Roadway Information Management System (TRIMS) database maintained by Tennessee Department of Transportation (TDOT). Initially, Pedestrian and bicyclist crash data was downloaded from TRIMS database for years 1999 to 2010 and was later cut to use only years 2003-2009 because data before 2003 was incomplete, and the accuracy of the data after 2009 was questionable because of a new system to record crash data was being developed.

The TRIMS database contained some micro-level information about pedestrian and vehicle crashes, such as beginning log mile, case number, person type, injury type, county, route, location, type of crash, year of crash, time of crash, total killed, total incapacitating injuries, manner of first collision, total injured, first harmful event, light conditions, weather conditions, relation to first junction, relation to first roadway, urban or rural, hit and run, hwy construction zone, age, alcohol, alcohol determination, drug type, pedestrian age, and gender.

## 3.2 Geospatial Road Data

In order to locate individual crash incidents on a map, geospatial data was requested from TDOT. TDOT provided the following separate geospatial data files in shapefile format: TDOT road geometrics, Tennessee Information for Public Safety (TIPS) for Tennesse Roads, Tennessee block level data for 2010, Tennessee block group level data for 2010, Tennessee secondary school district for 2010, and Tennessee unified school district for 2010. A shapefile is data file containing geospatial vector data for Geographic Information Systems (GIS) software. Each of these shapefiles consisted of different features and attributes. The TDOT road geometrics shapefile consisted of spatial data of the entire road network of Tennessee which contains information including the route number, begin log mile, and end log mile. The Tennessee Road TIPS shapefile also consisted of spatial data of the entire road network of Tennessee but with more detailed information, including the road name, speed limit, land use, number of lanes, location, terrain, and presence of school zone. All variables are listed in Appendix A. In addition to the shapefiles provided by TDOT, a Tennessee census tract shapefile was downloaded from the TIGER webpage of the US census website[24]. A census tract is composed of census blocks, which are the smallest geographic area for which the U.S. Census Bureau collects and tabulates decennial census data.

## 3.3 Demographic and Socioeconomic Data

US census demographic and socioeconomic data was downloaded from the US census website at census tract level from the 2010 census [25]. The downloaded demographic data consists of counts of population, housing, race, and age distribution while the socioeconomic data consists of income, vehicle ownership, employment rate, commuting to work, occupations, poverty status data. All variables are listed in Appendix A.

## 3.4 Traffic Count Data

A shapefile of traffic history data containing AADT count along specific locations on Tennessee's road network were downloaded from the TDOT website [26] and integrated into the GIS roadway map.

## 3.5 Crash Data Preparation

The pedestrian crash data for this project from TRIMS consisted of 5,587 pedestrian crashes from 2003 to 2009. In general, injury severity is listed in four categories, such as Property Damage Only (PDO), non-incapacitating injury, incapacitating injury, and fatality. Figure 1 shows the number of crashes with respect to injury severity level.

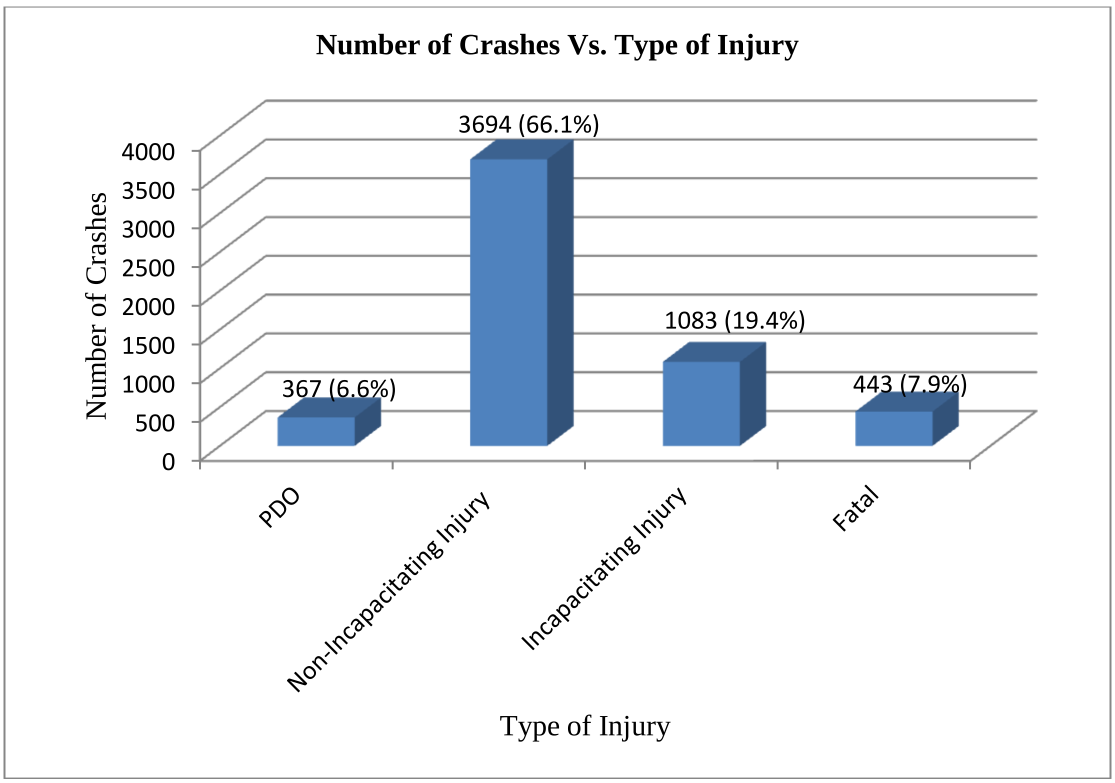


**Figure 1. Number of Crashes Vs. Injury Type.**

Out of the 5,5,87 crashes for this study, the crash distribution is 367 PDO, 3,694 non-incapacitating injuries, 1,083 incapacitating injuries, and 443 fatal crashes. An attempt was made to use bicycle crashes for this study but there was not enough crash data available for the 7 year period. From this point on, this study focuses only on pedestrian crashes.

### 3.6 Geo-Mapping of Crash Data

Geocoding of state highway incidents was undertaken using the linear referencing function of ArcGIS. ArcGIS is a mapping and spatial analysis software. Linear referencing is a method of determining geographic locations using relative positions along a linear feature. If location values are known for points A and B, the value for any point between them can be determined. The TDOT road geometric shapefile was used as a reference layer for mapping post mile location incidents because it has unique field, such as road number, beginning log mile and ending log mile which are required to identify the location of an incident along a highway. Post mile-coded incidents were then geocoded using the ArcGIS linear referencing tools. Each pedestrian crash is represented by a single dot on the map in Figure 2.

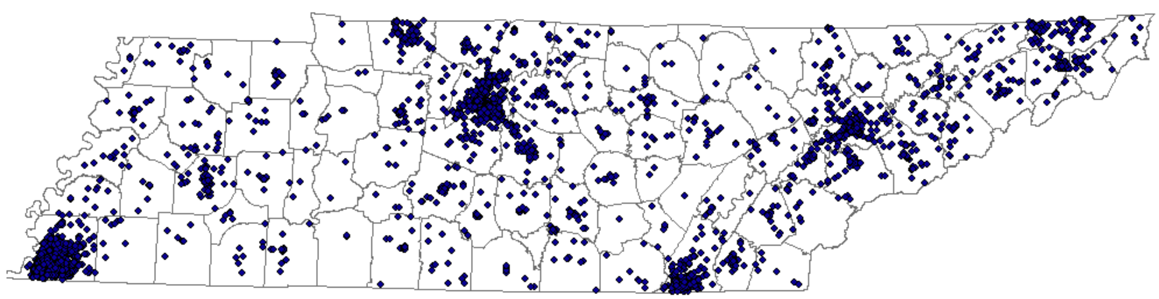

**Figure 2. Pedestrian Crash Locations.**

### 3.7 Integrating Statewide Data into a GIS Model

In order to integrate crash data, geospatial road data, demographic and socioeconomic census data, and traffic data, the “spatial join” feature in ArcGIS was used to populate an attribute table to list all of the data for each of the 5,587 crashes that was needed to develop the crash count and injury severity models. After the crash count and injury severity models were developed, the “spatial join” feature was used again to gather geospatial road data, demographic and socioeconomic census data, and traffic data in order to develop a final model to target harmful road segments.

## CHAPTER IV CRASH COUNT MODELING

### 4.1 Introduction

Crash data were integrated by road segments to develop a statistical crash count model to predict the number of crashes with influence to road geometrics, traffic count, and census data that were mentioned in the previous section. This model will provide insight to what variables increase the likelihood of a crash to occur. Summarized in Table 2 is the number of observations, mean, standard deviation, and range for the number of crashes, segment length, road geometrics, traffic count, and census data, which were used as either the independent or dependent variable in the crash count model. Independent variables that were removed from the model because they had no statistical impact on the model were total population, and population below poverty level. All crashes from 2003 to 2009 were merged on 168,920 uniform non-freeway roadway segments throughout the stat with each segment averaging 0.5 miles and 0.034 crashes.

**Table 2. Summary Statistics of Data Used for Pedestrian Crash Count.**

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **By Road Segment** | | | | | |
| Number of crashes (n) | 168920 | 0.034 | 0.411 | 0 | 48 |
| Segment Length in miles (n) | 168920 | 0.498 | 0.898 | 0 | 29.430 |
| **By Road Geometrics** | | | | | |
| Number of lanes in both directions (n) | 168920 | 1.941 | 0.680 | 1 | 10 |
| Speed limit 30 to35 mph (1/0) | 168920 | 0.115 | 0.319 | 0 | 1 |
| speed limit 40 to 55 mph (1/0) | 168920 | 0.087 | 0.281 | 0 | 1 |
| Presence of school zone (1/0) | 168920 | 0.019 | 0.137 | 0 | 1 |
| Central Business District (CBD), Commercial, Fringe, or Industrial Land Use (%) | 168920 | 0.095 | 0.293 | 0 | 1 |
| Residential or Public Land Use (%) | 168920 | 0.436 | 0.496 | 0 | 1 |
| **By Traffic Count** | | | | | |
| Average AADT (n) | 168920 | 7712.960 | 14148.340 | 0 | 170740 |
| **By Census Tract** | | | | | |
| Total Population (n) | 168920 | 4837.961 | 1962.759 | 0 | 21763 |
| White Population (%) | 168920 | 0.860 | 0.186 | 0 | 1 |
| Black Population (%) | 168920 | 0.091 | 0.170 | 0 | 1 |
| Hispanic Population (%) | 168920 | 0.037 | 0.044 | 0 | 0.528 |
| Population below poverty level (%) | 168920 | 0.149 | 0.091 | 0 | 0.796 |
| Population under 20 years old (%) | 168920 | 0.253 | 0.045 | 0 | 0.612 |
| Population 20 to 64 years old (%) | 168920 | 0.595 | 0.052 | 0 | 1 |

**Table 2. Continued.**

| | | | | | |
|---|---|---|---|---|---|
| Population above 65 years old (%) | 168920 | 0.150 | 0.053 | 0 | 0.567 |
| Average Household Income (n) | 168920 | 56,058.18 | 24,714.76 | 0 | 247,239 |
| Population in civilian labor force (%) | 168920 | 0.605 | 0.096 | 0 | 0.888 |
| Housing units with No vehicle (%) | 168920 | 0.057 | 0.059 | 0 | 0.733 |
| Housing units with 1 vehicle (%) | 168920 | 0.300 | 0.101 | 0 | 1 |
| Housing units with 2 or more vehicles (%) | 168920 | 0.640 | 0.140 | 0 | 0.962 |

### 4.2 Criteria for Modeling Crash Count

From the literature review, the Negative Binomial (NB) and Poisson distribution models were used most often when modeling pedestrian crash count data. The NB model was the preferred model to use for this study because of overdispersion, where the variance is much larger than the mean. The general form of the NB model is expressed as [27]:

$$\lambda_i = e^{\beta_i X_{in}}$$

Where;
λ is crash count
X is a vector of independent variables
β is a vector of estimated coefficients
*i* is a potential outcome.

### 4.3 Model Results

The purpose of the NB crash count model was to evaluate the impact of different variables with respect to crash count. Crash count is defined as the number of total crashes along a road segment and is the dependent variable. Independent variables that were left in the models with a significant impact of less than 90% were average AADT and percent of black population. Average AADT was left in the model because it has a significance greater than 80% and was an important factor that measures vehicle exposure. The impact and significance of each of the variables that influences pedestrian crash counts greater than 90% (except average AADT and percent of black population) are summarized in Table 3. Independent variables are listed under the variable column. A coefficient determines a percent an increase or decrease on the likelihood of a pedestrian crash to occur. A p-value less than 0.10 means that the independent variable is significant greater than 90%. The marginal effect indicates the influence that the independent variable has on the dependent variable by 1.000%. A large marginal effect means that the independent variable has a substantial effect towards the dependent variable compared to other independent variables in the model. For example, population 20 to 64 years old has a larger effect on crash count than any of the other variables in the models. All models have a p-value equal to 0.0000, which means that the overall model is statistically significant.

**Table 3. Pedestrian Crash Count Model with AADT Results.**

| Variable | Coefficient. | P-value | Marginal Effect |
|---|---|---|---|
| Segment length in miles (n) | 0.511 | 0.000 | 1.667 |
| Average AADT (n) | -0.00000224 | 0.145 | 1.000 |
| Number of lanes (n) | 0.584 | 0.000 | 1.794 |
| Speed limit 30 to35 mph (1/0) | 2.065 | 0.000 | 7.889 |
| Speed limit 40 to 55 mph (1/0) | 2.142 | 0.000 | 8.513 |
| Presence of school zone (1/0) | 0.166 | 0.078 | 1.180 |
| Central Business District (CBD), Commercial, Fringe, or Industrial Land Use (%) | 1.307 | 0.000 | 3.695 |
| Residential or Public Land Use (%) | 0.645 | 0.000 | 1.905 |
| Population 20 to 64 years old (%) | 2.573 | 0.000 | 13.102 |
| Average Household Income (n) | 0.00000678 | 0.000 | 1.000 |
| White Population (%) | -1.102 | 0.026 | 0.332 |
| Black Population (%) | 0.0907 | 0.852 | 1.095 |
| Hispanic Population (%) | 1.846 | 0.000 | 6.337 |
| Housing units with No vehicle (%) | 1.167 | 0.003 | 3.212 |
| Housing units with 1 vehicle (%) | 1.183 | 0.000 | 3.264 |
| Housing units with 2 or more vehicles (%) | -1.947 | 0.000 | 0.143 |
| Constant | -7.846 | 0.000 | |
| **Summary Results** | | | |
| Number of observation = 168,920 | | | |
| P-value = 0.0000 | | | |
| LR chi$^2$ (16) = 11865.34 | | | |
| Pseudo $R^2$ = 0.3032 | | | |

Since there is not AADT for local roadways another crash count model was designed without AADT and results are summarized in Table 4. The results are similar to the crash count model in Table 3.

**Table 4. Pedestrian Crash Count Model without AADT Results.**

| Variable | Coefficient. | P-value | Marginal Effect |
|---|---|---|---|
| Segment length in miles (n) | 0.511 | 0.000 | 1.667 |
| Number of lanes (n) | 0.585 | 0.000 | 1.795 |
| Speed limit 30 to35 mph (1/0) | 2.0661 | 0.000 | 7.894 |
| Speed limit 40 to 55 mph (1/0) | 2.143 | 0.000 | 8.523 |
| Presence of school zone (1/0) | 0.167 | 0.075 | 1.182 |
| Central Business District (CBD), Commercial, Fringe, or Industrial Land Use (%) | 1.306 | 0.000 | 3.691 |
| Residential or Public Land Use (%) | 0.644 | 0.000 | 1.903 |
| Population 20 to 64 years old (%) | 2.584 | 0.000 | 13.244 |
| Average Household Income (n) | 0.00000672 | 0.000 | 1.000 |
| White Population (%) | -1.108 | 0.025 | 0.330 |
| Black Population (%) | 0.0864 | 0.859 | 1.090 |
| Hispanic Population (%) | 1.838 | 0.000 | 6.287 |
| Housing units with No vehicle (%) | 1.178 | 0.002 | 3.248 |
| Housing units with 1 vehicle (%) | 1.177 | 0.000 | 3.246 |
| Housing units with 2 or more vehicles (%) | -1.943 | 0.000 | 0.143 |
| Constant | -7.865 | 0.000 | |
| **Summary Results** | | | |
| Number of observation = 168,920 | | | |
| P-value = 0.0000 | | | |
| LR $chi^2$ (15) = 11863.16 | | | |
| Pseudo $R^2$ = 0.3032 | | | |

In both models, most of the variables have a positive coefficient and are highly significant greater than 90% significance. A positive coefficient indicates variables that increase the likelihood of a pedestrian crash, while a negative coefficient decreases the likelihood of a pedestrian crash. Variables that increase the likelihood of crashes are segment length; number of lanes; speed limit; presence of school zones; CBD, commercial, fringe (mixed residential and commercial land use), residential, public (parks) land use; population between 20 to 64 years old; average household income, Hispanic population, housing units with 0 and 1 vehicle available. As lanes increase, the likelihood of a pedestrian crash increases too, which states that multilane highways are more likely have a pedestrian crash to occur than two or fewer lanes. Areas with a high percentage of housing units with no or 1 vehicle available indicate high pedestrian exposure that increases the likelihood of a pedestrian crash. Variables that decrease the likelihood of a pedestrian crash are AADT with greater than 85% significance and white population, and housing units with 2 or move vehicles available with greater than 90% significance. As AADT decreases, the likelihood of a pedestrian crash decreases, which states that pedestrian crashes are more likely to occur on roads with lower than average AADT (7,713 vehicles per day) with only 85% significance. As segment lengths increase in the model, the likelihood of a pedestrian crash increases. Speed limits, population between 20 to 64 years old, and vehicle availability have the largest marginal effect signifying that have a greater impact over other variables in the model. Average AADT has a marginal effect equal to 1.0 indicating a neutral response to the overall model.

## 4.4 Conclusion

Overall, both crash count models were developed to identify variables that influence pedestrian crash counts. Crashes increase in areas with high pedestrian exposure such as, school zones; CBD, commercial, fringe, residential, and public land use; and areas with a high percentage of households with no vehicles present. AADT and number of lanes provide insight to information about areas with high vehicle exposure. By looking at the marginal effect, posted speed limits are very significant to pedestrian crashes. As speed limits increases, crossing the street or walking along the street becomes more dangerous and becomes a visibility problem for vehicle drivers to see pedestrians, which increases the likelihood of a pedestrian crash. These models will be used again in the development of the pedestrian harm model.

# CHAPTER V INJURY SEVERITY MODELING

## 5.1 Introduction

Pedestrian crash injury severity modelling was used to identify design mitigation issues, such as AADT, roadway geometrics, and socioeconomic and demographic factors that influenced the outcome of pedestrian and vehicle crashes. Severity models also provided additional insight into pedestrian behavior (e.g. impairment by alcohol or drugs,) that contributed to the likelihood of an incapacitating injury or fatal crash. A total of four models were constructed, a preliminary model and final model, with and without AADT. The preliminary models were constructed first to capture all of the significant variables mentioned above. The final models were constructed with all of the significant variables from the preliminary model except pedestrian behavior. The final models were used to create the pedestrian harm model in Chapter 6. The decision to make separate models with and without AADT was because there are not any traffic count data for local roadways. Summarized in Table 5 is the number of observations, mean, standard deviation, and range for type of injury, traffic count, road geometrics, and census data, which were used as either the independent or depending variable in the injury severity model. For all crashes from 2003 to 2009, there were 4,061 (72.75%) PDO or non-incapacitating injuries, 1,083 (19.4%) incapacitating injuries, and 443 (7.9%) fatalities. PDO and non-incapacitating injuries were combined to focus on the two most severe levels of injury - incapacitating injury and fatality. Variables that were tested and proven to be statistically insignificant were type of terrain; access control; TDOT region -- east, middle, or west Tennessee; mode of commuting to work; census tract average population age; weather at time of crash; and roadways where commercial vehicle speed limit is posted.

**Table 5. Summary Statistics of Data Used for Preliminary Injury Severity Models.**

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **By Injury Type** | | | | | |
| PDO & Non-Incapacitating Injury (0/1) | 5587 | 0.727 | 0.446 | 0 | 1 |
| Incapacitating Injury (0/1) | 5587 | 0.194 | 0.395 | 0 | 1 |
| Fatality (0/1) | 5587 | 0.079 | 0.270 | 0 | 1 |
| **By Traffic Count** | | | | | |
| AADT less than 20,000 (0/1) | 3265 | 0.567 | 0.496 | 0 | 1 |
| AADT 20,000 to 40,000 (0/1) | 3265 | 0.342 | 0.475 | 0 | 1 |
| AADT 40,001 to 60,000 (0/1) | 3265 | 0.058 | 0.235 | 0 | 1 |
| AADT greater than 60,000 (0/1) | 3265 | 0.032 | 0.176 | 0 | 1 |
| **By Road Geometrics** | | | | | |
| Rural Land Use (0/1) | 5574 | 0.170 | 0.376 | 0 | 1 |
| Central Business District (CBD) Land Use (0/1) | 5574 | 0.007 | 0.082 | 0 | 1 |

**Table 5. Continued.**

| | | | | | |
|---|---|---|---|---|---|
| Commercial Land Use (0/1) | 5574 | 0.435 | 0.496 | 0 | 1 |
| Fringe Land Use (0/1) | 5574 | 0.135 | 0.342 | 0 | 1 |
| Industrial Land Use (0/1) | 5574 | 0.006 | 0.079 | 0 | 1 |
| Residential Land Use (0/1) | 5574 | 0.230 | 0.421 | 0 | 1 |
| Public Land Use (0/1) | 5574 | 0.017 | 0.129 | 0 | 1 |
| Presence of school zone (0/1) | 5587 | 0.042 | 0.202 | 0 | 1 |
| Speed Limit Unknown (0/1) | 5579 | 0.148 | 0.355 | 0 | 1 |
| Speed Limit 5 to 30 mph (0/1) | 5579 | 0.180 | 0.384 | 0 | 1 |
| Speed Limit 35 to 60 mph (0/1) | 5579 | 0.639 | 0.480 | 0 | 1 |
| Speed limit 65 mph or greater (0/1) | 5579 | 0.034 | 0.180 | 0 | 1 |
| Number of lanes in both directions (n) | 5580 | 3.388 | 1.459 | 1 | 10 |
| **By Police Report** | | | | | |
| Pedestrian Male Gender (0/1) | 5587 | 0.633 | 0.482 | 0 | 1 |
| Pedestrian Female Gender (0/1) | 5587 | 0.350 | 0.477 | 0 | 1 |
| Pedestrian Unknown Gender (0/1) | 5587 | 0.017 | 0.129 | 0 | 1 |
| Pedestrian Alcohol Present (0/1) | 5587 | 0.013 | 0.113 | 0 | 1 |
| Pedestrian Alcohol Not Present (0/1) | 5587 | 0.035 | 0.183 | 0 | 1 |
| Pedestrian Alcohol Unknown (0/1) | 5587 | 0.952 | 0.213 | 0 | 1 |
| Pedestrian Drug Present (0/1) | 5587 | 0.009 | 0.097 | 0 | 1 |
| Pedestrian Drug Not Present (0/1) | 5587 | 0.400 | 0.490 | 0 | 1 |
| Pedestrian Drug Unknown (0/1) | 5587 | 0.591 | 0.492 | 0 | 1 |
| Crash occurs during weekend (0/1) | 5587 | 0.228 | 0.420 | 0 | 1 |
| Crash occurs during weekday (0/1) | 5587 | 0.728 | 0.445 | 0 | 1 |
| Day of crash unknown (0/1) | 5587 | 0.044 | 0.205 | 0 | 1 |
| Pedestrian Age Under 20 (0/1) | 5587 | 0.266 | 0.442 | 0 | 1 |
| Pedestrian Age 21 to 40 (0/1) | 5587 | 0.308 | 0.462 | 0 | 1 |
| Pedestrian Age 41 to 60 (0/1) | 5587 | 0.300 | 0.458 | 0 | 1 |
| Pedestrian Age 61 to 80 (0/1) | 5587 | 0.081 | 0.273 | 0 | 1 |
| Pedestrian Age 81 and older (0/1) | 5587 | 0.010 | 0.098 | 0 | 1 |
| Pedestrian Age Unknown (0/1) | 5587 | 0.036 | 0.185 | 0 | 1 |
| Crash occurs along roadway (0/1) | 5587 | 0.378 | 0.485 | 0 | 1 |
| Crash occurs at intersection (0/1) | 5587 | 0.609 | 0.488 | 0 | 1 |
| Crash occurs at other location (e.g. bridge, railroad grade crossing, ramp, underpass) (0/1) | 5587 | 0.013 | 0.115 | 0 | 1 |
| AM Peak Time (07:01-10:00) (0/1) | 5572 | 0.101 | 0.301 | 0 | 1 |
| Day Time (10:01-17:00) (0/1) | 5572 | 0.369 | 0.483 | 0 | 1 |
| PM Peak Time (17:01-20:00) (0/1) | 5572 | 0.225 | 0.418 | 0 | 1 |
| Night Time (20:01-07:01) (0/1) | 5572 | 0.305 | 0.460 | 0 | 1 |
| **By Census Tract** | | | | | |
| Housing units with no vehicles (%) | 5587 | 0.137 | 0.128 | 0 | 0.73 |
| Housing units with 1 vehicle (%) | 5587 | 0.414 | 0.132 | 0 | 1 |
| Housing units with 2 vehicles (%) | 5587 | 0.297 | 0.120 | 0 | 0.70 |
| Housing units with 3 or more vehicles (%) | 5587 | 0.143 | 0.100 | 0 | 0.50 |
| Average Household Income (n) | 5576 | 48732 | 24,627.77 | 0 | 247,329 |
| Total Population Density (n) | 5587 | 516.423 | 578.701 | 0 | 5108.46 |

## 5.2 Criteria for Modelling Injury Severity

From the literature review, the Multinomial Logistic (MNL) regression model was used because it can assess the significance of each injury severity level (i.e. property damage and non-incapacitating injury, incapacitating injury, and fatal). Also, the MNL model allows flexibility and an unbiased approach to observe the maximum likelihood for all variables in the model. The general equation of the MNL regression is expressed as [27]:

$$P(i) = \frac{e^{\beta_i X_{in}}}{\sum_{i=1}^{I} e^{\beta_I X_{In}}}$$

Where;
P is probability of injury type
X is a vector of independent variables
β is a vector of estimated coefficients
*i* is a potential outcome.

## 5.3 Model Results

The purpose of the MNL models was to evaluate the impact of different variables with respect to a crashes injury severity level. In all models, there are three injury severity classifications: PDO and non-incapacitating injury, incapacitating injury, and fatal crashes. The models predict the probability of the three injury classifications as a function of independent variables. The preliminary models sets a threshold value of P-value less than 0.20, indicating that the variable is different than zero with 80% confidence. The final models sets a threshold value of P-Value less than 0.10, indicating that the variable is different than zero with 90% confidence, like the crash count model.  A coefficient puts a percent an increase or decrease on the likelihood of a pedestrian crash to have an incapacitating injury or fatality compared to a pedestrian crash with PDO & non-incapacitating injury. The marginal effect indicates the influence that the independent variable has on the dependent variable by 1.00%. A large marginal effect means that the independent variable has a substantial effect towards the dependent variable. There are two separate models for the preliminary and final models, one with AADT and one without AADT, to scale the impact of AADT because there is not any traffic count data for local roadways. Therefore, the number of crashes able to be observed for the models with AADT is 2,269 (69.5%) PDO & non-incapacitating injuries, 655 (21.0%) incapacitating injuries, and 311 (9.5%) fatalities. A P-Value closer 0.000 indicates that the independent variable has a higher significance with its respective injury severity category. All models have a p-value equal to 0.0000, which means that the overall model is statistically significant.

### 5.3.1 Preliminary Model Results

The preliminary models set the three injury severity categories as the dependent variables, and the traffic count, road geometrics, police report, and census tract as the independent variables. All variables in the preliminary models have at least one variable that is more than 80% significant to either incapacitating injury or fatality. Variables that were removed from the model because they had no statistical impact on the model were AADT below 40,001; CBD, commercial, fringe, industrial (only in the model with AADT), residential, and public (only in the model with AADT) land use; speed limit below 65 mph; pedestrians below 41 years old; at intersections and other locations; time from 07:01 to 17:01; and housing units with 3 or more vehicles. Other locations are defined as bridges, railroad grade crossing, ramps, and underpasses. The impact and significance of each of the variables that influences pedestrian crash injury severity are summarized in Table 6. The model in Table 6 observes 3, 253 crash records that involve crashes classified on freeway, arterial, and collector roads.

**Table 6. Preliminary MNL Regression Model for Pedestrian Injury Severity with AADT.**

| **Variable** | **Coefficient** | **P-Value** | **Marginal Effect** |
|---|---|---|---|
| **Property Damage & Non-incapacitating Injury** | (base outcome) | | |
| | | | |
| **Incapacitating Injury** | | | |
| AADT 40,001 to 60,000 (0/1) | 0.232 | 0.217 | 1.261 |
| AADT greater than 60,000 (0/1) | -0.0955 | 0.737 | 0.909 |
| Rural Land Use (0/1) | 0.031 | 0.810 | 1.032 |
| Presence of school zone (0/1) | -0.0498 | 0.831 | 0.951 |
| Pedestrian Male Gender (0/1) | 0.114 | 0.233 | 1.120 |
| Pedestrian Alcohol Present (0/1) | -0.316 | 0.584 | 0.729 |
| Pedestrian Drug Present (0/1) | -0.682 | 0.280 | 0.506 |
| Crash occurs during weekend (0/1) | 0.0497 | 0.641 | 1.051 |
| Pedestrian Age 41 to 60 (0/1) | 0.107 | 0.286 | 1.113 |
| Pedestrian Age 61 to 80 (0/1) | 0.288 | 0.083 | 1.334 |
| Pedestrian Age 81 and older (0/1) | 0.845 | 0.048 | 2.328 |
| Speed limit 65 mph or greater (0/1) | 0.531 | 0.028 | 1.700 |
| Crash occurs along roadway (0/1) | 0.199 | 0.039 | 1.220 |
| PM Peak Time (17:01-20:00) (0/1) | 0.114 | 0.341 | 1.120 |
| Night Time (20:01-07:01) (0/1) | 0.736 | 0.000 | 2.088 |
| Housing units with no vehicles (%) | -0.580 | 0.340 | 0.560 |
| Housing units with 1 vehicle (%) | -0.727 | 0.122 | 0.483 |
| Housing units with 2 vehicles (%) | 0.667 | 0.340 | 1.947 |
| Average Household Income (n) | -0.00000520 | 0.025 | 1.000 |
| Total Population Density (n) | -0.000275 | 0.017 | 1.000 |
| Constant | -1.208 | 0.004 | |
| | | | |

**Table 6. Continued.**

| **Fatal** | | | |
|---|---|---|---|
| AADT 40,001 to 60,000 (0/1) | 0.302 | 0.249 | 1.353 |
| AADT greater than 60,000 (0/1) | 0.645 | 0.037 | 1.907 |
| Rural Land Use (0/1) | 0.543 | 0.002 | 1.721 |
| Presence of school zone (0/1) | -1.568 | 0.033 | 0.209 |
| Pedestrian Male Gender (0/1) | 0.222 | 0.135 | 1.248 |
| Pedestrian Alcohol Present (0/1) | 1.951 | 0.000 | 7.039 |
| Pedestrian Drug Present (0/1) | 1.166 | 0.013 | 3.208 |
| Crash occurs during weekend (0/1) | 0.229 | 0.129 | 1.258 |
| Pedestrian Age 41 to 60 (0/1) | 0.984 | 0.000 | 2.675 |
| Pedestrian Age 61 to 80 (0/1) | 1.405 | 0.000 | 4.075 |
| Pedestrian Age 81 and older (0/1) | 2.533 | 0.000 | 12.597 |
| Speed limit 65 mph or greater (0/1) | 0.881 | 0.001 | 2.414 |
| Crash occurs along roadway (0/1) | 0.628 | 0.000 | 1.874 |
| PM Peak Time (17:01-20:00) (0/1) | 0.660 | 0.000 | 1.935 |
| Night Time (20:01-07:01) (0/1) | 1.242 | 0.000 | 3.462 |
| Housing units with no vehicles (%) | -0.289 | 0.749 | 0.749 |
| Housing units with 1 vehicle (%) | -1.147 | 0.090 | 0.318 |
| Housing units with 2 vehicles (%) | 1.828 | 0.056 | 6.222 |
| Average Household Income (n) | -0.0000141 | 0.000 | 1.000 |
| Total Population Density (n) | -0.000193 | 0.282 | 1.000 |
| Constant | -3.384 | 0.000 | |
| **Summary Results** | | | |
| Number of observations = 3253 | | | |
| LR $chi^2(40)$ = 484.22 | | | |
| P-value = 0.0000 | | | |
| Pseudo $R^2$ = 0.0926 | | | |

Most of the independent variables from the preliminary injury severity model with AADT (Table 6) have a positive coefficient. A positive coefficient indicates variables that increase the likelihood of a crash and a negative coefficient indicates variables that decrease the likelihood of a crash with either incapacitating injury or fatality. Variables that are significant and increase the likelihood for incapacitating injury and fatality with a significance greater than 90% are roads with speed limit 65 mph and greater and crashes occurring along a roadway, as opposed to at intersection or other location, and pedestrians greater than 60 years old, and housing units with 1 vehicle available. The only variable that is significant and decreases the likelihood of an incapacitating injury and fatality with significance greater than 90% is average household income. Total population density is significantly greater than 90% and decreases the likelihood of an incapacitating injury. Presence of school zones is significantly greater than

90% and decreases the likelihood of a fatal crash. Crashes involving males and occurring on the weekends increase the likelihood of a fatal crash with 85% significance. Significant variables greater than 90% that increase the likelihood of a crash with a fatality are roadways with AADT greater than 60,000, rural land use, pedestrians under influence of alcohol and/or drugs, pedestrians 41 to 60 years old, crashes occurring during PM peak hours, and housing units with 2 vehicles. AADT from 40,001 to 60,000 is not statistically significant to the 80% level but shows that AADT increases greater than 60,000 the likelihood of a fatality increases.

The model in Table 7 removes AADT in order to observe all roadway classifications. STATA, the statistical software package used for this study, removes all incomplete rows of data with respect to the crash being observed. Therefore, this model observes 5,554 crashes out of the total 5,587 crashes.

**Table 7. Preliminary MNL Regression Model for Pedestrian Injury Severity without AADT.**

| **Variable** | **Coefficient** | **P-Value** | **Marginal Effect** |
|---|---|---|---|
| **Property Damage & Non-incapacitating Injury** | (base outcome) | | |
| | | | |
| **Incapacitating Injury** | | | |
| Rural Land Use (0/1) | 0.0395 | 0.699 | 1.040 |
| Industrial Land Use (0/1) | -1.079 | 0.081 | 0.340 |
| Presence of school zone (0/1) | -0.0194 | 0.915 | 0.981 |
| Pedestrian Male Gender (0/1) | 0.145 | 0.053 | 1.156 |
| Pedestrian Alcohol Present (0/1) | -0.0305 | 0.935 | 0.970 |
| Pedestrian Drug Present (0/1) | -0.534 | 0.280 | 0.586 |
| Crash occurs during weekend (0/1) | -0.00501 | 0.953 | 0.995 |
| Pedestrian Age 41 to 60 (0/1) | 0.187 | 0.018 | 1.206 |
| Pedestrian Age 61 to 80 (0/1) | 0.483 | 0.000 | 1.621 |
| Pedestrian Age 81 and older (0/1) | 0.798 | 0.027 | 2.221 |
| Speed limit 65 mph or greater (0/1) | 0.391 | 0.047 | 1.478 |
| Crash occurs along roadway (0/1) | 0.235 | 0.002 | 1.265 |
| PM Peak Time (17:01-20:00) (0/1) | 0.179 | 0.057 | 1.196 |
| Night Time (20:01-07:01) (0/1) | 0.766 | 0.000 | 2.151 |
| Housing units with no vehicles (%) | -0.928 | 0.040 | 0.395 |
| Housing units with 1 vehicle (%) | -1.079 | 0.002 | 0.340 |
| Housing units with 2 vehicles (%) | 0.580 | 0.285 | 1.787 |
| Average Household Income (n) | -0.00000490 | 0.006 | 1.000 |
| Total Population Density (n) | -0.000204 | 0.010 | 1.000 |
| Constant | -1.176 | 0.000 | |
| | | | |

**Table7. Continued.**

| | | | |
|---|---|---|---|
| **Fatal** | | | |
| Rural Land Use (0/1) | 0.468 | 0.001 | 1.596 |
| Industrial Land Use (0/1) | 0.724 | 0.112 | 2.064 |
| Presence of school zone (0/1) | -0.980 | 0.038 | 0.375 |
| Pedestrian Male Gender (0/1) | 0.245 | 0.043 | 1.278 |
| Pedestrian Alcohol Present (0/1) | 1.660 | 0.000 | 5.258 |
| Pedestrian Drug Present (0/1) | 0.999 | 0.012 | 2.715 |
| Crash occurs during weekend (0/1) | 0.169 | 0.173 | 1.185 |
| Pedestrian Age 41 to 60 (0/1) | 0.957 | 0.000 | 2.604 |
| Pedestrian Age 61 to 80 (0/1) | 1.547 | 0.000 | 4.698 |
| Pedestrian Age 81 and older (0/1) | 2.761 | 0.000 | 15.821 |
| Speed limit 65 mph or greater (0/1) | 0.998 | 0.000 | 2.712 |
| Crash occurs along roadway (0/1) | 0.794 | 0.000 | 2.212 |
| PM Peak Time (17:01-20:00) (0/1) | 0.917 | 0.000 | 2.503 |
| Night Time (20:01-07:01) (0/1) | 1.485 | 0.000 | 4.413 |
| Housing units with no vehicles (%) | -0.119 | 0.864 | 0.888 |
| Housing units with 1 vehicle (%) | -1.199 | 0.028 | 0.302 |
| Housing units with 2 vehicles (%) | 1.883 | 0.017 | 6.576 |
| Average Household Income (n) | -0.0000123 | 0.000 | 1.000 |
| Total Population Density (n) | -0.000164 | 0.188 | 1.000 |
| Constant | -3.808 | 0.000 | |
| **Summary Results** | | | |
| Number of observations = 5,554 | | | |
| LR $chi^2(38) = 775.87$ | | | |
| P-value = 0.0000 | | | |
| Pseudo $R^2 = 0.0930$ | | | |

Like the preliminary injury severity model with AADT, most of variables in the preliminary injury severity model without AADT (Table 7) have positive coefficients. Variables that are significant and increase the likelihood for incapacitating injury and fatality with greater than 90% significance are crashes involving males, pedestrians greater than 40 years old, roads with speed limit 65 mph or greater, crash occurs along a roadway, occurs during PM peak hours and night time hours. Significant variables that decrease the likelihood of an incapacitating injury or fatal crashes at levels greater than 90% are housing units with 1 vehicle available and average household income. Industrial land use, total population density, and presence of school zones are the variable that decreases the likelihood of a crash with an incapacitating injury with greater than 90% significance. Significant variables that increase the likelihood of a crash with a fatality greater than 90% are crashes occurring on rural land use and pedestrians under influence of alcohol and/or drugs, while crashes occurring on industrial land use and total population density are statistically significant greater than 80%. Housing units with no vehicles available is not statistically significant to the 80% level but shows that as vehicle ownership increases the likelihood of an incapacitating injury or fatality increases.

### 5.3.2 Preliminary Model Conclusion

The preliminary injury severity models provide insight to variables that may increase or decrease the likelihood of an incapacitating injury or fatality for pedestrians. There are several reoccurring variables that increase the likelihood of a fatal pedestrian crash in both injury severity models with and without AADT, which were rural land use, areas with high speed limits; PM peak and night time hours; located along a roadway, as opposed to at an intersection; pedestrians greater than 40 years old; male pedestrians; pedestrians under the influence of alcohol and/or drugs; crashes occurring on the weekend. Pedestrians walking on high speed rural roadways at night have the highest risk of incapacitating or fatal injury. These areas are often areas that are not well lit. School zones were significant but with negative coefficients meaning these are safe areas with respect to injury severity. Pedestrians greater than 80 years old had the largest marginal effect because as people age they become feeble. Night time and housing units with 2 vehicles available also have high marginal effect compared to the rest of the model.

### 5.3.3 Final Model Results

The final models for injury severity were built using the significant variables from the preliminary model. All variables in the final models have at least one variable that is more than 90% significance to either incapacitating injury or fatal injury, like the crash count models. The final model contains all of the same data except pedestrian behavior (e.g. gender, pedestrian age, presence of alcohol and/or drugs). The purpose of the final model was to build a model with 90% significance level to use with the crash count models from Chapter 4 to develop the pedestrian harm models in Chapter 6. The final models will contain two models, one model with AADT and one model without AADT. Summarized in Table 9 are the impact and significance of each of the variables that influences pedestrian crash injury severity with AADT. Variables that were removed from the model because they had no statistical impact on the model were AADT below 60,001; CBD, commercial, fringe, industrial (only in the model with AADT), residential, and public (only in the model with AADT) land use; and speed limit less than 35 mph.

**Table 8. Final MNL Regression Model for Pedestrian Injury Severity with AADT.**

| Variable | Coefficient | P-Value | Marginal Effect |
|---|---|---|---|
| **Property Damage & Non-incapacitating Injury** | (base outcome) | | |
| | | | |
| **Incapacitating Injury** | | | |
| AADT greater than 60,000 (0/1) | -0.145 | 0.622 | 0.865 |
| Rural Land Use (1/0) | 0.163 | 0.225 | 1.177 |
| Presence of school zone (1/0) | -0.118 | 0.607 | 0.888 |
| Speed limit 35 to 60 mph (1/0) | 0.0646 | 0.577 | 1.067 |
| Speed limit 65 mph or greater (0/1) (1/0) | 0.531 | 0.045 | 1.701 |
| Housing units with no vehicles (%) | -0.830 | 0.162 | 0.436 |
| Housing units with 1 vehicle (%) | -0.939 | 0.041 | 0.391 |
| Housing units with 2 vehicles (%) | 0.743 | 0.277 | 2.102 |
| Average Household Income (n) | -0.00000588 | 0.010 | 1.000 |
| Total Population Density (n) | -0.000338 | 0.004 | 1.000 |
| Number of lanes (n) | 0.0825 | 0.036 | 1.086 |
| Constant | -0.893 | 0.027 | |
| | | | |
| **Fatal** | | | |
| AADT greater than 60,000 (0/1) | 0.560 | 0.082 | 1.751 |
| Rural Land Use (1/0) | 0.737 | 0.000 | 2.090 |
| Presence of school zone (1/0) | -1.649 | 0.022 | 0.192 |
| Speed limit 35 to 60 mph (1/0) | 0.471 | 0.010 | 1.602 |
| Speed limit 65 mph or greater (0/1) (1/0) | 1.174 | 0.000 | 3.235 |
| Housing units with no vehicles (%) | -0.686 | 0.413 | 0.503 |
| Housing units with 1 vehicle (%) | -1.289 | 0.041 | 0.275 |
| Housing units with 2 vehicles (%) | 2.202 | 0.014 | 9.041 |
| Average Household Income (n) | -0.0000154 | 0.000 | 1.000 |
| Total Population Density (n) | -0.000438 | 0.018 | 1.000 |
| Number of lanes (n) | 0.122 | 0.033 | 1.130 |
| Constant | -2.237 | 0.000 | |
| **Summary Statistics** | | | |
| Number of observations = 3,262 | | | |
| LR $chi^2(22)$ = 229.23 | | | |
| P-value = 0.0000 | | | |
| Pseudo $R^2$ = 0.0437 | | | |

The final injury severity model with AADT (Table 8) has a distribution of positive and negative coefficients with variables greater than 90% significance. Variables that are significant and increase the likelihood for incapacitating injury and fatality with greater than 90% significance are roads with speed limits greater than 65 mph. Significant variables that decrease the likelihood of an incapacitating injury or fatal crash with 90% significance levels are average household income, total population density, and households with 1 vehicle available. The only variables that increases the likelihood of a crash with an incapacitating injury is crashes occurring on roadways with speed limits greater than 65 mph. Significant variables that increase the likelihood of a crash with a fatality with greater than 90% significance are roadways with AADT greater than 60,000, rural land use, and roadways with speed limits 35 to 60 mph. The presence of school zones and housing units with 1 vehicle available decrease the likelihood of a fatality with levels greater than 90%.

The model in Table 9 removes AADT and accounts for all roadway classification observing 5,569 crashes.

**Table 9. Final MNL Regression Model for Pedestrian Injury Severity without AADT.**

| Variable | Coefficient | P-Value | Marginal Effect |
|---|---|---|---|
| **Property Damage & Non-incapacitating Injury** | (base outcome) | | |
| | | | |
| **Incapacitating Injury** | | | |
| Rural Land Use (1/0) | 0.163 | 0.120 | 1.177 |
| Industrial Land Use (1/0) | -0.817 | 0.184 | 0.442 |
| Presence of school zone (1/0) | -0.0911 | 0.611 | 0.913 |
| Speed limit 35 to 60 mph (1/0) | 0.0611 | 0.486 | 1.063 |
| Speed limit 65 mph or greater (0/1) (1/0) | 0.377 | 0.090 | 1.458 |
| Housing units with no vehicles (%) | -1.056 | 0.016 | 0.348 |
| Housing units with 1 vehicle (%) | -1.176 | 0.001 | 0.309 |
| Housing units with 2 vehicles (%) | 0.761 | 0.146 | 2.141 |
| Average Household Income (n) | -0.00000585 | 0.001 | 1.000 |
| Total Population Density (n) | -0.000271 | 0.001 | 1.000 |
| Number of lanes (n) | 0.0685 | 0.021 | 1.071 |
| Constant | -0.815 | 0.007 | |
| | | | |
| **Fatal** | | | |
| Rural Land Use (1/0) | 0.736 | 0.000 | 2.087 |
| Industrial Land Use (1/0) | 1.096 | 0.013 | 2.991 |
| Presence of school zone (1/0) | -1.122 | 0.015 | 0.326 |
| Speed limit 35 to 60 mph (1/0) | 0.445 | 0.002 | 1.561 |
| Speed limit 65 mph or greater (0/1) (1/0) | 1.164 | 0.000 | 3.203 |
| Housing units with no vehicles (%) | -0.441 | 0.482 | 0.644 |
| Housing units with 1 vehicle (%) | -1.481 | 0.003 | 0.227 |
| Housing units with 2 vehicles (%) | 2.315 | 0.001 | 10.123 |
| Average Household Income (n) | -0.0000146 | 0.000 | 1.000 |
| Total Population Density (n) | -0.000399 | 0.004 | 1.000 |
| Number of lanes (n) | 0.160 | 0.000 | 1.173 |
| Constant | -2.481 | 0.000 | |
| **Summary Statistics** | | | |
| Number of observations = 5,573 | | | |
| LR $chi^2(22)$ = 347.48 | | | |
| P-value = 0.0000 | | | |
| Pseudo $R^2$ = 0.0415 | | | |

Variables in the final injury severity model without AADT (Table 9) have a distribution of positive and negative coefficients for variables with 90% significance. Variables that are significant and increase the likelihood for incapacitating injury and fatalities with 90% significance are number of lanes and housing units with 2 vehicles available. Rural land and housing units with 2 vehicles available are positively significant at the 80% level for incapacitating injury and at the 90% level for fatality. Variables that are significant and decrease the likelihood of an incapacitating injury or fatal crash with greater than 90% significance are housing units with 1 vehicle available, average household income, and total population density. Roadways with speed limits from 35 to 60 mph are significantly greater than 90% and increase the likelihood of a crash with a fatality. Industrial land use is significant at the 85% level for incapacitating injury but positively significant at the 90% level for fatality. Variables that decrease the likelihood of a crash with a fatality with greater than 90% significance are presence of school zones and industrial land use. Increasing speed and vehicle ownership have the highest marginal effect, which indicate that these two variables have the most influence on pedestrian incapacitating injury or fatality.

#### 5.3.4 Final Model Conclusion

The final MNL model displays similar results to the preliminary models. The final MNL model gives key insight to roadway geometrics, traffic volumes, and socioeconomic and demographics for each roadway segment. Variables proven to be significant to increase the likelihood of a fatality in both MNL models from Table 8 and Table 9 are as areas with rural land use and roadways with posted speed limit greater than 35 mph, housing units with 2 vehicles available, and number of lanes. As the number of lanes increase, the likelihood of a pedestrian fatality increases. Presence of school zone, total population density, and average household income are proven statistically significant with negative coefficients in both models. Total population density was significant but with a negative coefficient meaning that the likelihood of a crash with an incapacitating injury or fatality will occur in areas with low population density. Housing units with 2 vehicles has the largest marginal effect indicating that the increase in vehicle ownership heavily increases the likelihood of a pedestrian fatality. Both models, with AADT and without AADT, will be used in the following chapter to calculate pedestrian harm for each road segment by predicting the capability of estimating the probability of severe crashes as a function of exogenous variables that are readily available.

### 5.4 Conclusion

In conclusion, all four models evaluate issues affecting severe crashes such as, AADT, roadway conditions, socioeconomic and demographic factors, land use, and pedestrian behavior. The key component from all four models is that severe pedestrian crashes occur on roadways with high speed, rural land use, and low population densities. These areas are often areas that are away from local city streets and not well lit.  As number of households with vehicles increases, the likelihood of a pedestrian incapacitating injury or fatality increases, which means pedestrian crashes with severe injuries are occurring on census tracts where there are more vehicles present. Also, the models with AADT show that roadways with high AADT increase the likelihood of a severe injury, which is opposite of the crash count model. All four models indicate that the presence of school zones decrease the likelihood for severe injuries. This is because within school zones speed limits are generally reduced by 15 mph of the regular posted speed limit in Tennessee. Although MNL models cannot point at the exact location at where crashes with high injury severity occur, it can provide key insight to general areas that can be focused on safety related pedestrian projects. These models provide a predictive capability to estimate probability of severe crashes as a function of exogenous variables that are readily available. Some of the findings in the injury severity model are opposite of our findings in Chapter 4 with crash count modelling and demonstrates the need for a combined model to calculate pedestrian harm for all road segments (Chapter 6) by combining crash count and injury severity.

# CHAPTER VI PEDESTRIAN HARM MODELING

## 6.1 Introduction

The main innovative part to this study was to model pedestrian harm for each road segment in Tennessee from the TDOT road geometrics shapefile. To the author's knowledge, this framework has never been performed. In this case, pedestrian harm is defined as a roadway that may lead to incapacitating injury or fatality for pedestrians if struck by a vehicle. The pedestrian harm model combined crash count models and injury severity models with and without AADT. There will be two separate models, one with AADT and one without AADT. By using two separate models, the impact of AADT on pedestrian harm can be addressed because the traffic count dataset does not contain AADT for local roadways. These models will make it possible to identify roadways with high injury severity levels along with high crash counts to maximize the reduction of state-wide pedestrian crashes.

## 6.2 Criteria for Modeling Pedestrian Harm

In order to calculate pedestrian harm, there were four parts needed: road geometrics and traffic count data, surrounding socioeconomic and demographics for each roadway segment used from the injury severity and crash count models; coefficients from the crash count models in Chapter 4; coefficients form the injury severity final models in Chapter 5; and lastly a relative weight factor to distinguish the difference between PDO and non-incapacitating injury, incapacitating injury, and fatality. To determine the relative weight factor, a crash cost was calculated using the 2010 Highway Safety Manual Crash Cost Estimates [28] guidelines, which gives four steps approach on how to calculate crash cost estimates for a given year. These calculations are listed in section 6.4 along with the pedestrian harm equation used for each road segment.

Data used for the pedestrian harm model was AADT data from the TDOT website [26] and socioeconomic and demographics from the 2010 census [25], and TDOT road geometrics shapefile. AADT and census data were joined onto TDOT road geometrics using the "spatial join" feature in ArcGIS. These were the same datasets used for the crash count and injury severity modeling except without the police reported crash data. The outcome of the joined files was 193,574 road segments throughout Tennessee, excluding local roadways in West Tennessee. See Appendix B for a map of all roadways used in this study.

## 6.3 Pedestrian Harm Calculation

In order to calculate pedestrian harm for each roadway segment, several calculations had to be made using Microsoft Excel. The first calculation was to generate three separate equations for the probability of each injury severity level (PDO and non-incapacitating injury, incapacitating injury, and fatality) for each road segment based the coefficients from the MNL final injury severity models from

Chapter 5 and the road geometrics, traffic data, and socioeconomic and demographic data , which will be used as the independent variables. The  MNL general equation is [27]:

$$P(i) = \frac{e^{\beta_i X_{in}}}{\sum_{i=1}^{I} e^{\beta_I X_{In}}}$$

Where;
P is probability of injury type
X is a vector of independent variables
β is a vector of estimated coefficients
*i* is a potential outcome.

The second calculation was to calculate crash count for each road segment using the coefficients from the NB crash count models from Chapter 4 and the road geometrics, traffic data, and socioeconomic and demographic data, which will be used as the independent variables. The NB general equation is [27]:

$$\lambda_i = e^{\beta_i X_{in}}$$

Where;
λ is crash count
X is a vector of independent variables
β is a vector of estimated coefficients
*i* is a potential outcome.

The third calculation is to determine estimated crash severity rate by combining each injury severity equation and crash count equations above for each road segment. The estimated crash severity rate for PDO and non-incapacitating injury is calculated as:

$$E(\lambda PDO \;\&\; Non - Incapacitaitng\ Injury) = P(PDO \;\&\; Non - Incapacitating\ Injury) * \lambda.$$

The estimated crash severity rate for incapacitating injury is calculated as:

$$E(\lambda Incapacitaitng\ Injury) = P(Incapacitating\ Injury) * \lambda.$$

The estimated crash severity rate for fatalities is calculated as:

$$E(\lambda Fatality) = P(Fatality) * \lambda.$$

Where;
E($\lambda$) = Crash Severity Rate
P = Probability of injury type
$\lambda$ = Crash Count.

The next section provides the steps used calculate crash cost based on injury severity categories and will determine an equation to calculate pedestrian harm for each roadway segment.

## 6.4 Adjustment of Crash Costs

Crash costs were obtained from the Federal Highway Administration (FHWA) Crash Cost Report [29]. The FHWA report presents human capital crash costs and comprehensive crash costs for each category of injury severity for the year 2001 (Table 10) and will be the base year to adjust for crash cost for the year 2012. The year 2012 was chosen because it was the last full year at the time that this study was completed. For future pedestrian harm models, the year will need to be updated to a more current time frame.

**Table 10. Human and Comprehensive Crash Costs in the Year 2001.**

| Collision Type | Human Costs | Comprehensive Crash Costs |
|---|---|---|
| Fatality | $1,245,600 | $4,008,900 |
| Disabling Injury | $111,400 | $216,000 |
| Possible Injury | $28,400 | $44,900 |
| PDO | $6,400 | $7,400 |

***Step 1: Adjust Human Capital Costs Using Consumer Price Index (CPI)***
Human capital costs were multiplied by a ratio of the CPI for the year 2012 and divided by the CPI for 2001. Based on US Bureau of Labor Statistics data [30] the average annual CPI for the South urban area of the United States for the year 2001 was 171.1 and for January 2012 was 220.497.

$$CPI\ RATIO_{(2001-2012)} = \frac{CPI_{2012}}{CPI_{2001}}$$

CPI = 220.497/171.1=1.29

The 2012 CPI-adjusted human capital costs were estimated by multiplying the CPI ratio by the 2001 human capital costs. For fatal crashes the CPI-Adjusted Human Capital Costs were calculated as:

2012 Human Capital Cost of Fatal Crash = $1,245,600×1.29 = $1,606,824 [per fatal crash]

The 2012 human capital costs for all categories of injury severity are summarized in Table 11.

**Table 11. 2012 CPI-Adjusted Human Crash Costs.**

| Collision Type | 2001 Human Costs | 2012CPI-Adjusted Human Costs |
|---|---|---|
| Fatality | $1,245,600 | $1,606,824 |
| Disabling Injury | $111,400 | $143,706 |
| Possible Injury | $28,400 | $36,636 |
| PDO | $6,400 | $8,256 |

***Step 2: Adjust Comprehensive Costs using ECI***

To adjust the portion of the comprehensive costs that are not human capital costs, the difference between the comprehensive cost and the human capital cost were identified. For example, the unit crash cost difference in 2001 dollars for fatal crashes was calculated as:

$4,008,900 - $1,245,600 = $2,763,300 [per fatal crash]

The differences for each crash severity level are shown in Table 12.

***Step 3: Adjust the Difference Calculated in Step 2 Using the Employment Cost Index (ECI)***

The comprehensive crash cost portion that does not include human capital costs was adjusted using a ratio of the ECI for 2012 divided by the ECI for 2001. Based on US Bureau of Labor and Statistics data [31] the Employment Cost Index in March for year 2001 was 84.7 and in 2012 was 116.2. The ECI ratio was then be calculated as:

$$ECI\ RATIO_{(2001-2012)} = \frac{ECI_{2012}}{ECI_{2001}}$$

ECI ratio =116.2/84.7=1.37

This ECI ratio was then multiplied by the calculated difference between the 2001 human capital and 2001 comprehensive cost for each injury severity category and is shown in Table 12. For example, the 2012 ECI-adjusted difference for the fatal crash cost is

1.37 × $2,763,300=$3,785,727 [per fatal crash]

**Table 12. ECI-Adjusted Crash Costs.**

| Collision Type | 2001 Human Costs | 2001 Comprehensive Crash Costs | Crash Cost Difference | 2012 ECI-Adjusted Crash Cost Difference |
|---|---|---|---|---|
| Fatality | $1,245,600 | $4,008,900 | $2,763,300 | $3,785,721 |
| Disabling Injury | $111,400 | $216,000 | $104,600 | $143,302 |
| Possible Injury | $28,400 | $44,900 | $16,500 | $22,605 |
| PDO | $6,400 | $7,400 | $1,000 | $1,370 |

***Step 4: Calculate the 2012 Comprehensive Costs***

The sum of the 2012 CPI-adjusted costs (Table 11) and the 2012 ECI-adjusted cost differences (Table 12) was taken, as shown in Table 13, to determine the 2012 Comprehensive Costs. For example, the 2012 Comprehensive Cost for a fatal crash was calculated as:

2012 Comprehensive Fatal Crash Cost = $1,606,824 + $3,785,721= $5,392,545 [per fatal crash]

**Table 13. 2012 Societal Crash Costs.**

| Collision Type | 2012 CPI-Adjusted Human Costs | 2012 ECI-Adjusted Crash Cost Difference | 2012 Comprehensive Crash Costs |
|---|---|---|---|
| Fatality | $1,606,824 | $3,785,721 | $5,392,545 |
| Disabling | $143,706 | $143,302 | $287,008 |
| Possible Injury | $36,636 | $22,605 | $59,241 |
| PDO | $8,256 | $1,370 | $9,626 |

Finally, the weight factors for each category of injury severity was calculated by expressing the 2012 comprehensive crash cost as a ratio of the cost for non-incapacitating injury and PDO shown in Table 14 below. Disabling injury was interpreted as incapacitating injury, and possible injury was interpreted as non-incapacitating injury. Since there are four types crash types and the MNL injury severity models from Chapter 5 only use three crash types, PDO and non-incapacitating injuries were combined used 2012 comprehensive crash costs and the percentage of PDO and non-incapacitating injuries from the TRIMS crash data. Calculations are also shown in Table 14. The 2012 Comprehensive Crash Cost Ratio is:

2012 Comprehensive Crash Cost Ratio = 98.48*Fatal + 5.24*Incapacitating + 1.00*Non-Incapacitating & PDO

**Table 14. Comprehensive Crash Costs Ratio for 2012.**

| Collision Type | 2012 Comprehensive Crash Costs | Number of Crashes | Weight Factor | 2012 Comprehensive Crash Costs Ratio |
|---|---|---|---|---|
| Fatal Injury | $5,392,545 | 443 | 5,392,545 | 98.48 |
| Incapacitating Injury | $287,008 | 1,083 | 287,008 | 5.24 |
| Non-Incapacitating Injury | $59,241 | 3,694 | | |
| PDO | $9,626 | 367 | 54,757 | 1.00 |

Finally, the pedestrian harm equation used for data on each the 193,574 road segment is:

$$\text{Pedestrian Harm} = 98.48 * \mathrm{E}(\lambda\text{fatality}) + 5.24 * \mathrm{E}(\lambda\text{Incapacitaitng injury}) + 1.00 * \mathrm{E}(\lambda\text{pdo } \& \ non - \text{incapacitaitng injury}).$$

Recall from the previous subsection that $\mathrm{E}(\lambda)$ is crash severity rate for each category of injury severity level.

## 6.5 Pedestrian Harm Model Results

The results of the pedestrian harm models provide a pedestrian harm score based on the "Pedestrian Harm" equation in Section 6.4. This equation was used for all 193,574 roadway segments throughout Tennessee for both pedestrian harm models, with and without AADT. Roadway segments are divided up as geometric, traffic, and census attributes change the composition of the roadway. Summarized in Table 15 are the results of the pedestrian harm model with AADT, and summarized in Table 16 are the results of the pedestrian harm model without AADT. All interstates and State Route (SR) 155 (Briley Parkway, Davidson County), SR 153 (Hamilton County), and SR 385 (Bill Morris Parkway, Shelby County) were set at a pedestrian harm score equal to 0.000000 for both models because these were all high speed arterials that are illegal for pedestrians to walk along and do not have any signs of high pedestrian exposure. For the pedestrian harm model with AADT, all roadways classified as local were removed from the model because the injury severity model with AADT in Chapter 5 did not have traffic data for local roadways. Pedestrian harm scores are summarized in Tables 15 and Table 16. By using the layer properties feature in ArcGIS, all roadway segments were able to be split into 10 separate classifications. The 10 classifications allows for variation of the variables, such as road geometrics, traffic data, and socioeconomic and demographics data, to determine. The number of lanes is for both directions and an odd number of lanes indicate the presence of middle turn lane.

**Table 15. Pedestrian Harm with AADT Results.**

| **Pedestrian Harm with AADT Classification** | **Attributes contributing to each classification of pedestrian crash** |
|---|---|
| 0.000000 (155,903 roadway segments) | Interstates; State Routes 155, 153, 385; and local roadways |
| 0.0000002 – 0.025000 (3,941 roadway segments) | 1 to 6 lanes, speed limit 15 to 70 mph, all types of lane use, presence of school zones |
| 0.025001 – 0.050000 (1,491 roadway segments) | 1 to 4 lanes, speed limit 15 to 70 mph, all types of lane use, presence of school zones |
| 0.050001 – 0.100000 (1,685 roadway segments) | 1 to 4 lanes, speed limit 15 to 70 mph, all types of lane use, presence of school zones |
| 0.100001 – 0.250000 (13,112 roadway segments) | 1 to 6 lanes, speed limit 15 to 70 mph, all types of lane use, presence of school zones |
| 0.250001 – 0.750000 (9,563 roadway segments) | 2 to 6 lanes, speed limit 20 to 70 mph, all types of lane use |
| 0.750001 – 1.000000 (1,603 roadway segments) | 2 to 6 lanes, speed limit 30 to 65 mph, all types of land use |
| 1.100001 – 3.000000 (4,174 roadway segments) | 2 to 6 lanes, speed limit 30 to 55 mph, all types of land use |
| 3.000001 – 5.000000 (960 roadway segments) | 42% of roadway segments are in Shelby County (19% in Davidson, 11% in Hamilton, 7% in Knox, and 21% in counties other than Shelby, Davidson, Hamilton, and Knox); 2 to 7 lanes; speed limit 30 to 55 mph; CBD, commercial, fringe, or industrial land use |
| 5.000001 – 70.000000 (1,142 roadway segments) | State Routes 177, 1, 175 and 176 in Shelby County are the roadways with the four highest pedestrian harm scores and have AADT volumes greater than 25,000; 65% of roadway segments are in Shelby County; 3 to 8 lanes; speed limit greater than 40 mph; CBD, commercial, fringe, industrial, residential, or public land use |

The pedestrian harm model with AADT in Table 15 lists State Routes 177, 1, 175, and 6 in Shelby County as the four most harmful roadways segments in Tennessee, and they also have AADT volumes greater than 25,000. From looking at these three roadways in Google Maps, they all have unfinished or no sidewalks and are along a stretch of roadway designated as commercial land use [32]. As AADT, speed limit, and number of lanes increase, the pedestrian harm score increases as well. Land use marked as CBD, commercial, fringe, industrial, residential, or public have the highest pedestrian harm scores, while rural land use has the lowest pedestrian harm scores. Table 16 contains a detailed list of attributes that influence the pedestrian harm model without AADT.

**Table 16. Pedestrian Harm without AADT Results.**

| Pedestrian Harm without AADT Classification | Attributes contributing to each classification of pedestrian crashes |
|---|---|
| 0.000000 (1,402 roadway segments) | Interstates and State Routes 155, 153, 385 |
| 0.0000002 – 0.025000 (123,884 roadway segments) | Majority of roads are classified as local, 1 to 6 lanes, speed limit 5 to 70 mph, all types of lane use, presence of school zones |
| 0.025001 – 0.050000 (19,114 roadway segments) | Majority of roads are classified as local, 1 to 7 lanes, speed limit 5 to 70 mph, all types of lane use, presence of school zones |
| 0.050001 – 0.100000 (6,860 roadway segments) | Even distribution between state routes and local roadways, 1 to 4 lanes, speed limit 15 to 40 mph, all types of lane use, presence of school zones |
| 0.100001 – 0.250000 (23,279 roadway segments) | Even distribution between state routes and local roadways, 1 to 6 lanes, speed limit 10 to 70 mph, all types of lane use, presence of school zones |
| 0.250001 – 0.750000 (10,882 roadway segments) | State routes and local roadways; 1 to 7 lanes, speed limit 15 to 70 mph, all types of lane use, presence of school zones |
| 0.750001 – 1.000000 (1,702 roadway segments) | State routes; 2 to 6 lanes, speed limit 30 to 65 mph, all types of land use |
| 1.100001 – 3.000000 (4,310 roadway segments) | State routes, 2 to 6 lanes, speed limit 30 to 55 mph, all types of land use |
| 3.000001 – 5.000000 (935 roadway segments) | State routes; 41% of roadway segments are in Shelby County (19% in Davidson, 11% in Hamilton, 7% in Knox, 22% in counties other than Shelby, Davidson, Hamilton, and Knox); 2 to 7 lanes; speed limit 30 to 55 mph; CBD, commercial, fringe, or industrial land use |
| 5.000001 – 70.000000 (1,206 roadway segments) | State Routes 177, 14, 175 and 176 in Shelby County are the roadways with the four highest pedestrian harm scores; 65% of roadway segments are in Shelby County (15% in Davidson, 8% in Hamilton, 4% in Knox, 7% in counties other than Shelby, Davidson, Hamilton, and Knox); 4 to 6 lanes; speed limit 30 to 55 mph; CBD, commercial, fringe, industrial, residential, or public land use |

The pedestrian harm model without AADT lists State Routes 177, 14, 175, and 176 in Shelby County as the roadway segments with the highest pedestrian harm. State Routes 177, 175, and 176 were also listed as the roadway segments with the highest pedestrian harm in the pedestrian harm with AADT. The model without AADT allows for all roadway segments (expect interstates and State Routes 155, 153, and 385) to be included which leads to an increased range of attributes, such as speed limit, land use, and number of lanes. When comparing state routes and local roadways, state routes are perceived to be more harmful to pedestrians than local roads.

Overall, the pedestrian harm models with and without AADT have similar results on categorizing roadway segments that may be harmful to pedestrians. School zones rank in the bottom half of both pedestrian harm models indicating that these areas are not as harmful as expected from the crash count model. Land use, such as CBD, commercial, fringe, industrial, residential, or public use, have high pedestrian harm scores, which was found to be significant from the crash count model. Rural land use does not have any indication on pedestrian harm, which is opposite of findings from the injury severity models. An increase in total population density leads to an increase in pedestrian harm scores for both model. For both models, roadway segments in Shelby County are listed as the county with the highest pedestrian harm with 65% of roadway segments. Also, Shelby, Davidson, Hamilton, and Knox Counties had the most roadway segments with the highest pedestrian harm scores in both models.

### 6.6 Pedestrian Harm Results in GIS

The final part of this study was to create a GIS tool using ArcGIS. The tool can be used to locate pedestrian harm scores for roadways throughout Tennessee. The final outcome gives a map of all roadways (except local roads in West Tennessee) in Tennessee with their respective pedestrian harm score based on graduated colors with green , yellow, orange, and red, which are in order of lowest to highest for pedestrian harm for their respective category from Table's 15 and 16. The GIS map is a large file and has to be zoomed in to be able to see the roadways with graduated colors. Therefore, maps of Shelby (Memphis), Davidson (Nashville), Hamilton (Chattanooga), and Knox (Knoxville) County can be found in Appendix C. These counties were the four counties in both pedestrian harm models with the highest pedestrian harm score. Also, the complete map has a detailed attribute table that lists names of roadways, locations of roadways, all independent variables used in crash count and injury severity models, and pedestrian harm calculations. Displayed in Figure 3 is an example of pedestrian harm with AADT for SR 177 in Shelby County. Below Figure 4 which shows the Google Street View of the roadway segment from Figure 3 [32].

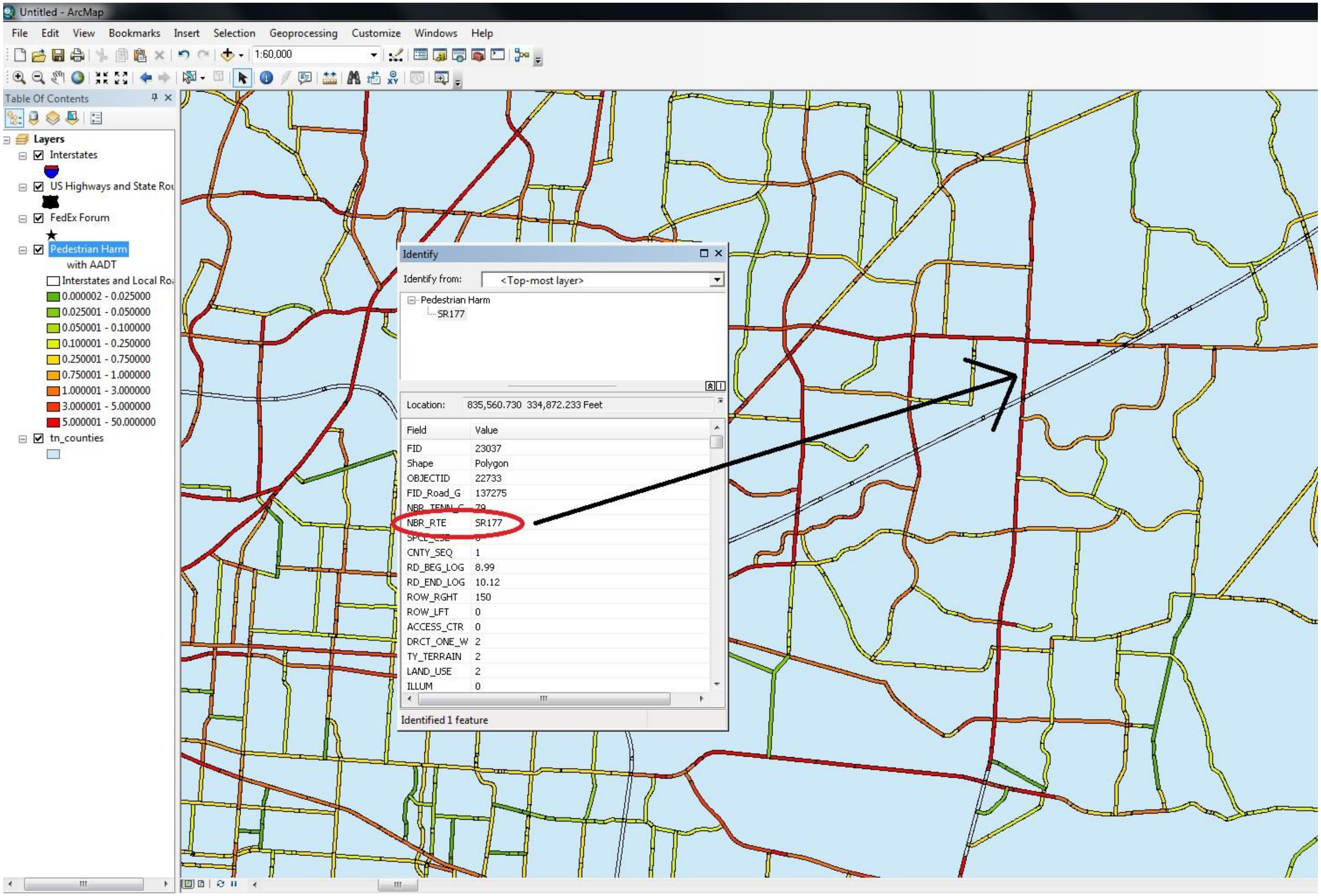


**Figure 3. Sample of Pedestrian Harm with AADT for SR 177 in Shelby County, Tennessee.**

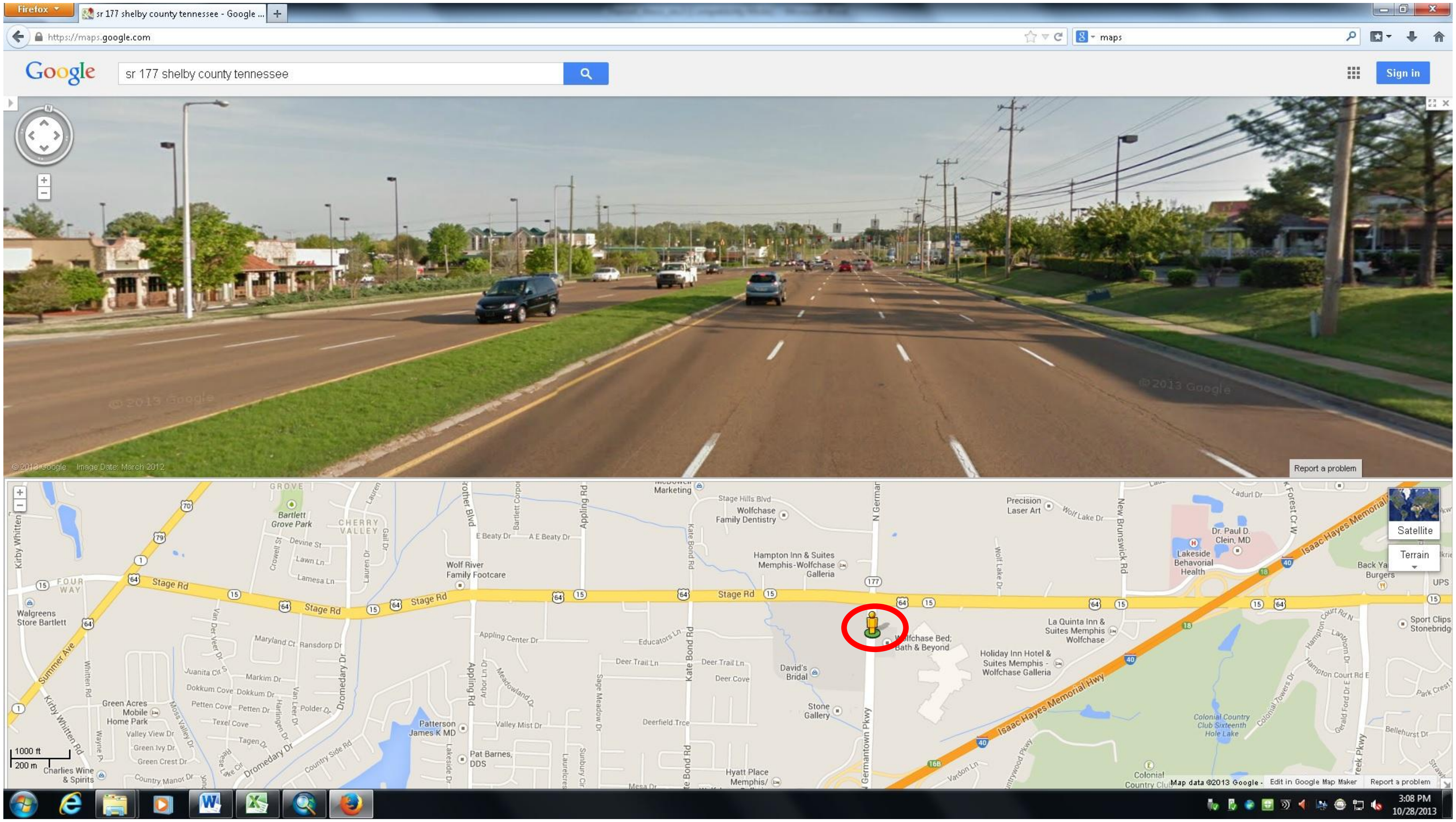


**Figure 4. Google Street View of SR 177 in Shelby County, Tennessee.**

From Figure 3, there are networks of roadways in Shelby County, Tennessee, which are shaded by10 different colors. The route number for this example is circled in red. Public transportation organizations now have the capability to use this tool to look at roadways that are potentially harmful to pedestrians in order to prioritize funding for pedestrian infrastructure projects. Instead of going out and looking at streets in person, one may use Google Street View [32] (Figure 4) to look at contributing attributes that may cause a roadway to be harmful for pedestrians. The example in Figures 3 and 4 is of SR 177 (Germantown Parkway) in Shelby County. The section of road is located in a commercial business district with 8 lanes of traffic and a vehicle posted speed limit of 45 mph. Sidewalk are provided but are located close to the roadway with no protection for the pedestrians. Also crosswalks are marked at signalized, but are located at distance far apart from each other, which may cause pedestrian mid-block crossing. This tool may be updated yearly to keep forecasting road segments that are harmful to pedestrians.

# CHAPTER VII CONCLUSION

In conclusion, this study provides a framework on where to target roadways to protect pedestrians from severe crashes and reduce the number of incapacitating injuries and fatalities in the future. This study used a total of  5,587 pedestrian crashes throughout a six year period (2003-2009) as the dataset for statistical modeling.The same pricipal applies when attempting to recreate this study with bicycylists. The two most important parts of this study are the crash count and injury severity statistical models, which were used to develop the pedestrin harm models.

Modeling pedestrian harm is an innovative framework to predict roadways that are harmful to pedestrians. The decision to make two seperate models was becasuse the model with aadt does not have aadt for local roads and excludes all local roads which make up a large portion of roadways in the state. Therefore, the model with aadt uses state routes and calcuates a higher pedestrian harm  score for roadways with the following characteristics: multilane (3 to 8 lanes) road segments; speed limts greater than  40 mph; and CBD, commercial, fringe, industrial, residential, or public land use. Roadways with low pedestrian harm scores are often roadways with low speed limits, rural land  use, and less than 6 lanes. These are often areas  with low populaiton density. In general, roadways with lower speed limits usually result in a less severe injury for pedestrians. Over 60% of the roadways in the highest category (0.000001 – 50.000000) of pedestrian harm are in Shelby County.  Both pedestrian harm  models calculate the highest scores for the same three roadways, which are SR 177 (Germantown Parkway), SR 175 (East Shelby Drive), and SR 176 (New Getwell Road) and are all in Shelby County. Also, both models list the highest pedestrian harm scores for the following counites: Shelby, Davidson, Hamilton, and Knox Counties. Shelby, Davidson, Knox, and Hamilton Counties have the highest crash counts in in Tennessee from 2003 to 2009. Both models specify that rural land use and presence of school zones  have low pedestrian harm scores. Unlike the model with aadt, the model without aadt give pedestrian harm scores for a broad range of roadway classifications. Roadways with the highest pedestrian harm score are are state routes with 4 to 6  lanes; speed limits between 30 to 55 mph; and CBD, commercial, fringe, industrial, residential, or public use land uses. The model without AADT also provides high pedestrian harm scores for downtown areas in Shelby, Davidson, Hamilton, and Knox Counties. Downtown areas are often areas with with high pedestrian exposure. According to the pedestrian harm model without AADT, local roadways have low pedestrian harm scores. Overall, AADT has a only a maringal increase when comparing scores from the pedestrian harm model with AADT to the pedestrian harm model without AADT. This may be do the fact that in the crash count model  has no marginal effect and has a coefficient equal to -0.00000224. In the injury severity model, AADT does not become significant and increase the likelhood of a fatal crash unitil AADT is greater than 60,000. State routes usually do not have an AADT greater than 60,000, but in  1.2% state routes of in this study do have an AADT greater than 60,000. These state routes are located in Shelby, Hamilton, and Rutherford County.

By looking at Davidson, Hamilton, and  Knox Counties, the roadways with the highest pedestrian harm score for the model with AADT are:  SR 1 (West End Avenue), SR 6 ( Briarville Road/end of Ellington Parkway), and SR 24 (Lebanon Pike) in Davidson County; SR 2 (Broad Street), SR 58 (near the Tennessee River), and SR 389 ($4^{th}$ Street) in Hamilton County; and SR 1 (Kingston Pike), SR 115 (Alcoa Highway), and SR 33 (North Broadway). The roadways with the highest pedestrian harm scores for the model without AADT are: SR 12 (Ashland City Highway), SR 1 (West End Avenue), SR 6 ( Briarville Road/end of Ellington Parkway),  in Davidson County, SR 1 (Kingston Pike), SR 62 (Western Avenue), SR 33 (North Broadway) in Knox County, and SR 2 (Broad Street), SR 58 (near the Tennessee River), and SR 389 ($4^{th}$ Street) Hamilton Couny. These given roadway are the roadways with the highest pedestrian harm score in both models.

The study is useful because it provides transportation organinzaions a framwork on how to develop a pedestrian harm model. The pedestrian harm models are tools that identify roadways that are harmful  to severe injuries for pedestrian crashes. The models allow state, county, and city tranportation orgainzations, as well as metropolian planning orgainzaions the ability to provide a proactive framework on where to priortize HSIP funding for pedestrian related projects to improve pedstrian safety.

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# APPENDICES

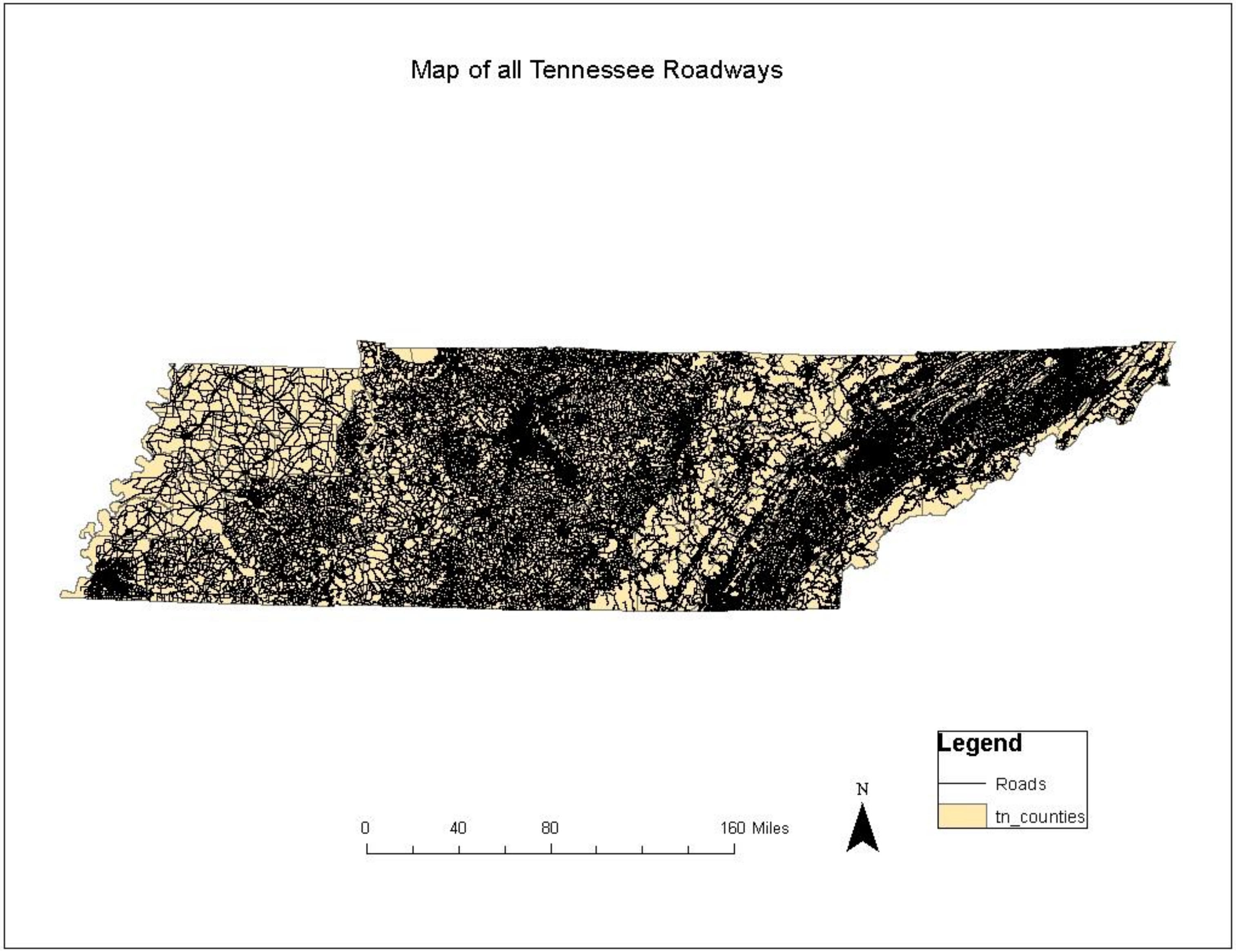
**Appendix A – List of Data Variables**

| CRASH DATA VARIABLES |
|---|
| Person type (Ped or Bike) |
| Injury type |
| Crash County |
| Crash route |
| Crash location |
| Type of crash |
| Time of crash |
| Total killed in a crash |
| Total incapacitated injuries |
| Total other injuries |
| Manner of first Collision |
| Total injured |
| First harmful event |
| Total vehicles in a Crash |
| Lighting conditions |
| Weather condition |
| Relation to first junction |
| Relation to first roadway |
| Urban or rural |
| Hit and run |
| Cons. zone |
| Age |
| Alcohol |
| Alcohol determination |
| Gender |
| Total vehicles |
| Crash city |
| Location highway street |
| Location estimate |
| Location direction |
| Location mile post |
| Report date |
| Manner of collision |
| Total persons |
| Highway type |

| CENSUS DATA VARIABLES |
|---|
| Total Population by Age groups |
| Total Male Population by Age groups |
| Total Female Population by Age groups |
| Total Population by Race |
| Total Population in household |
| Total Population Density |
| Total households |
| Family households by Age groups |
| Non Family households by Age groups |
| Average household size |
| Average family size |
| Total housing units |
| Occupied housing units |
| Vacant housing units |
| Vacant housing units For rent |
| Vacant housing units Rented, not occupied |
| Vacant housing units For sale only |
| Vacant housing units Sold, not occupied |
| Rental vacancy rate (percent) |
| Occupied housing units |
| Owner-occupied housing units |
| Population in owner-occupied housing units |
| Household size of owner-occupied units |
| Renter-occupied housing units |
| Population in renter-occupied housing units |
| Household size of renter-occupied units |

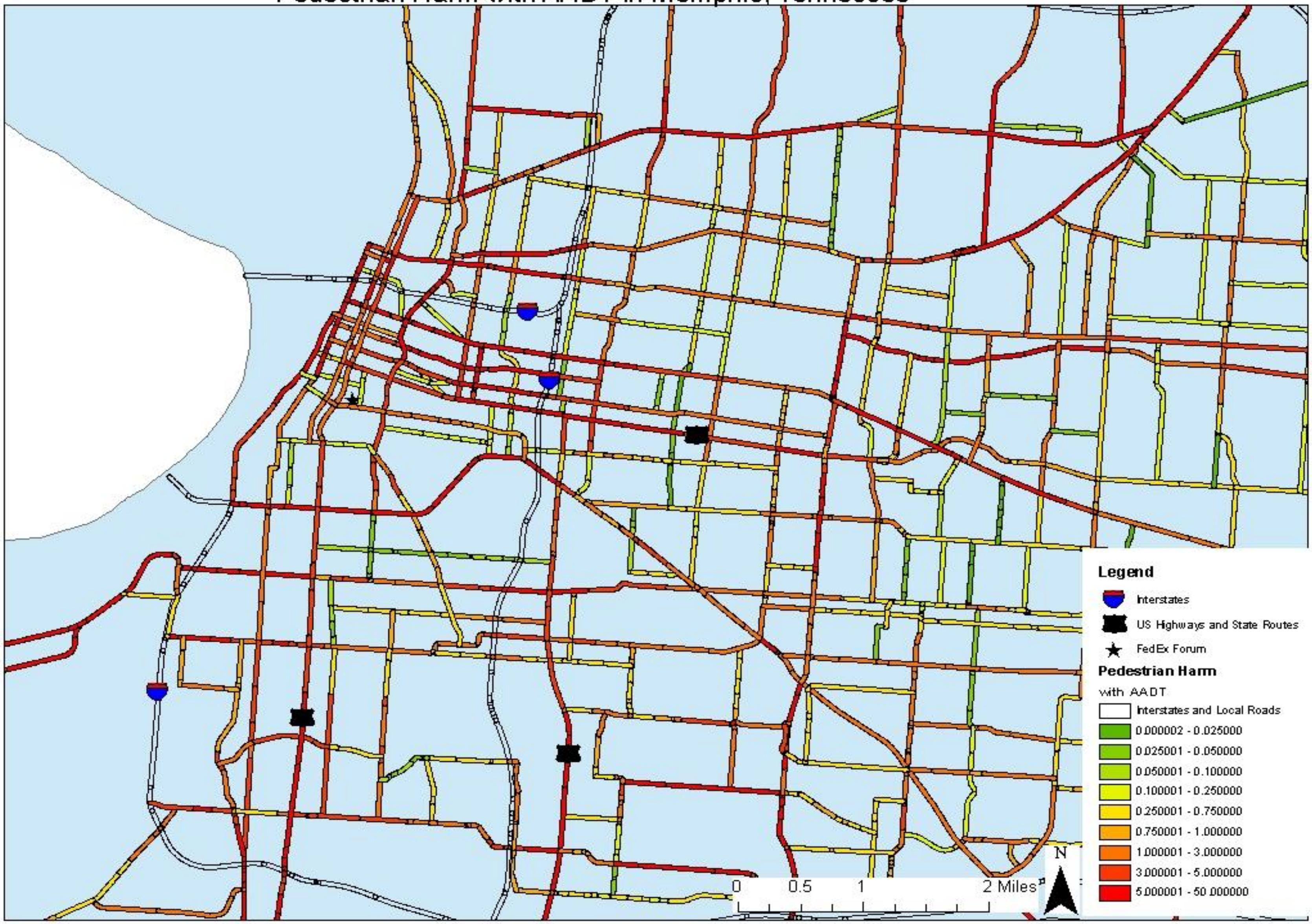
| SOCIO-ECONOMIC DATA VARIABLES |
|---|
| Population by Labor Force |
| Population by Gender and Labor Force |
| Number of Children |
| Workers by Labor Force |
| Wages and Salary |
| Public or Private Worker |
| Average Household income |

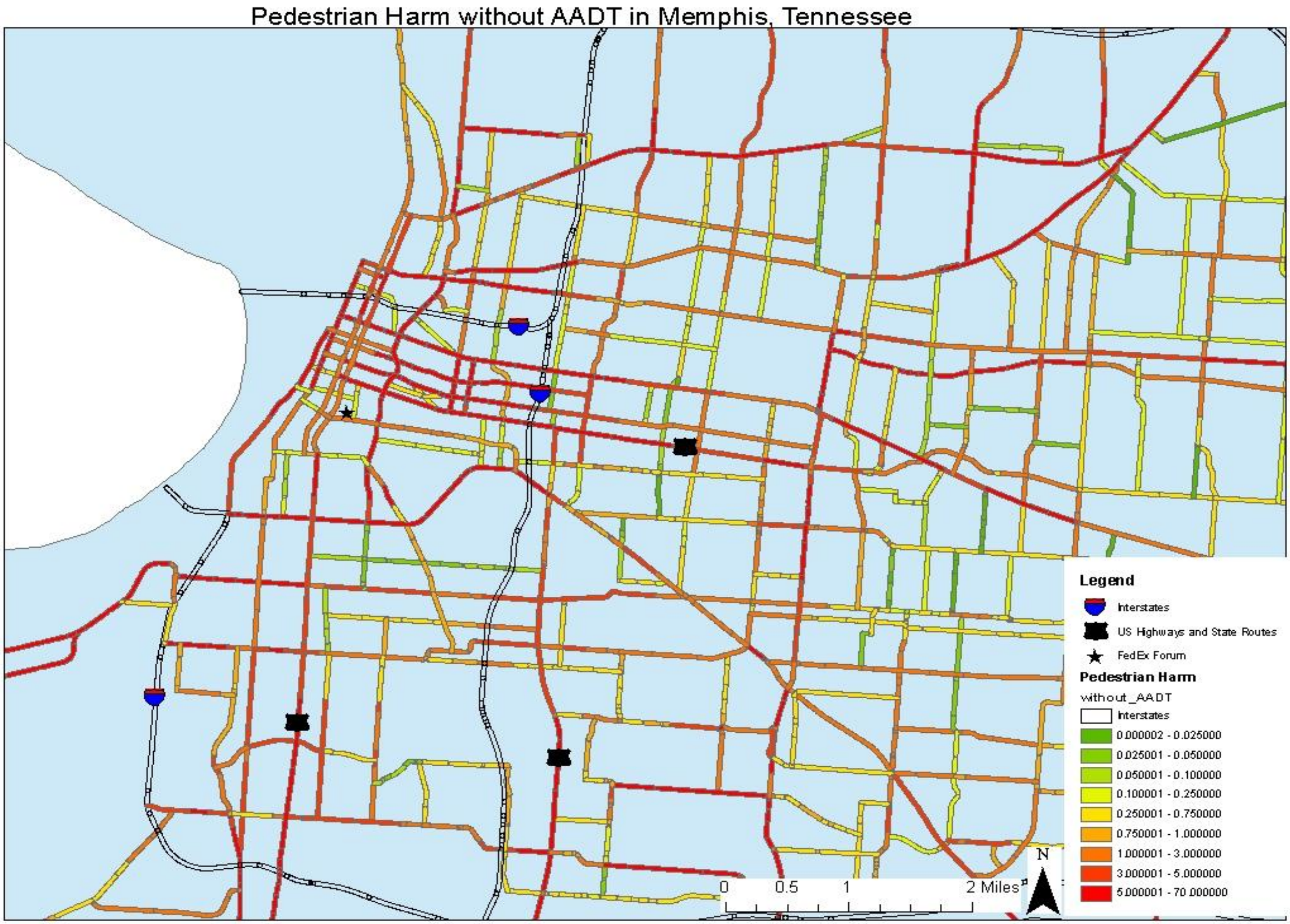
## Appendix B – Map of Tennessee Roadways


Map of all Tennessee Roadways
Legend
Roads
tn_counties
0
40
80
160 Miles
N

**Appendix C – Pedestrian Harm in GIS**

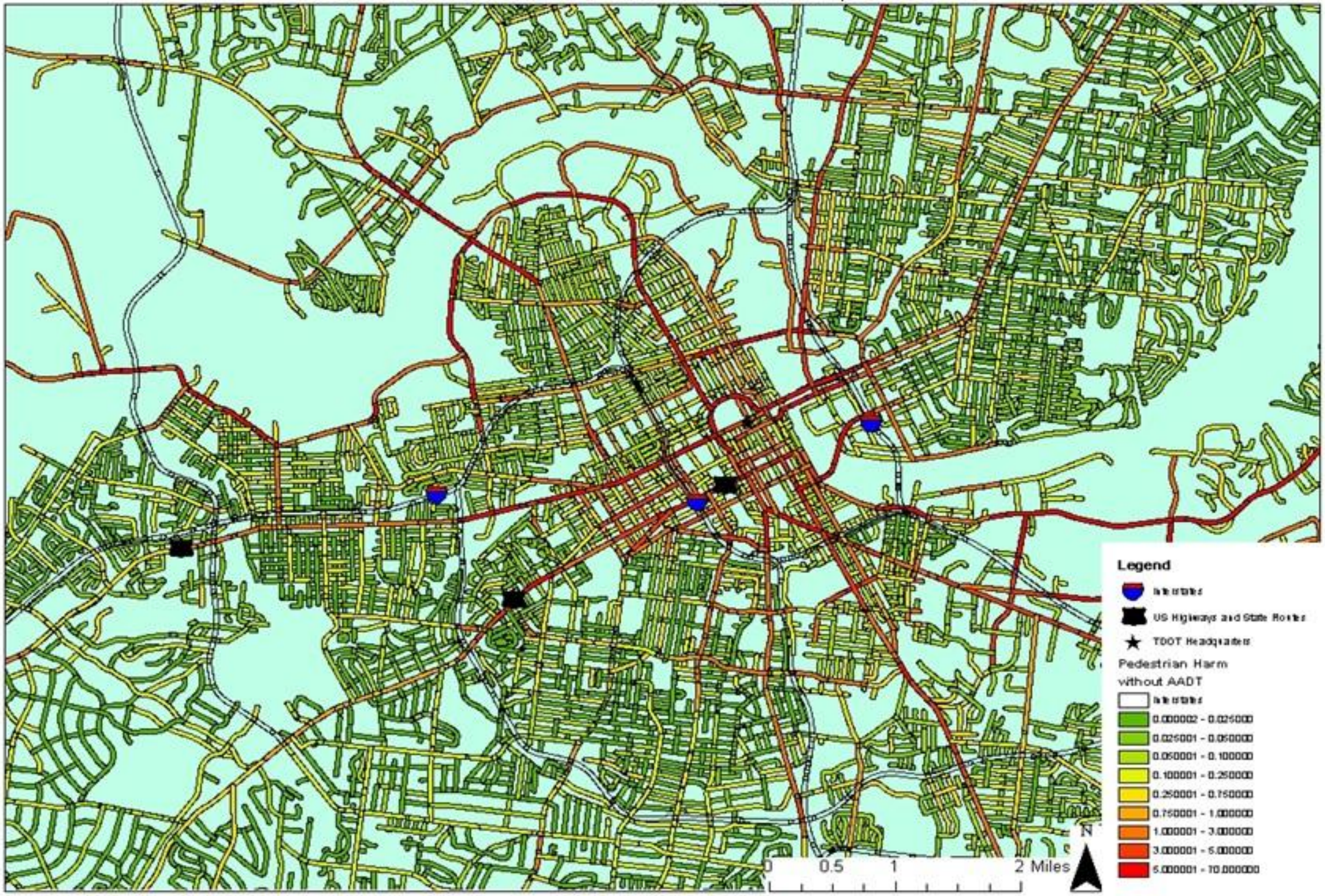
Pedestrian Harm with AADT in Memphis, Tennessee



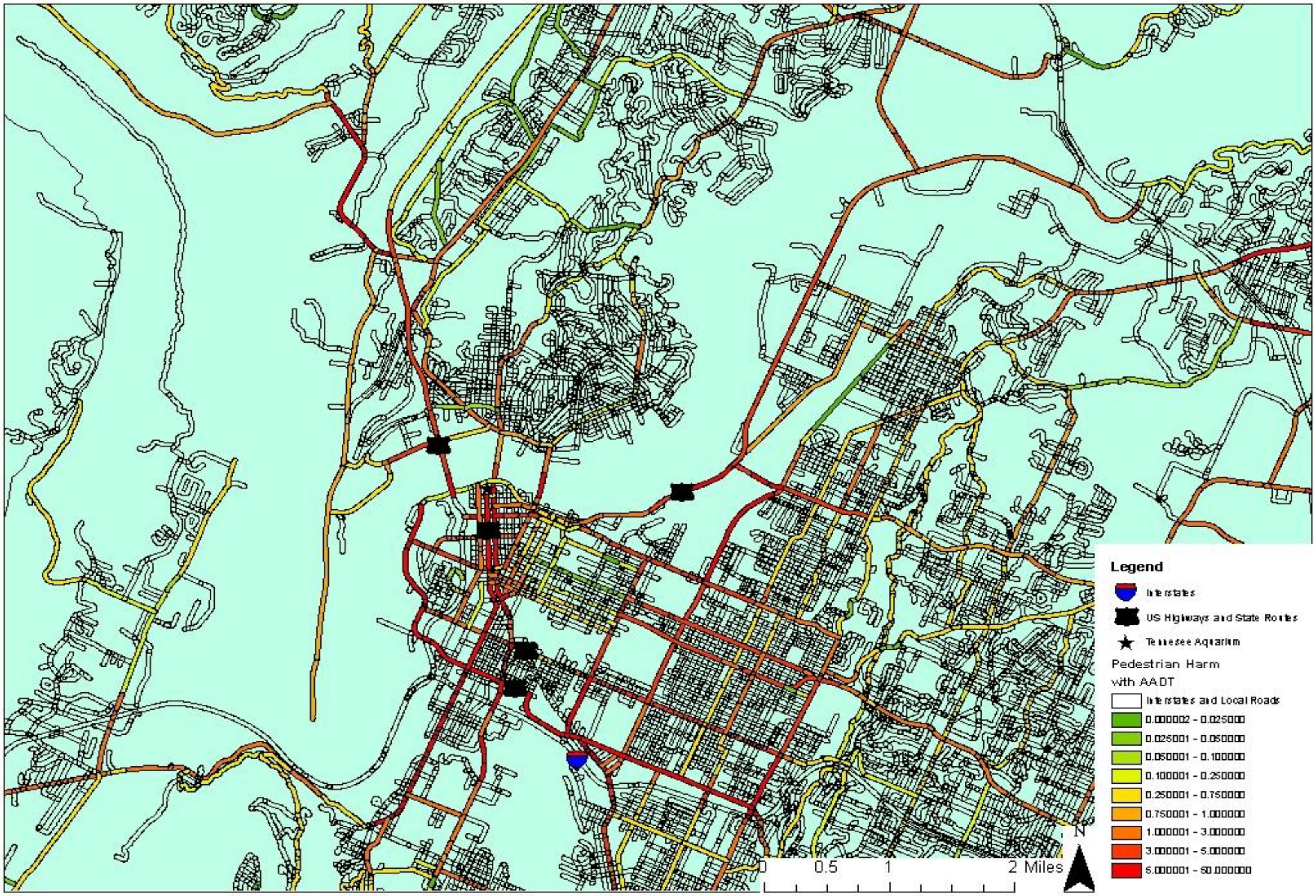

Pedestrian Harm without AADT in Memphis, Tennessee
Legend
Interstates
US Highways and State Routes
FedEx Forum
Pedestrian Harm
without_AADT
Interstates
0.000002 - 0.025000
0.025001 - 0.050000
0.050001 - 0.100000
0.100001 - 0.250000
0.250001 - 0.750000
0.750001 - 1.000000
1.000001 - 3.000000
3.000001 - 5.000000
5.000001 - 70.000000
0 0.5 1 2 Miles
N

Pedestrian Harm with AADT in Nashville,Tennessee

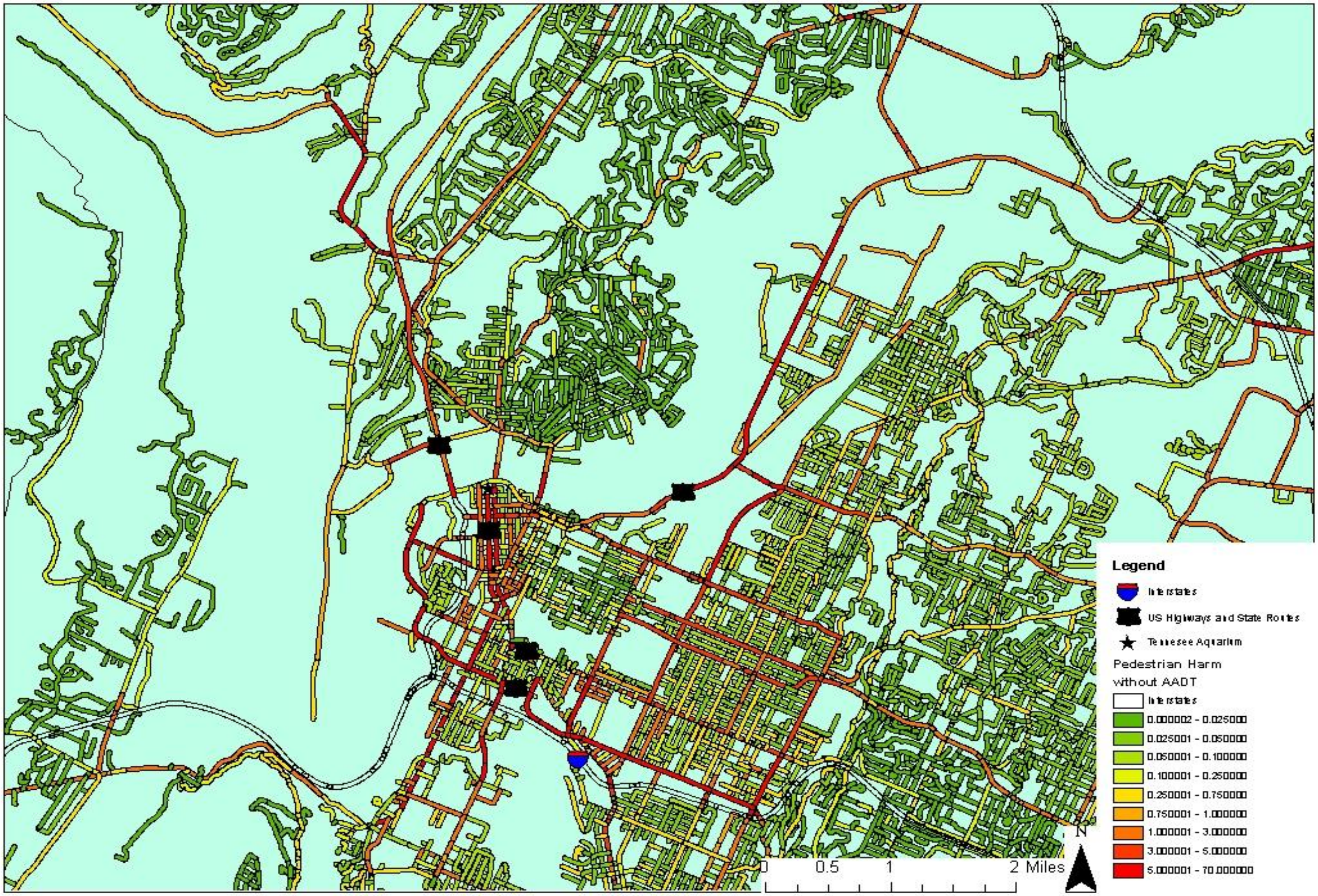
Pedestrian Harm without AADT in Nashville,Tennessee



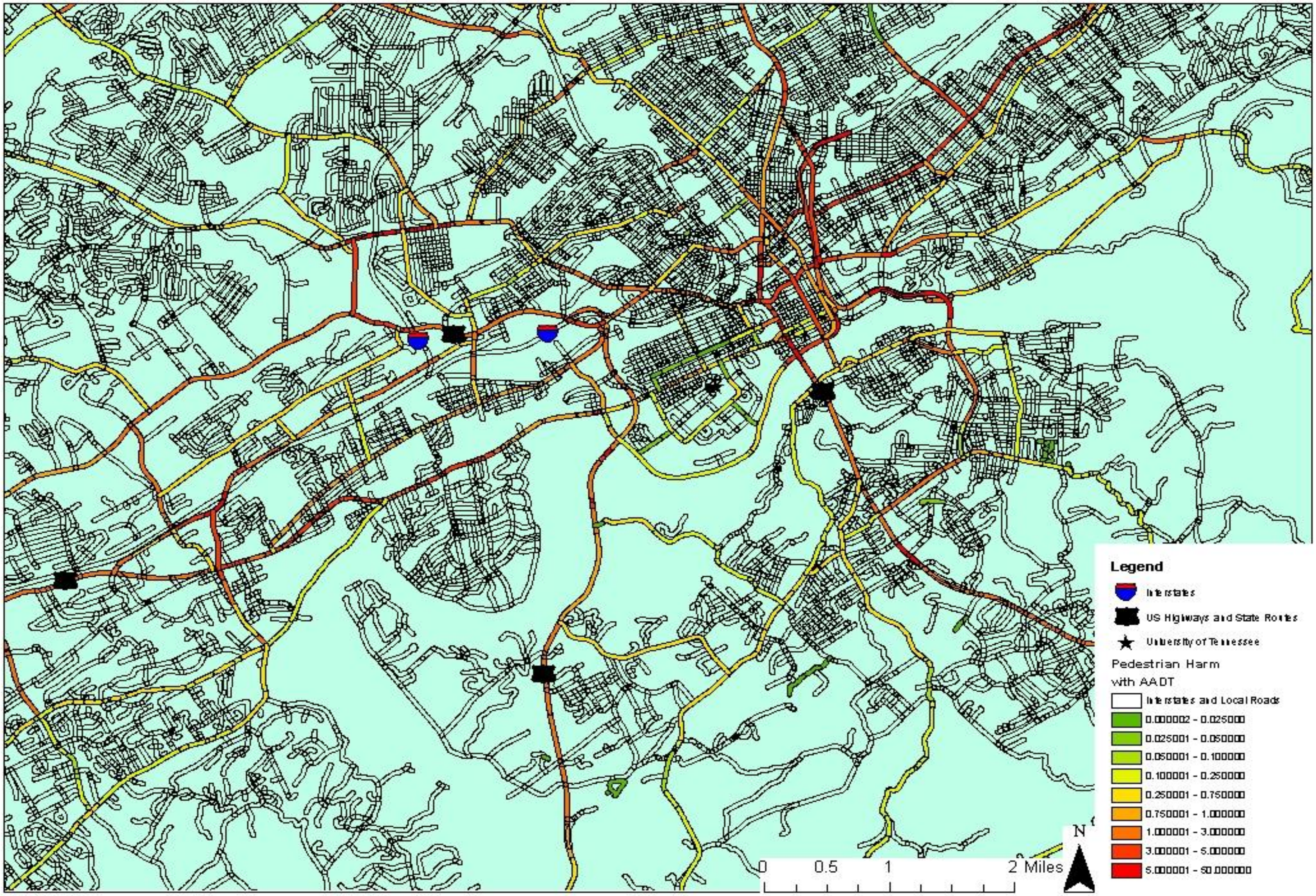
Pedestrian Harm with AADT in Chattanooga, Tennessee



# Pedestrian Harm without AADT in Chattanooga, Tennessee



Pedestrian Harm with AADT in Knoxville, Tennessee



Pedestrian Harm without AADT in Knoxville, Tennessee

# VITA

Zane H. Pannell started his career in transportation engineering in 2009 at Oak Ridge National Laboratory (ORNL) as a summer intern in commercial motor vehicle technology research and development. He continued this internship at ORNL for the following two summers while attending the University of Tennessee to obtain a Bachelor of Science degree in civil engineering. During his senior year, he started working for Dr. Chris Cherry as an undergraduate research assistant on a commercial motor vehicle safety project and assisted in the construction of CycleUShare, which is North America's first shared electric bicycle station and featured on ESPNU's *SEC Stories of Success*. Upon graduation in May 2012, Zane took a position as a graduate research assistant and worked on a project sponsored by TDOT to develop a pedestrian and bicycle safety-based policy, which later became his thesis project. During summer 2013, he had the opportunity to study electric bicycle crashes in Beijing and Kunming, China which was funded by the National Science Foundation East Asia Pacific Summer Institute and University of Tennessee's W.K. McClure Scholarship. He was also a member of the University of Tennessee Institute of Transportation Engineers traffic bowl team that won state and southern district and placed second in international competition.  Zane graduated with his Master of Science in December 2013.