Addis Ababa University
Addis Ababa Institute of Technology
School of Civil and Environmental Engineering
Road and Transport Engineering Stream

Road Traffic Crashes Severity Analysis in Nifas-Silk/Lafto Sub City, Addis Ababa, Ethiopia

By

Helen Abebe

A thesis submitted to the school of graduate studies of Addis Ababa University
in partial fulfillment of the requirement for the Degree of
Master of Science
in

Road and Transport Engineering

Advisor
Dr. Getu Segni

June, 2018

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Approved by the board of examiners

DECLARATION

I declare that this thesis entitled "ROAD *TRAFFIC CRASHES SEVERITY ANALYSIS IN NIFAS-SILK/LAFTO SUB CITY, ADDIS ABABA, ETHIOPIA*" is my original work. This thesis has not been presented for any other university and is not concurrently submitted in candidature of any other degree, and that all sources of material used for the thesis have been duly acknowledged.

Candidate:

Name: ________________________

Signature: _____________________

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Abstract

Road crashes are one of the main causes of deaths worldwide. The total number of road traffic deaths has plateaued at 1.25 million per year, with the highest road traffic fatality rates in low-income countries (WHO, 2015). The probability of crash occurring is influenced by numerous factors like roadway Geometric characteristics, vehicle characteristics, pavement conditions and weather conditions each of these factors contribute its own share towards occurrence of crashes.

Reducing the severity of injuries resulting from Road Traffic crashes has long been the emphasis of highway agencies and road traffic safety policy makers. While progress can be simply measured by the reduction in injury levels over time, insights into the effectiveness of injury-reduction technologies, policies, and regulations require a more detailed empirical assessment of the complex interactions that vehicle, roadway (Road Geometry) and human factors have on resulting crash-injury severities. Over the years, researchers have used a wide range of methodological tools to assess the impact of such factors on disaggregate-level injury-severity data, and recent methodological advances have enabled the development of sophisticated models capable of more precisely determining the influence of these factors.

The main objective of this study was to identify factors which affect the severity of crashes in Addis Ababa specifically in N/lafto sub city and map the hot spot. Multinomial Logistic Regression has been used to analyze the crash data to identify significant factors which affect the severity of crashes. Secondary data which obtained from Addis Ababa Traffic Police Commission and the respective sub-city from July 01, 2013(G.C) to June 30, 2015(G.C). The contestant variables for the study were driver's age, driver's sex, driver's education status, driver's experience, driver's defect, vehicle type, vehicle ownership, Land use, Road Type, weather condition, light condition and time.

In order to make interpretation on factors affecting the injury severity of crashes in Addis Ababa N/silk Lafto sub city, Multinomial model was used. The results indicated that driver's age, sex, education status, experience and vehicle type were positively associated with injury severity.

Therefore, the variables that were found those factors contribute to crashes severity were driver related factors such as age, education level, experience, gender, time related factors and land use. In order to reduce injury severity in Addis Ababa, it is important to refine those factors that affect the road traffic crash severity. Studying how those factors contribute to crashes help concerned bodies to give attention to the factors which were positively associated with injury severity and these findings can serve as a base for safety measures and policies.

Keywords: Road crashes, Geometric characteristics, vehicle characteristics, pavement conditions, MNL Model, Descriptive Analysis, Injury severity, crash severity

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List of Acronyms

AACRA: Addis Ababa City Roads Authority
AADT: Average Anual Daily Traffic
AAPC: Addis Ababa Police Commusion
ANSI: American National Standard Manual
GIS: Geographic Information System
HIC: High Income Country
KML: Keyhole Markup Language
LIC: Low Income Country
RTC: Road Traffic Crash
SPSS:Statistical Package for the Social Sciences
UNECA: United Nations Economic Commission for Africa
WHO: World Health Organization

1. Introduction

1.1. Background

Road traffic crash is the cause of significant loss of human and economic resources worldwide. The World Report projects that global road fatalities will increase by more than 65% between 2000 and 2020 with trend varying across regions, if no systematic and concerted action is undertaken. 68 countries have seen a rise in the number of road traffic deaths since 2010. Low-income countries (LIC) have fatality rates more than double those in high-income countries (HIC) and there are a dis-proportionate number of deaths relative to these countries' level of motorization: 90% of road traffic deaths occur in low- and middle-income countries, yet these countries have just 54% of the world's vehicles (Safway Right way 2012). Road deaths and injuries are projected to be the third leading contributor by 2020 to the global burden of disease and injury (WHO World Report on road traffic injury prevention 1, 2004).

Road traffic injuries cause considerable economic losses to victims, their families, and to nations as a whole. These losses arise from the cost of treatment (including rehabilitation and incident investigation) as well as reduced/lost productivity (e.g. in wages) for those killed or disabled by their injuries, and for family members who need to take time off work (or school) to care for the injured.

For Africa, traffic injury is an escalating burden causing a vast amount of social and economic loss in terms of injuries, emotional harm, fatalities, loss of income and property damages.

The population of Ethiopia has reached 102,403,196 of which urban population was 20,202,815 accounting for 19.7% of the total population. The population of Addis Ababa was 3,384,569 as per the 2007 population enumeration, with yearly growth rate of 3.8% (World meters www.Worldometers.info). The expansion of the city, increasing population size coupled with the economic growth has required respective transport service supply for the increasing mobility needs of the People (Central Statistical Agency Ministry of Finance and Economic Development, 2007).

According to the World Health Organization's WHO report, published in April 2014, traffic crashes in Ethiopia account for the deaths of 37.28 persons per 100,000. This is 2.77 % of the total deaths in the country, placing Ethiopia 12th in the world (WHO 2014).

Addis Ababa is the capital city of Ethiopia with a population of 3,384,569 covering an area of 527 km². It has 10(districts), Nifas Silk-Lafto, is one of the 10 sub cities and as of 2011 its population was of 335,740, area (Km^2) 68.30, Density 4,915.7. The district is located in the southwestern suburb of the city. It borders with the districts of Kolfe Keranio, Lideta, Kirkos and Bole and Akaky Kaliti (Transport policy of Addis Ababa 2011).

Data from the Bureau indicates that 90% of the crashes occurring in the city can be caused on faulty driving. Pedestrians can be held responsible for four percent of the crashes, with other factors including road usage problems, weather conditions and the vehicles' mechanical issue. But the data on crashes indicate that most of them occur on tangent and suitable road condition as well as in good weather conditions, looking at the growing trend of crashes in the city. Another major reason that is commonly raised in relation to the causes of traffic crashes is the quality of training schools. Training is given on even ground, then the drivers come and drive in the cities; some drivers even do not know the behavior of the vehicles they drive and there are gaps at the training schools as the Bureau admitted which it follows up to see the impact of the training and the proper usage of the curriculum that the is prepared (Addis Ababa City Roads and Transport Bureau, 2016).

As data from the Addis Abeba Police Commission (AAPC) indicate, during the year 2013/14, there were 391 deaths, 1,484 serious injuries and 1,128 minor injuries incurred.

The data on the age of the drivers that cause the fatalities show that three fatal crashes were caused by drivers under 18, 172 deaths by drivers between 18 and 30, 137 deaths by drivers between 31 and 50 and 51 deaths by drivers over the age of 51. Male drivers caused 361 of the deadly crashes, with female drivers being responsible for two while 28 are unidentified (Addis Abeba Police Commission (AAPC) 20113/14 report). The number of crashes in the city is increasing from 2,067 in 2010/11 to 2,379 in 2011/12 then to 2,966 in 2012/13, to 3,003 in 2013/14. And in the half year of 2014/15, the road fatalities totaled 224 (Addis Abeba Police Commission (AAPC) report).

1.2. Statement of the Problem

Urban transport serves as veins to accelerate developments in Industry, trade, education, health and other services. However, there is no compatible urban transport supply and effective management to meet the increasing trip frequency and mobility needs of the people and goods which resulted in the seriousness of the issue. Among the challenges of the urban transport is high rate of traffic crashes. These traffic crashes will have a negative impact on the socio-economic development of the city.

Addis Ababa, the capital city of Ethiopia and it is where the African Union and its predecessor the OAU are based. It also hosts as the headquarters of the United Nations Economic Commission for Africa (UNECA).

The traffic growth in Addis Ababa city with regards to the growth in the road network, Addis Ababa City Roads Authority (AACRA) constructed 2,150Km of asphalt road as of 2013/14 fiscal year, The total road length of the city including gravel and cobble stone roads also reached 4,614Km as of June 2014. (http://ethiopianbusinessreview.net) which indicates that the total road length of the city is increasing from time to time. However, the road safety issue has become a major concern of the Addis Ababa city. Road traffic crash is a pressing problem leading to fatalities and severely impacting the society.

According to Ethiopian Federal Police(2008/09-2010/11 report, each year more than two thousand people die and ten thousand people injured in road traffic crashes. Road traffic injuries are the leading cause of death among people aged between 15 and 29 years (WHO May 2017).

In Ethiopia, the rate of road traffic crash is very high; because of road transport is the major transportation mechanism along with poor road infrastructure, poor enforcement of traffic laws and other factors. The Ethiopian traffic control system archives data on various aspects of the traffic system, such as traffic volume, concentration, and vehicle crashes; with more vehicles and traffic, the capital, Addis Ababa, takes the lion's share of the risk, with an average of more than 20 crashes being recorded every day and even more going unreported (WHO, 2009). The costs of fatalities and injuries due to Road traffic crashes have a tremendous impact on societal well-being and socio-economic development endeavors. However, public policy responses to this epidemic have been muted at national and international levels (Nantulya and Reich, 2002). Hence, the issue of road traffic crases in Addis Ababa is worthy of investigation. The causes, effects and measures in reducing or preventing vehicle crashes in Addis Ababa context need to be analyzed to point out what should be done in a manner that contributes to the reduction of road traffic crashes. Generally, the central argument of the study is to assess how much vehicle crashes affects the life and livelihood of peoples and the country's aspiration to development. Under this research the road traffic crashes severity in Addis Ababa specifically in Nifas-Silk Lafto sub city is carry out and this academic thesis stemmed from the raise of road traffic crashes on the highways and its effect on the lives and livelihood of individuals.

This study was attempted to address the following questions.

- Which variables are significantly affecting occurrence of injuries severity?
- How multinomial model can be applied and interpret to crash injury severity data?

1.3. Significance of the Study

The research could have the advantage of pointing out the causes and severity of the crashes. More specifically, this research has the following major significance.

1. Assist concerned bodies in identifying and screening out of the major factors contributing to crash frequency and severity in Addis Ababa and more especially in N/Lafto Sub-city as well as to recommend possible road safety mechanisms.
2. It helps concerned government institutions and policy makers to visualize and associate the effects of road traffic crashes and identify and locate areas of intervention.
3. It could also serve as launching pad for further studies to undertake research in road safety

1.4. Strength and Limitation of the Study

Strength –This research tries to find out the relationship of the crash severity and associated factors of fatalities and injury crashes in Addis Ababa city specifically in N/silk Lafto sub-city considering geometric elements. Finally this study contributes to analyse and prepare in advance so as to save human lives and protect any property damage.

Limitation – Since the crash data in the respective Sub-City police department registered in hand there are some information missed which make the analysis difficult.

- In the respective sub-city police department there is no fatal data
- The Addis Ababa Police commission documents all the sub-city fatal data together and it is not identified by each sub-city so to select the respective sub-city fatal crash data it was tedious and time taking.
- The data was no recorded in well manner for the purpose of hotspot analysis
- The data collection and recording method was manual
- The place where car crash was happened areas are not specific because of this the data collection and digitalization process will missed up and got wrong analysis output

1.5. Objective of the study

1.5.1 General Objective

The study aims to assess the Road traffic crashes severity in Nifas-Silk Lafto Sub City, Addis Ababa.

1.5.2 Specific Objectives

- To describe and identify the main contributing factors to crash injuries severity by applying multinomial logit model to crash injury severity data.
- To identify and map crash Black spots in N/silk Lafto sub city.

2. Literature review

2.1. Road Traffic Crashes (RTCs) Defined

The NSW Centre for Road Safety, November2016 defines any unplanned event involving a road vehicle on a road that results in death, injury or property damage and is reported to the police.

2.2. The main risk factors for road traffic injuries (RTCs) and vulnerable road users

Although all types of road user are at risk of being injured or killed in a road traffic crash, there are notable differences in fatality rates between different road user groups. In particular, the "vulnerable" road users such as pedestrians and two-wheeler users are at greater risk than vehicle occupants and usually bear the greatest burden of injury. This is especially true in low-income and middle-income countries, because of the greater variety and intensity of traffic mix and the lack of separation from other road users. Of particular concern is the mix between the slow-moving and vulnerable non-motorized road users, as well as motorcycles, and fast-moving, motorized vehicles. Several studies have revealed marked differences in fatality rates between various groups of road users, as well as between road users in high-income countries and those in low-income and middle-income countries. A review of 38 studies found that pedestrian fatalities were highest in 75% of the studies, accounting for between 41% and 75% of all fatalities. Passengers were the second largest group of road users killed, accounting for between 38% and 51% of fatalities (Global status report on road safety 2013).

The distribution of road traffic mortality rates by sex and age, young adults aged between 15 and 44 years and the rates for this age group are higher in low-income and middle-income countries. In 2002, males accounted for 73% of all road traffic deaths, with an overall rate almost three times that for females: 27.6 per 100 000 population and 10.4 per 100, 000 population, respectively.

Road traffic mortality rates are higher in men than in women in all regions regardless of income level, and also across all age groups (World report on road traffic injury prevention Geneva, WHO, 2004).

Since 2005 official crash records have included information on contributory factors. These insights have recently been correlated and have provided significant insights into the causes of road crashes

According to the key findings by Richard Jenkins a total of 77 categories of contributory factors, grouped together under 9 headings have been established.

The headings are: Driver/rider error or reaction, injudicious action, Behavior or experience, Road environment, Pedestrian only, Impairment or distraction, Vision affected, Special codes, Vehicle defects.

Pedestrian factors are reported in a larger proportion of crashes in urban areas than rural areas. Driver's experience and gender difference is also considered as the cause of crashes. Learner and Inexperienced Drivers are more vulnerable on rural roads than urban ones. Also they are more likely to crash due to 'error or reaction' factors than drivers between 30 and 70. Car drivers under 25 have 'exceeding the speed limit', 'travelling too fast for the conditions' and 'learner/inexperienced' recorded more frequently than drivers over the age of 25. Behavior and inexperience factors are almost three times higher for the under 20's than the average for all ages. Comparisons between men and women car drivers show little difference in the contributory factors reported, but 'careless, reckless or in a hurry, 'travelling too fast for the conditions' and 'impaired by alcohol' are recorded more frequently for men than women, while 'learner or inexperienced' is recorded more frequently for women (ANALYSIS OF ACCIDENT RATES BY AGE, GENDER, AND TIME OF DAY NATIONWIDE PERSONAL TRANSPORTATION SURVEY by Dawn L. Massie and Kenneth L. Campbell).

The association between the factors that contribute to crashes and crash occurrence is irreducibly statistical. By studying crashes without having any idea of how frequently various hazards occur in traffic, no conclusions whatsoever can be drawn concerning the relative importance of factors contributing to crashes (Benedetto, 2008).

McMahon and Ward (2005) identified three major classes of causes of vehicle crashes; road user's error/human factors, vehicle defects and road condition or environment. Among the most prominent factors, is the human factor of which drivers' errors takes the majority of the blames. Drivers' errors that are hazardous include driving too fast, failing to give way, improper over taking and following too close. All of which could result from aggressive or irresponsible behavior, deficient actions, perceptual errors or impairments. Nonetheless, Van Elslande et al (2008) argued that, in the field of road safety research, most crash analysts tend to conclude by considering 'human error' as the main cause of crashes. The problem behind such a statement is that, it leads to oversimplification of the problem.

On the other hand, Salmon et al (2005) stated that, there are two theoretical approaches to human error: the 'person approach' which focus upon the last step of system operation and by so treats human error as the cause of most of the crashes; and the 'safe system approach' which looks further in the crash process considering the role of the various organizational levels that contribute to the production of system outputs (rules, design, management, etc.) and looking for the 'holes' or 'weaknesses' in the various defense layers which are supposed to constitute a safe system, well adapted to its users.

Van Elslande et al (2008) argued that, most safety studies have been based upon a person approach and stress the role of human error in the production of 75-90% of crashes. But, it would be wrong to regard this 'error' as the primary cause of crashes. A safe system approach will rather consider it as a consequence of malfunctions further upstream, so that human error is only a link in the chain of events leading up to crashes. And, he is a necessary link as far as the driving system is unable to function without drivers.

Moreover, traffic volume, traffic speed and traffic compositions have adverse effect on the frequency and severity of RTCs. As the volume of traffic grows; opposing vehicles increases, intervals for passing vehicles are less available, the crashes due to improper passing become frequent, and the frequency of crashes grows approximately in direct proportion to the average traffic volume (ibid). Hijaret al (2003) asserts that, as the volume of traffic increases, the speed of vehicles drops and the main kind of crash becomes a nose-tail collision.

McMahon and Ward (2005) and Hobbs (1979) claimed that, vehicle defects lead significantly to crashes which are mainly those related to the lack of regular maintenance, of which defective tires and brakes failure most frequently. Vehicle defects contribute to less than 5% of crashes. The rise in the number of motor vehicles and the amount of motorized traffic along with economic development are key determinates of risk of road crashes. The quality of road network, vehicle compositions, increase in car ownership and the extent of public transport and facilities for more vulnerable road users such as pedestrians and cyclists, all contribute to the level of risk. In low income and middle income countries, rapid growth in motorization has not been accompanied by sufficient improvements in the road design to allow for such growth to take place without an increase in the rate of road traffic crashes.

Generally, every crash is not usually attributable to a single cause but to a chain of unique multiple factors or failures associated with the road design deficiencies, vehicle defects, and road user errors. In most cases the traffic police associate traffic crash with a single most important cause on the spot of crash and do not list the multiple factors.

2.3. Level of Crash injury Severity

An effective road safety management requires a good insight into the factors that are believed to be related to road traffic crashes. Based on this framework, several research studies have been conducted over the years to identify factors that may influence both the frequency and the severity of road traffic crashes.

However, as pointed out by Savolainen et al.(2011), one has to be aware that the factors influencing road traffic crash frequency may vary from the ones affecting the severity; hence, it is suggested that their analysis should be performed individually.

In the area of crash severity research, continuous efforts have been conducted in order to investigate the relationship between the level of severity (dependent variable) and a set of explanatory variables, which usually include: driver attributes (e.g., age and gender), vehicle features (e.g., body type, vehicle age and number of vehicles involved in the accident), road characteristics (e.g., number of lanes, road surface conditions, intersection control and types of road), and crash characteristics (e.g., crash's main cause). Occasionally, the influence of other variables on crash severity like speed limit, day of the week, time of the day, average traffic characteristics (AADT), weather and traffic

Conditions have also been scrutinized (Delen et al., 2006; Manner and Ziegler, 2013; Torrão, 2013). A recent study carried out by Christoforou et al.(2010), mainly because it offers a comprehensive literature review on the subject. By assessment of the results from 28 studies, the authors found that the factors which have consistently shown to be connected to an increased severity were: (1) aging; (2) driving while intoxicated; (3) head-on collisions; (4) crashes with heavy-vehicles and motorcycles; (5) poor lighting conditions; (6) vertical and horizontal curvature; (7) rural versus urban areas; and (8) speeding. In contrast, the use of helmet or seat belt was associated to a high decrease of the severity outcome. Other factors like gender, intersection type, road surface conditions, seating position, weather and average traffic characteristics led to conflicting findings –in some studies these factors were related to increased severity, while in other studies the opposite was concluded.

The crash severity investigations attempted to examine the influence of driver attributes, vehicle features, crash characteristics, and road, weather, and traffic conditions on the severity outcome. Recently, Savolainenet al. (2011) conducted a research, which intended to assess the characteristics of road crash severity data and the methodological approaches most commonly used for the analysis of such data. The authors highlighted that the “appropriate methodological approach can often depend heavily on the available dataset, including the number of observations, quantity and quality of explanatory variables, and other data-specific characteristics”. Still, they found that the majority of the modeling approaches were framed in the discrete response models which include:
binary response models (e.g., binary probit and binary logit), ordered discrete response models (e.g. bivariate ordered probit and generalized ordered logit), unordered multinomial discrete response models (e.g. multinomial logit, Markov switching multinomial logit, nested logit, and mixed logit); other less common approaches have also been used and include: artificial neural networks, and some data mining techniques such as the classification and regression tree analysis. A complete review of this literature is provided pointing out the strengths and the weaknesses of each one of the approaches typically employed for examining crash severity data.

The ordered probit modeling methodology was also used by Abdel-Aty (2003) in an attempt to analyze the driver injury severity levels at several roadway entities. Three separated models were developed for signalized intersections, roadway sections, and toll plazas. Older and male drivers, those not wearing a seat belt, drivers of passenger cars (i.e., vehicle type), vehicles struck at driver’s side (i.e., point of impact/crash characteristics), and those who speed revealed a higher probability of a severe injury in all the models. Other variables were found sign if cant only in specific models: alcohol, dark lighting conditions, and the existence of horizontal curvatures affected the likelihood of injuries in the roadway sections' model; a driver's error was significant in the model for signalized intersections; vehicles equipped with an electronic toll collection affected the likelihood of higher injury severity in the toll plazas'model; lastly, both signalized intersections and road way sections models revealed higher probability of injuries in rural areas. Furthermore, the author tested other modelling approaches, namely a multinomial logit and a nested logit with different nesting structures, and compared the results produced by those models with the results provided by the ordered probit model. This comparison showed that the ordered probit model, besides being simpler, has also produced better results than the multinomial logit; by comparing the ordered probit model with the best nesting structure of the nested logit model, the author recommended the former to model driver injury severity because, in spite of the similarity found in the results provided by both models, the latter has introduced considerable complexity in the modeling process(Analysis of driver injury severity levels at multiple locations using ordered probit models by Abdel-Aty M).

Accounting for the ordinal nature of injury data is an important consideration in road crash severity modeling (Savolainen et al., 2011). Unordered response models, such as the multinomial logit and probit models, or the nested logit model, regardless of accounting for the categorical nature of the injury data, would fail to account for the ordinal nature of the injury classes (Green, 2002). Furthermore, the multinomial logit model is associated to undesirable properties, such as the independence of irrelevant alternatives (Ben Akiva and Lerman, 1985) and the multinomial probit is related to a lack of a closed-form likelihood (Greene, 2002). Alternatively, ordered response models, namely the ordered probit (OP) or logit (OL) models have increasingly been employed for modeling injury severity when it is recorded in multiple ordinal categories (Eluru et al., 2008). Both formulations give very similar results, although the OP is more often selected than the OL. In this study, the modeling methodology used to analyze the injury severity sustained by non-motorists is the OP model. The OP model is especially appropriate to model injury severity because, besides identifying statistically significant relationships between explanatory variables and a dependent variable, it also discerns unequal differences between ordinal classes in the dependent variable

(Duncan et al., 1998). Additionally, it also requires smaller samples when compared to unordered response models (Ye and Lord, 2014).

In the area of crash severity research studies, where the injury severity was a target variable. Furthermore, two relevant issues were the focal points; first, models used to estimate the contribution of each significant variable to injury severity, second, the variables which were identified as significant determinants of injury severity. A sufficient number of studies with injury severity as dependent variable were reviewed. Various modeling approaches used by the researchers are presented.

Ordered Probability Models

Ordered Regression Models (ORM) includes Ordered Probit (OP) and Ordered Logit (OL). In this modeling technique, the dependent variable is assumed to be Categorical and ordinal.

O'Donnell and Connor (1996) were first researchers to apply ORM in road safety. They developed two models using OP and OL modeling methodologies. The study used the data from 1991 police reported crashes in New South Wales, Australia. Models could estimate probabilities of four injury severity levels for the vehicle occupants, given a crash has occurred. Among the selected explanatory variables, age of the occupant and vehicle speed led to slight increase in the probability of serious injury and death. The remaining independent variables in the model such as, blood alcohol level, vehicle type, vehicle make and type of collision had various influence on the probabilities of injury severity levels.

Duncan et al. (1998) applied OP modeling methodology to estimate injury severity sustained by passenger cars' occupants involved in rear-end crashes with trucks on divided roadways. The study used data from North Carolina crashes during 1993-1995. The following attributes were used as ordinary and dummy variables: passenger car rear impact, impact speed differential, impact speed differential & rear impact, station wagon & rear impact, speed limit, congestion (AADT/lane), AADT/lane not reported, grade, grade & wet road, darkness, lighted darkness, icy or snowy road surface, wet road surface, age under sixteen, child restraint, drinking driver, female, station wagon, defective brakes, and car rollover. Among these variables darkness, high speed differentials, high speed limits, grades, wet grades, being a female, and driving while drunk increased occupant injury severity. Furthermore, variables that decrease injury severity include snowy or icy road, young children being in a child restraint, and being in a station wagon struck.

Renski et al. (1999) researched the effect of speed limit increases on injury severity due to single vehicle crashes. They applied OP methodology, odds ratio tests, and quasi-experimental research design. The two years of data (1995 and 1997) from North Carolina was used in this study.

It is worth noting that speed increase went into effect in 1996. In their design, they used the data from one year before the policy change and one year after. The results showed that increasing the speed from 55 mph to either 60 mph or 65 mph did affect the likelihood of evident and complaint of pain injuries. In 7 the case of raising the speed limit from 65 mph to 70 mph no significant changes in the level of injuries were identified.

Khattak (2000) investigated the injury severity sustained by the drivers of two and three car rear-end crashes. He included the role of the information and vehicle technology in an OP modeling scheme. The data was obtained from the Highway Safety Information System (1994-1995) for North Carolina. Three separate OP models were estimated. Each model was conditioned on injury severity sustained by the driver of car 1, 2, or 3 (car 1 was the leading vehicle). From the data, in a two-vehicle crash, the leading vehicle-driver as likely to be injured more severely. In regard to three-vehicle crashes, the driver of the second car was likely to be injured more severely. The variable (technology) was statistically significant across three models.

Khattak et al. (2002) identified significant variables contributing to injury severity sustained by drivers 65 years of age and older. They applied OP modeling technique for estimating significant variables. They used the police reported crash data (1990-1999) from the State of Iowa. The following variables were statistically significant for this age group: driver’s age, driver’s gender, alcohol usage, level terrain, speed limit, farm vehicles, and crashes in the dark with no lighting.

Kockelman and Kweon (2002) calibrated six OP regression models to estimate various parameters corresponding to a set of preselected independent variables. Three sets of data from the 1998 National

Automotive Sampling System (NASS) were extracted. The injury severities sustained by vehicle drivers under all crash types, two-vehicle crashes, and single vehicle crashes were analyzed.
The results of the analysis indicated that the following variables played an important role: manner of collision, 8 numbers of vehicles, gender, vehicle type, and driver alcohol use. Head-on collisions and rollovers were major contributors. Females sustained more severe injuries than males. In two vehicle crashes, light-duty trucks protect the drivers better. Moreover, pick-ups and SUVs cause more severe injuries on the colliding partner and they are more prone to rollover.

Abdel-Aty (2003) calibrated three models for driver injury severity levels for roadway sections, signalized intersections, and toll plazas in central Florida. 1996-1997 crash data from the central Florida area were used for both road way section and signalized intersection. Crash data from 1999-2000 was used for toll plazas. He applied OP modeling methodology and the results for the three models indicated that drivers age, gender, seatbelt use, point of impact, speed, and vehicle type were statistically significant on the drivers injury severity level. There were other statistically significant variables for each specific case. For signalized intersections drivers' violation and for the case of toll plazas vehicles with electronic toll collection apparatus had higher impact on the probability of driver injury severity. In the roadway section model, lighting condition, alcohol, and the presence of horizontal curve affected the likelihood of injuries.

Donnell and Mason (2004) estimated median-related crash severity using OL and unordered regression models (ordered logistic and multinomial logit). Response variable (injury severity) was divided into three categories: no injury, injury, and fatality. The data for this study was collected from the field and provided by Pennsylvania Department of Transportation. The results showed that, explanatory variables such as daily traffic, crash cause, pavement surface, crash type, horizontal alignment, and presence of interchange entrance ramps affect the crash severity.

Ma and Kockelman (2004) accessed data from six freeways in the Orange County areas of southern California (1998) to estimate injury severity levels. They fitted OP into the data. Their findings were consistent with other researchers; namely, females and older persons are more at risk than others and dense traffic flow reduces the likelihood of sustaining severe injury.

Abdel-Aty and Keller (2005) explored explanatory predictors contributing to injuries occurred at signalized intersections. They used the data from central Florida areas (2000-2001).
Several models were estimated using OP and tree-based regression methodology. The results of the study conveyed that left turn, pedestrians, and bicyclist crashes had the highest probability of more severe injury. Moreover, the speed limit, median, crash type, and, intersection characteristics on the minor road were significant in their final ordered probit model.

Wang and Kockelman (2005) used a Heteroscedastic Ordered Logit (HOL) and an OL for estimating injury severity sustained by vehicle occupants in single and two vehicle crashes. The major difference between the HOL and OL is that the HOL allows the error-term's variance to vary. They obtained (1998-2001) data from National Automotive Sampling System's Crashworthiness Data System (NASS CDS). The results of the model indicated that vehicle weight, seating position, seatbelts, crash type, posted speed limit, weather condition, roadway medians, and drivers age were significant determinants of injury severity.

Rifaat and Chor (2005) analyzed injury severity due to single-vehicle crashes in Singapore. They used police-reported accidents data from the year 1992-2001. The methodological approach in the study was the calibration of an OP model. The results of 10 their study indicated that the most important determinants of the crash injury were the crash type, vehicle type, roadside objects, trees, expressways, night time, young and male drivers. Among the statistically significant variables, colliding with trees had the highest probability of fatal injury.

Wang and Abdel-Aty (2008) calibrated three partial proportional odds models (generalization of ordered regression) to estimate injury severities due to left-turn at signalized intersections. Six years of data was used from the central Florida area. The models showed that traffic entering the intersection, traffic of opposing approach, left turning traffic, left-turn lane offset, alcohol or drug use, drivers age (very young and very old), and point of impacts of both vehicles affect the injury severity.

Wang et al. (2009) calibrated OP and partial proportional odds models to identify variables contributing to injury severity at freeway diverge-areas in the state of Florida. They tested the parallel regression assumption of OP using Wald test and since the assumption did not hold, they used proportional odds model (relaxing the assumption).

The significant variables were: crash type, surface condition, average daily traffic, number of lanes, and length of deceleration lanes, light condition, weather condition, and alcohol/drug involvement.

Xie et al. (2009) investigated injury severity sustained by drivers of passenger cars, SUVs, and vans. They calibrated a Bayesian Ordered Probit (BOP) and an OP modeling scheme using data from the 2003 National Automotive Sampling System General Estimates System (NASSGES). The results from both the BOP and OP methodologies indicated that, the following factors were statistically significant: age, gender, alcohol, vehicle type, vehicle age, crash type, point of impact on the vehicle, 11 crash location type, road surface, and lighting condition.

To evaluate the impact of sample size, the authors reduced the sample size from 76,994 records to 100 and calibrated new models using both methodologies. The new results indicated that for small samples the BOP could be a better estimator than OP. One of the shortcomings of the BOP modeling methodology is that it requires a prior distribution assumption, which is subjective and difficult to determine. Variable coefficients lack t-values and corresponding confidence intervals.

Unordered Probability Models

In the case where the dependent variable was assumed to be categorical and unordered Multinomial Logit and its extensions were used.

Chang and Mannering (1999) estimated two separate nested logit models. The focus of their study was to investigate the relationship between injury severity and occupancy for truck-involved and non-truck-involved crashes. They used data from police reported crashes on principal arterials, state highways, and interstate highways in King County of Washington state during 1994. For truck-involved crashes high speed limits, rear end, and vehicles making right or left turns significantly increased injury severity. Moreover, effects of trucks on injury severity of PV occupants are more significant for multi-occupants vehicles than single occupant vehicles.

Abdel –Aty and Abdelwahab (2002) calibrated three models to investigate the role of Light Truck Vehicles (LTV) in four rear-end crash configurations. They used multinomial logit (MNL), heteroscedastic extreme value (HEV), and bivariate probit (BVP) modeling schemes.
The latter two are considered as the extensions to MNL 12 (relaxing the irrelevant alternative assumption). The data from the General Estimates System (GES 2000) was used to estimate the above mentioned models. In the case of MNL, the significant variables were: driver age, gender, distraction, and lighting condition. The significant variables in the calibrated HEV were the same as MNL with an addition of traffic signals.

The significant variables for BVP were consistent with MNL and HEV. The models results indicated that when a passenger car is behind an LTV, the driver of a passenger car would experience sight distance and discomfort problems. Moreover, the probability of rear end crashes increases when the driver of the following vehicle is distracted. Furthermore, young drivers and old drivers are more likely to be involved in rear end crashes.

Ulfarsson and Mannering (2004) estimated the differences in injury severity sustained by male and female drivers involved in single and two-vehicle crashes. To estimate the predicted probability for four levels of injury severity, they estimated fourteen multinomial logit models conditioned on the drivers gender, number, and type of vehicles involved. They obtained data from the Washington State Department of Transportation. The dataset contained reported accidents from January 1993 to July 1996. Due to the vast number of models involving multinomial logit schemes, some of the most significant findings are listed here. For both genders, drivers who did not use seat belts experienced more severe injuries. The predicted probabilities of higer injury severity were increased for drivers age 25 or younger and for 65 and older. Defective tires increased the predicted probability of possible or evident injury for female drivers. Wet, icy or snowy roads reduced the severity of injuries for both genders. Female drivers striking a barrier or guard rails increased the probability of fatal/disabling injury.

Khorashadi et al. (2005) investigated the differences in passenger vehicle and large truck drivers injury severity in rural and urban areas. They used four years (1997-2000) of data provided by the

California Department of Transportation (Caltrans). Two multinomial logit models were estimated, one for rural and the second one for urban areas.

Some of their major findings were; crashes involving large trucks at intersections in rural areas result in 725% increase in the likelihood of severe/fatal injuries, whereas, in urban area the same kind of crash would result in 10% decrease in the likelihood of the same injury. The most significant variable across the models was influence of alcohol or drug.

Furthermore, roads with median barriers in rural areas reduced the likelihood of severe/fatal injury by 69%. Hold ridge et al. (2005) estimated multivariate nested logit models to determine the impact of fixed roadside objects that affect crash severities. The data was from state of Washington from January 1993 to July 1996. From the database all single-vehicle crashes which involved roadside objects in an urban setting were selected. The results of their research showed that utility poles, trees, leading ends of guardrails, traffic poles, overhead poles, sign boxes, and bridge rails would increase the probability of fatal injury. Moreover, the following factors increased the predicted probability of fatal injury: driving above the posted speed limit and alcohol usage.

Milton et al. (2007) calibrated a mixed logit model (random parameter logit) to estimate accident severities on Washington highways. The data for 274 roadway segments from 1990-1994 was obtained from Washington State Department of Transportation.

The model was estimated by incorporating injury severity proportions for individual roadway segments. In a mixed logit scheme, parameters can vary randomly 14 across roadway segments. The average daily traffic per lane, average daily truck traffic, truck percentage, interchange per mile, and snow falls were random parameters. The number of horizontal curves, number of grade breaks per mile, and pavement friction were fixed parameters.

Malyshkina and Mannering (2008) estimated the influence of posted speed limit on the injury severities in the State of Indiana. They used the data for rural interstate and non-interstate routes from 2004 and 2006. They estimated the parameters using MNL models. The findings of the models indicated that increasing the posted speed limit on interstate highways did not have statistically significant impact on increasing the severity of the crashes in 2006. With regard to non-interstate highway crashes, increasing the speed limits were statistically significant. Angel and Hickman (2009) used ten years of the crash records from state of Utah to estimate injury severity sustained by occupants in two-vehicle crashes. They calibrated two models using MNL and linear models. The statistically significant variables were: age, alcohol usage, population density, crash type, seating position, gender, use of seatbelts, and vehicle curb weight. Furthermore, the data shows that children are least likely to get injured while the older people are more likely to sustain more severe injury.

Schneider et al. (2009) estimated drivers injury severity due to single-vehicle crashes on horizontal curves on rural two-lane highways in the state of Texas. Separate multivariate MNL models were developed for small, medium, and large radius curves. To estimate these models, five years of crash data (1997-2001) for rural two-lane normal cures were obtained. The findings of the models indicated that female drivers were more likely to sustain more severe injury than male drivers. Moreover, older drivers were more 15 likely to sustain more severe injuries. The following variables were found to increase the probability of severe injury: not wearing safety belts, fatigue, and drug or alcohol use.

Logistic Regression Models

Researchers used Logistic regression models when there were two levels of injury severities.

Farmer et al. (1997) investigated the relationship between crash characteristics and injury severity on two-vehicle side impact crashes. The data (1988 -1992) was obtained from National Accident Sampling System Crashworthiness Data System (NASS/CDS). Logistic regression (binary) technique was employed to estimate the various effects of the predictors. The results of the model showed that light trucks were 14 times as likely as cars to roll when struck. The occupants of the cars seating closer to the point of impact were more likely to suffer more severe injury than the occupants in a light truck. The occupants of the heavier vehicle were less likely to suffer high injury severity. Elderly were particularly at high risk of injury in side-impact crashes, specifically those 65 and older.

Al-Ghamdi (2002) applied a logistic regression methodology to estimate two levels of injury severities. A sample of 560 serious crashes from city of Riyadh in Saudi Arabia during August 1997 to November 1998 was extracted. The sample was divided into two categories; namely, fatal and non-fatal crashes. Nine independent variables were selected. These variables were: location, collision type, and accident type, and accident cause, age of driver at fault, nationality, vehicle type, and license status. Two variables (location and cause) were found to be statistically significant at 5% level. Furthermore, the models results conveyed that the probabilities of fatal crashes occurring at intersections are lower. The author mentioned that the data in the study suffered a great deal of validity because of the unskilled police processing crash reports. Variables such as: crash type (collision type), vehicle type, accident type, and age should have been statistically significant.

Hill and Boyle (2006) estimated the relative risk of severe injury for older female occupants involved in car crashes. They calibrated a logistic regression model using the General Estimates System (GES) data from the year 2000. Female occupants between 55 years and 74 years of age were at high risk. Seat belts, front seat, head on, side impact were significant variables. The risk of serious injury decreases after age of 75 for females, while it increases for male occupants. Occupants seated in the front seats are in a higher risk compared to the ones in the rear seats. Among these seating positions, seating in right front seat increased the risk.

Other Models

Kim et al. (1995) studied causal relationship among driver characteristics and behaviors and injury severity. The study was a part of Hawaii CODES project (Crash Outcome Data Evaluation System). All the police-reported crashes from 1990 in Hawaii were analyzed. To achieve a structural model that could illustrate the causal links among driver characteristics, crash severity, and injury severity, they used a log linear model.

The study's categorical causal relationship of injury severity with respect to, driver behavior, driver age, sex, alcohol or drug use, driver error, and crash type were established. They constructed a structural model which could estimate the odds multiplier for each factor. Odds multiplier is defined as, how much each factor increases or decreases the odds of injury severity. The results indicated that drug or alcohol use and no seat belt greatly increased the odds of more severe injury. Furthermore, driver error had small impact while drivers age and sex were insignificant variables in determining causal relationship of injury severity.

Abdelwahab and Abdel-Aty (2002) applied Artificial Neural Networks (ANN) theory to predict injury severity level sustained by driver involved in vehicle crashes on highways, signalized intersections, and toll plazas. Two databases from central Florida (1996-1997) and (1999-2000) were used. Explanatory variables in the study were alcohol, age, gender, violation, seat belt use, point of impact, speed ratio (running speed/posted speed), vehicle type, time of crash, area type, day of the week, pavement type, traffic condition, road alignment, type of toll plaza (epay or manual), and weather condition. Different models yi

elded different results. The following factors were significant in all three models: age, gender, seat belt, point of impact, and vehicle type. Day of the week and traffic condition was insignificant across all models.

Kweon and Kockelman (2003) estimated the risk of injury to different drivers across various vehicle types. They used multinomial probability models to estimate the probability of injury severity sustained by different groups of drivers. The data in this study was from the 1995 Nationwide Personal Transportation Survey (NPTS).

Furthermore, to estimate vehicle miles driven by various drivers, they incorporated the results from NPTS to that of General Estimates System (GES). They estimated a series of crash exposure rates, such as: crash rates for different crash types, young drivers, middle aged drivers, old drivers, and vehicle types.

The results suggest that women driving light 18 duty trucks are in a higher risk groups comparing to men and older drivers are in low risk group. Moreover, SUVs and PUs are more often involved in rollovers comparing to other passenger vehicles.

Delen et al. (2006) utilized a series of ANN models to prioritize importance of crash-related variables as they apply to various levels of crash severity sustained by the driver. Data for the study were acquired from General Estimating System (GES). The GES data is a nationally representative sample of all police reported crashes in the US. The dataset contained 30,358 crashes from 1995-2000. The independent variables were as follows: age, sex, alcohol or drugs, vehicle age, body type, restraint system, highway type (interstate highway versus other), light conditions, road surface conditions, crash-type, time of day, and day of week. Rollover was important predictor in all models except one. The importance of driver's gender diminished as the level of injury severity increased. Age was an important predictor for injury severity level. Striking and struck variables had reverse impact on the severity of injury; importance of striking decreases with increased injury severity. Body type had various impacts across different models and could not have been explained singularly. Weather conditions or time of crash had no impact on severity of the crash.

Chang and Wang (2006) developed a Classification and Regression Tree (CART) model which established the relationship between injury severity and twenty explanatory variables. They used National Traffic Accident Investigation Reports crash data from Taipei area during 2001. The data were divided into two subsets; one was used for learning and the other for testing. Model prediction accuracy for individual level of severity was over 94% for both learning and testing data. In the case of fatality, model failed in both learning and testing data (0% prediction). Model identified that pedestrian, motorcycle and bicycle riders are the most vulnerable groups. Crash type, contributing circumstances, and driver actions were found to be important factors in determining the injury severity.

3. Research Methodology

3.1. Study Design

This research methodology requires gathering crash data from Addis Ababa Police Commission(AAPC), the N/Silk Lafto sub city police department, Police register on all road traffic crashes with fatalities that occurred in N/Silk Lafto sub city for three years(2013-2015).Variables related to the crash events such as crash location, crash type, time of day, day of week, date, year, Driver profile Vehicle types, Crash Location, Land use, Road Type, Road Geometry, Intersection type, Type of pavement, Road condition, Lighting conditions, Road users injury severity, Defendant Vehicle maneuvering condition and weather conditions are included.

3.2. The Materials and Equipment

The standardized data collection checklist which is N/Silk Lafto Sub-city police department uses for the crash record and the log book. The past three (3) years Crash data which I have collected. These Crash data were collected from N/Lafto Sub-city Police Stations and the Road geometric parameters, Road type, Road Geometry, Intersection type, type of Road Pavement included in the crash data to analyze statistically and to evaluate the selected parameters on crashes and finally to obtain the relationship between the crashes severity and the selected important factors (Road Geometry) which affects the crash rate.

3.3. Software used in the Analysis

SPSS (Statistical Package for the Social Sciences), Google earth, Arch GIS, ArcMap and the Microsoft Excel was used.

3.4. The study area

Addis Ababa, with an area of 540 km² is divided into 10 sub-cities and 116 woredas. The city is the country's political and economic center, the seat of Head Offices of African Union and United Nations Economic commission for Africa. It also accommodates many international Aid and Development organization and more than 100 embassies. The city's population is estimated to be 3 million. With the current population growth rate of 2.1% the city population is estimated to reach 5 million after 10 years. Addis Ababa is exhibiting high social, economic, structural and change is found to be a fast growing city. More than 70% of registered vehicles in the country are found in Addis Ababa. (Transport Policy of Addis Ababa, August 2011).

The road length envisaged by the Addis Ababa 2003 Master plan was 800 km. As of April 2010, constructed road and pedestrian Walkway was 620km and 423km respectively. Currently the road coverage of the built area is 11.3% and it is envisioned to have the road network coverage about 20% by the year 2020. As the data shows, mobility has been improved; but the total number of Road crashes has also gone up (Transport Policy of Addis Ababa, August 2011).

The study area would be the road sections from N/silk Lafto Sub-sity.Nifas Silk-Lafto, is one of the 10 sub cities and as of 2011 its population was of 335,740, area (Km2) 68.30, Density 4,915.7. The district is located in the southwestern suburb of the city. It borders with the districts of Kolfe Keranio, Lideta, Kirkos and Bole and Akaky Kaliti(Transport Policy of Addis Ababa, August 2011).

The location of the study area and the different types of roads that exist within the boundary are shown in Figure 1 below.

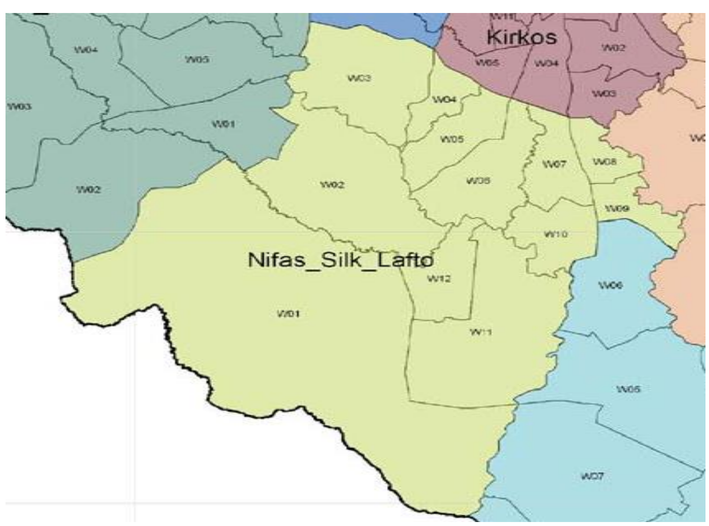

Figure 3. 1 Layout of the Study Area

3.5. Data Analysis

Data analysis is the process of observing the data, transforming it, and modeling it to obtain useful information. The study has been conducted in N/Lafto sub city Addis Ababa Ethiopia. Crashes are recorded by the traffic police on daily basis. This study based on a secondary data which obtained from N/lafto sub-city police department and Addis Ababa Traffic Police Commission Bureau from July 01, 2013(G.C) to June 30, 2015(G.C).

3.6. Descriptive Analysis

Road traffic crash data base variables which were supplied by the Ethiopian Police Commission and the traffic police department include time of day, day of week, education, age and gender of drivers, driving experience, driver's relationship with vehicle (employee/owner/other), vehicle service years, vehicle type, vehicle ownership, road type, land use, median and junction types, terrain, pavement type, pavement conditions, illumination, weather conditions and reason for the crash and the data obtained was checked and edited manually and then characterized using descriptive analysis to examine the relationships among factors and to identify possible causes and contributing factors and the crashes were analyzed it terms of:

1. Analysis by Time variation of Crashes (Number of crashes Vs time of day): To identify the most crash-prone hours of the day
2. Analysis of crash Rates by Age group
3. Analysis of Crash type(Fatal, Injury, Property) with respect to Educational status of the driver
4. Analysis of Crash type (Fatal, Injury and Property) with respect to Driver Gender.
5. Analysis of crashes by Road types
6. Analysis of Road Traffic Crashes by type (Fatal, Injury and Property) with respect to Road Pavement (Surface) Type
7. Analysis of Crash type (Fatal, Injury and Property) with respect to Intersection Type
8. Analysis of Crash type (Fatal crashes ,Injury crashes) with respect to Road Type
9. Analysis of Crash type (Fatal crashes ,Injury crashes) with respect to Road Geometry
10. Analysis of Crash type (Fatal crashes ,Injury crashes) with respect to Lighting conditions

11. Analysis of Crash type (Fatal crashes ,Injury crashes) with respect to Land Use
12. Analysis of Crash type (Fatal crashes ,Injury crashes) with respect to Type of crash
13. Analysis of Crash type (Fatal crashes ,Injury crashes) with respect to vehicle type

3.6.1. GIS Based Road Traffic Crash Analysis

The main objective of this part of the study was to map the crash on the study area and identify and map the main traffic crash spots using Geographic Information System (ArcGIS 10.) Geographic Information System (GIS) is a computer system for capturing, storing, checking, integrating, manipulating, analyzing and displaying data related to positions on the Earth's surface and is an ideal tool to use to analyze and solve multiple criteria problems. Multi-Criteria Decision Making (MCDM) is the study of methods and procedures by which concerns about multiple conflicting criteria can be formally incorporated into the management planning process, and have potential in selecting suitable sites by considering an important criterion effectively and within short period of time. Therefore, GIS can be used to build traffic crash databases and to record the accurate location of crash spots which contribute in reducing the road crashes and can be used to reduce the fatality of the road crashes.

KML (Keyhole Markup Language) - A KML file stores geographic modeling information in XML format. It includes points, lines, polygons, and images. KML files are used to identify and label locations, create different camera angles, overlay textures, and add HTML content.

Layer files- is a just a link\reference to actual data, such as a shape file, feature class, etc. It is not actual data because it does not store the data's attributes or geometry. A layer file primarily stores the symbology for a feature and other layer properties related to what is seen when the data is viewed in a GIS application.

Shape file - is a simple, non-topological format for storing the geometric location and attribute information of geographic features. Geographic features in a shape file can be represented by points, lines, or polygons (areas).

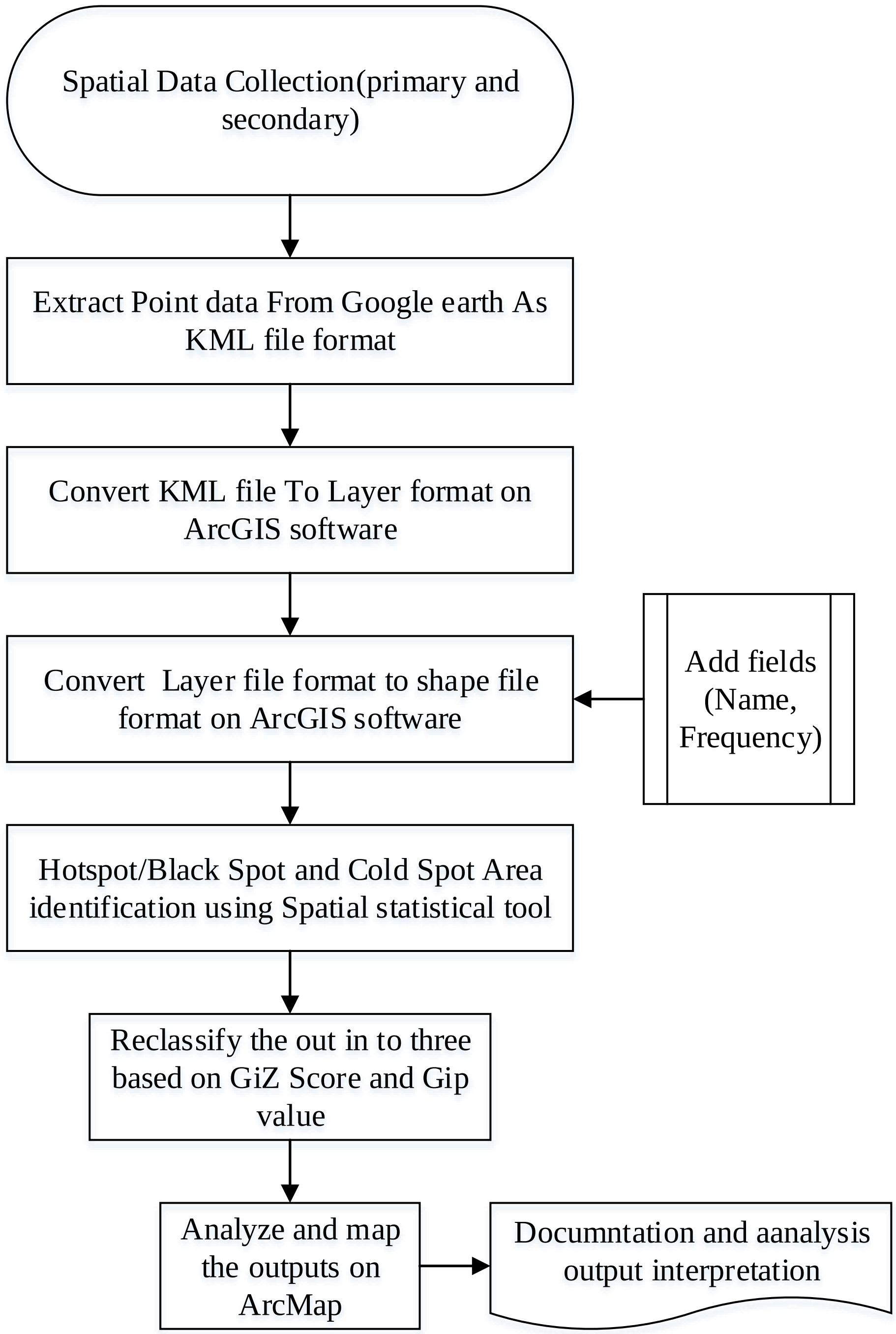

Figure 3. 2 Schematic diagram of the hot spot identification methodology

The first step in identifying hazardous locations on a specific segment of a roadway was to collect crash data. All the crash data in the N/silk lafto sub city is compiled into Microsoft office gathered from the respective police department.

There are two ways of analyzing spatial pattern in GIS: Global and local measures. Using spatial association Global-measures measures spatial pattern on a large scale to show whether they are clustered, dispersed or random. On the other hand, local measures do the same analysis but on small scale. Both distance statistics i.e. Anselin Local Morans I and Getis-OrdGi* are most commonly used local measures of spatial association.

Anselin Local Morans I: - Given a set of weighted features, the Cluster and Outlier Analysis tool identifies spatial clusters of features with attribute values similar in magnitude. The tool also identifies spatial outliers. To do this, the tool calculates a local Moran's I value, a z-score, a p-value, and a code representing the cluster type for each feature. The z-scores p-values represent the statistical significance of the computed index values.

A positive value for **I** indicate that a feature has neighboring features with similarly high or low attribute values; this feature is part of a cluster. A negative value for **I** indicates that a feature has neighboring features with dissimilar values; this feature is an outlier. In either instance, the p-value for the feature must be small enough for the cluster or outlier to be considered statistically significant.

The local Moran's I index (**I**) is a relative measure and can only be interpreted within the context of its computed z-score or p-value and results are only reliable if the input feature class contains at least 30 features.

Getis-Ord Gi* – The resultant z-scores and p-values tell you where features with either high or low values cluster spatially. This tool works by looking at each feature within the context of neighboring features.

A feature with a high value is interesting by may not be a statistically significant hot spot. To be a statistically significant hotspot, a feature will have a high value and be surrounded by other features with high values as well.

The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is very different from the expected local sum, and that difference is too large to be the result of random choice, a statistically significant z-score results.

The Gi* statistic returned for each feature in the dataset is a z-score. For statistically significant positive z-scores, the larger the z-score is, the more intense clustering of high values (hot spot). For statistically significant negative z-scores, the smaller the z-score is, the more intense the clustering of low values (cold spot). It is used when the Results aren’t reliable with less than 30 features.

3.6.1.1. Reclassifying the Hot spot using Getis-OrdGi*

The Hot Spot Analysis tool, Getis-OrdGi*calculates the local spatial statistic for each location. This tool works by comparing proportionally the local sum for a location and its neighbors to the sum of all locations. When the local sum is significantly different than expected local sum, then that location maybe the statistically significant Hot Spot.

A location with a high value may not be the statistically significant hot spot. For being the significant hot spot, each location will have a high value and has to be surrounded by high values as well. (ESRIb 2010).The formulation of the Getis-OrdGi*statisticis given is as follows (ESRIb 2010):

The Getis-Ord local statistic is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \quad (1)$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \quad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \quad (3)$$

The G_i^* statistic is a z-score so no further calculations are required.

Where Xi is the value of location, Wijis the spatial weight between locations i and j, n is the total number of locations.

The p-values are numerical approximations of the area under the curve for a known distribution, limited by the test statistic

The Gi* statistic returned for each feature in the dataset is a Z score. For statistically significant positive Z scores, the larger the Z score is, the more intense the clustering of high values (hot spot). For statistically significant negative Z scores, the smaller the Z score is, the more intense the clustering of low values (cold spot).

The Hot Spot Analysis tool calculates the Getis-OrdGi* statistic for each feature in a dataset. The resultant Z score tells you where features with either high or low values cluster spatially. This tool works by looking at each feature within the context of neighboring features. A feature with a high value is interesting, but may not be a statistically significant hot spot.

To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance, a statistically significant Z score results(*resources.esri.com/...toolref/spatial_statistics_tools/how_hot_spot_analysis_colon_geti)*.

3.6.2. Multinomial Logistic Regression (MLR)

This research has been carried in Addis Ababa, Ethiopia – specifically in N/silk Lafto sub city. Crashes records that were collected by the traffic police of Addis Ababa on daily basis were used from the year 2013(G.C) to 2015(G.C).

In order to analyze car crash injury severity, one can use various analyzing methods; however, taking their strength, and weakness into consideration: the Multinomial Logit (MNL) model is often used to predict the crash injury severity. Therefore, this research uses a multinomial logistic regression to model injury severity of a crash, specifically multinomial logit.

3.6.2.1. Why it is used in this study

Binomial logistic regression has two (Binary) outcomes but for more than two outcomes (polychromous): in this study the outcome has four categories)

<u>Re-categorize into 2 outcomes</u>

Challenges with this approach:

- Results in an inevitable loss of information
- Results can change depending on how the categories collapsed
- Could lead to seriously misleading conclusions

<u>Ordinary Least Squares (linear) regression with categorical outcome</u>

Challenges with this approach:

- The residuals cannot be normally distributed (OLS assumption)
- The OLS model makes nonsensical predictions, since the dependent variable is NOT continuous
- The coding is completely arbitrary i.e. recoding the dependent variable can give very different results.

Delete one of the categories

- Challenges with this approach
- Losing information, data, and power
- Potentially systematically biasing the sample

Multinomial Logistic Regression

- Another model which considers the full form of the outcome is called the 'multinomial' or 'polychromous' logistic model because the outcome is no longer assumed to be BINOMIAL but rather MULTINOMIAL, Powerful and Slightly more complicated interpretation because here no longer comparing two outcomes.

3.6.2.2. Variables Considered in the Study

Dependent Variable:

The aim of this research is to find and describe the contributing agents of crash Severity; taking this into consideration the study regards crash severity as the dependent variable in the crash severity prediction model. Crash severity is mostly reported in three or more categories, such as fatal, incapacitating, PDO, etc. In this study the severity divided into four categories: fatal, serious injury, slight injury and property damage only (PDO).

According to, if death occurs within 30 days of the crash data because of the car crash, the injury is called fatal; if at least one person involved in the car crash gets to hospital, and treated for 24 hours or more it is called serious injury, slight injury if the treatment takes less than 24 hours (ANSI Manual D-16.1-1996 7th Edition).

Independent Variables:

In Ethiopia, the road traffic crash database consists of many variables that are related to the crash; this includes information about the driver, vehicle features, information about the roadway characteristics and environment, and location and time of crash.

In this study, 8 variables used that are considered as an independent variable that contribute to crash injury. Table 7shows these variables, including frequencies.

The main concern of this study is to identify and describe the contributing factors to crash Severity and therefore crash Severity is the dependent variable in a crash severity prediction model. This modeling process allows the identification of statistically significant factors that contribute to crash severity in specific sub-city in Addis Ababa. Regression Analysis is a statistical process of estimating relationships between variables. There are different types of regression analysis for different type of data. The methodology used to model the crash data (In order to make interpretation on factors affecting the injury severity of crashes) was Multinomial Logistic Regression (MLR). The raw data set consists of values which are ordinal and nominal.

Multinomial Regression is used when the dependent variable is nominal and for which the number of categories are more than two. There is no natural ordering in the independent variables.

One of the assumptions of MLR is that the dependent variable cannot be perfectly predicted by the independent variables for any case. It is an extension of the Binomial Logit model. Multinomial Regression uses the maximum likelihood ratio to determine the probability of the categorical membership of the dependent variable. Crash severity in the crash dataset was divided into four categories: fatal, severe injury, slight injury and PDO. The independent variables are Driver related Variables, Road and Environment related Variables and Time related variables and for the analysis the statistical software SPSS has used. Statistical Package for the Social Sciences (SPSS) that can analyze data in in three basic ways by describe data using descriptive statistics, allows to examine relationships between variables (statistical technics to explore relationships includes correlation analysis and regression analysis) and enable to compare groups to determine if there are significant differences.

Multinomial Logistic Regression Model

– Dependent variable with M=4 categories
j =1, 2, 3, 4 for PDO, Slight Injury, Serious Injury, Fatal

– Probability of person "i" having category "j" all sum to 1. (Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). Multivariate Data Analysis 5th ed. Upper Saddle River, NJ: Prentice Hall).

$$p_i : \sum_{j=1}^{M} p_{ij} = 1$$ ---------eq. (4)

– Probability of each outcome j is:

$$p_{ij} = \frac{e^{\sum_{k=1}^{K} \alpha + \beta_{kj} X_{kji}}}{\sum_{j=1}^{M} e^{\sum_{k=1}^{K} \alpha + \beta_{kj} X_{kji}}}$$ --------eq.(5)

i = cases, j categories,

K = independent variables

– Solved by adding constraint Coefficients sum to zero

$$\sum_{j=1}^{M} \beta_{jk} = 0$$ --------------------eq.(6)

i = cases, j categories,

K = independent variables

– Solved by adding constraint Coefficients sum to zero

–

Table 3. 1 Dependent Variable

Severity	Code
Property Damage Only (PDO)	1
Slight Injury	2
Serious Injury	3
Fatal	4

Table 3. 2 Independent Variable

Variable Name	Categories	Code
Time period	0-6	1
	6-9	2
	9-12	3
	12-15	4
	15-18	5
	18-21	6
	21-24	7
Age group	24 & below	1
	24-40	2
	40-54	3
	54^+	4
Gender	Male	1
	Female	2
Diver Education level	0-8	1
	8-12	2
	12^+	3
Driver Experience	0-2	1
	2-5	2
	5^+	3
Vehicle Ownership	Other	1
	Employee	2
	Owner	3
Land Use	Residential	1
	Commercial	2
	Other	3
Road Type	Straight	1
	Slope	2
	Curve	3
	Roundabout	4
	Other	5

3.6.2.3. Performance measures

The analysis of the model uses three performance measures:

1) P value: This is a significance test. It is normally tested at a threshold value of 5% or 1%. If the p-value is less than the threshold value, we reject the null hypothesis and accept the test hypothesis to be valid. For our model, we test at a 5% level. Therefore, if the p-value is less than 0.05, we can conclude that it is statistically valid.

2) ß value: The beta coefficients show the effect of the independent variables on the dependent variable. A positive coefficient for ß, shows a positive impact while a negative coefficient shows a negative impact. For our analysis, a positive ß value shows that the category is more likely to impact category of dependent variable with respect to the reference category. If ß > 0, it is more likely to impact the dependent variable. If ß < 0, it is less likely to impact the dependent variable. If ß =0, the particular category and the reference category are equally likely to impact the dependent variable.

3) Exponential Beta value: This value gives us the odds ratio for the independent variables. It is an exponentiation of the regression coefficients (ß). The odds ratio shows the change in odds of the dependent variable being in a particular category compared to the reference category, corresponding to one unit change of independent variable. An odds ratio > 1 indicates that the risk of the outcome falling in the comparison group relative to the risk of the outcome falling in the referent group increases as the variable increases. So it is more likely to fall in the comparison group. An odds ratio < 1 indicates that the risk of the outcome falling 14 in the comparison group relative to the risk of the outcome falling in the referent group decreases as the variable increases. In general, if the odds ratio < 1, the outcome is more likely to be in the referent group.

4. Results and Discussions

4.1. Descriptive Statistics

4.1.1. Variation in Crashes by Time of Day and Day of Week

Most of the crashes occurred during daylight hours. Figure 1 shows that crashes increased rapidly from 5:00am to 6:00am and more or less steady until 7:00 pm after which they declined in most cases, though not as steeply as the morning increase.

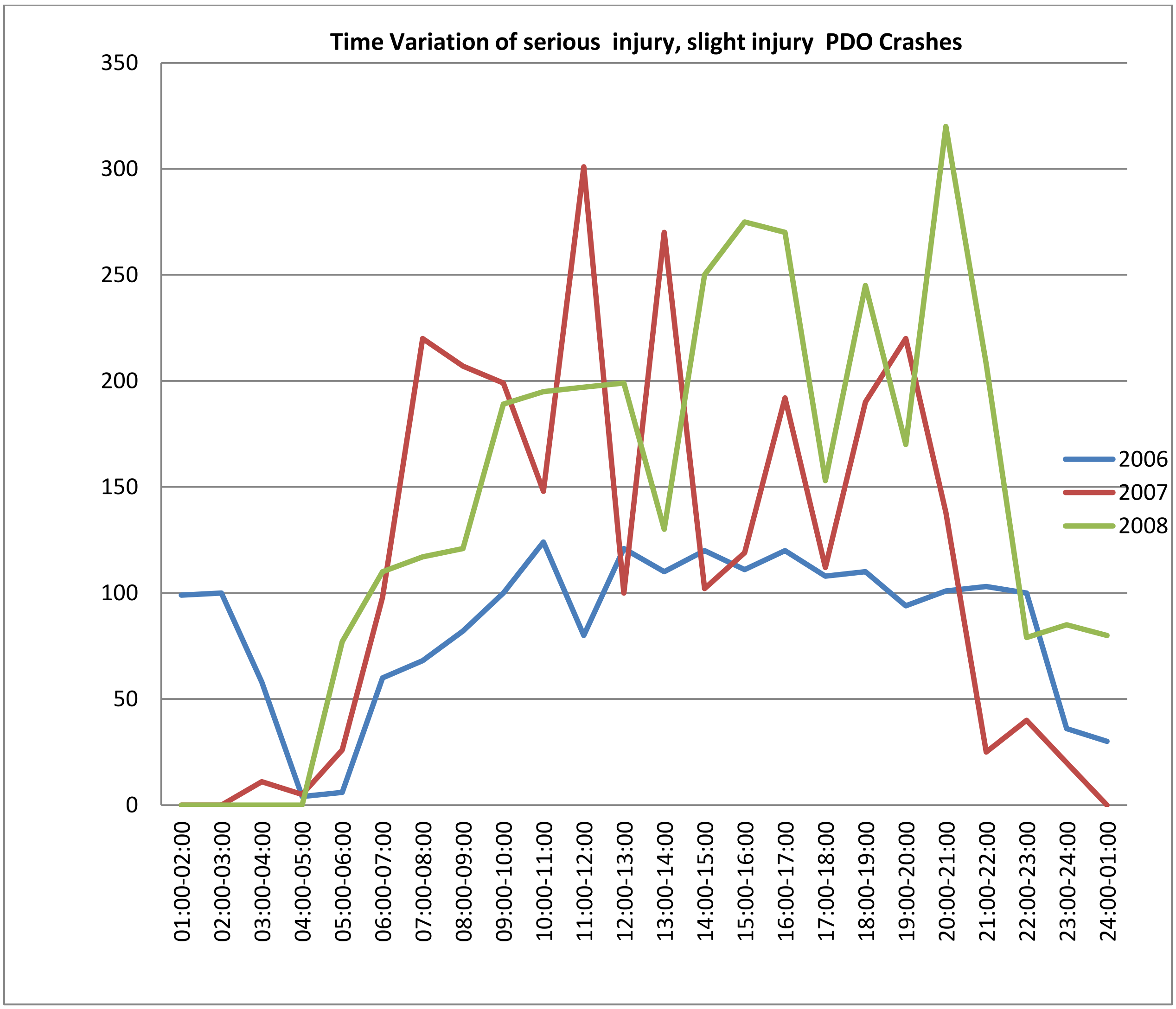

Figure 4. 1 Variations in Road Traffic Crashes (serious injury, slight injury and PDO) by Time of Day, July 2013-June 2015

4.1.2. Drivers' profile

The highest number of crashes (fatal, injury, and property damage) involved drivers in the 18–30 year age group (74.31%) and in the 31-50 year age group (22.12%). The drivers in the age group 18-30 were involved in more crashes, followed by the age group 31-50. The age range of drivers involved in crashes is shown in Table 1.

The educational status of the drivers was analyzed and among all most of attended Junior High school and High school 51.32% and 22.77% respectively lastly followed by Elementary school comprising 16.35%.

There is a big difference in crash involvement by Gender and in the three years period, male and female drivers were involved in 87(77.68%) and 7(6.25%) fatal crashes respectively or 18 (16.07 %) unknown because they neither left the scene after the crash and neither report to the police nor bring the victim to the hospital. The composition of fatalities and injuries was 1.56% and 13.24% respectively. Fatalities in terms of road users (drivers, passengers, and pedestrians) were 16.96%, 26.78%, and 56.25% respectively. The possible reasons for the high proportion of male drivers involved in crashes may relate with the travel characteristics Male drivers account for about 65% of total passenger vehicle kilometers travelled. This reflects both the fact that males are more likely to have a driver's license and that, on average, male drivers travel more each year. While males of all ages travel more than females; the difference is particularly high for those over the age of 45. The type of travel performed also differs for male and female drivers. For example, female drivers tend to do relatively more travel during weekdays and during daytime hours. They also engage in relatively less driving associated with work and relatively more for personal business, such as shopping, driving others and visiting.

The relationship of drivers with the vehicle they were driving is 60.61% of those drivers were recruited mostly being commercial cars; others (either borrowed from a friend or family accounts for 17.06% and owners involved were 22.08% the remaining 0.49% unknown.

Table 4. 1 Crashes by Driver Age, Education, Gender, Relationship of the driver with the vehicle and Driving experience in years 2013-2015

Driver Age	**Fatal**	**severe Injury**	**slight Injury**	**Property**	**Total**	%
Less than 18	4	1	0	0	3	0.0365
18-30	48	360	266	5456	6112	74.31
31—50	33	228	168	1404	1820	22.128
More than 51	18	20	15	210	257	3.1246
Unclassified age	9	24	2	1	33	0.4012
Total	**112**	**633**	**451**	**7071**	**8225**	**100**
Driver Education Level						
Illiterate	0	0	0	2	2	0.0278
Writing & reading	0	2	3	18	23	0.3198
Elementary school	9	132	84	951	1176	16.352
Junior high school	34	309	212	3136	3691	51.321
High school	41	87	77	1433	1638	22.775
Above high school	19	11	9	587	626	8.7041
Unknown	9	24	2	1	36	0.5006
Total	**112**	**565**	**387**	**6128**	**7192**	**100**
Driver Gender						
Male	87	478	337	4910	5812	80.812
Female	7	80	48	1217	1352	18.799
Unclassified	18	24	2	1	45	0.6257
Total	**112**	**565**	**387**	**6128**	**7192**	100
Relationship of the driver with the vehicle						
Owner	27	123	84	1354	1588	22.08
Recruited	61	388	245	3665	4359	60.609
Other	16	47	56	1108	1227	17.061
unknown	8	24	2	1	35	0.4867
Total	**112**	**565**	**387**	**6128**	**7192**	**100**
Driving experience in years						
Less than one year	4	0	0	2	6	0.0834
1-2	3	6	8	102	119	1.6546
2-5	11	51	59	452	573	7.9672
5-10	28	201	135	1610	1974	27.447
Above ten years	34	194	118	2617	2963	41.199
Unknown	24	89	65	1344	1522	21.162
Not Applicable	8	24	2	1	35	0.4867
Total	**112**	**565**	**387**	**6128**	**7192**	**100**

Most researches shows that Elevated rates were observed for drivers aged 16–19 and 75 and over. The oldest drivers had the highest fatal involvement rate, while the youngest drivers had the highest rate of involvement in all police-reported crashes. Men had a higher risk than women of experiencing a fatal crash, while women had higher rates of involvement in injury crashes and all police-reported crashes (Brian C. Tefft November 2012).

People aged between 15 and 44 years account for 48% of global road traffic deaths. From a young age, males are more likely to be involved in road traffic crashes than females. About three-quarters (73%) of all road traffic deaths occur among men.

Table 4. 2 Road Traffic Crashes by Road Type and Road Pavement (2013-2015)

No	**Road Type**	**Fatal**	**severe Injury**	**slight Injury**	**Property**	**Total**	%
1	Interstate	0.00	0.00	0.00	0.00	0.00	0.00
2	Collector	0.00	0.00	0.00	0.00	0.00	0.00
3	Access	0.00	0.00	0.00	0.00	0.00	0.00
4	City	112.00	633.00	451.00	7071.00	8267.00	100.00
5	Total	**112.00**	**633.00**	**451.00**	**7071.00**	**8267.00**	100.00
	Road Traffic Crashes by Road Pavement (Surface) Type						
1	Asphalt roads	72.00	575.00	383.00	6767.00	7797.00	94.31
2	Asphalt roads with some distress	14.00	6.00	16.00	68.00	104.00	1.26
3	Gravel roads	16.00	4.00	6.00	68.00	94.00	1.14
4	Earth roads	10.00	48.00	46.00	168.00	272.00	3.29
	Total	**112.00**	**633.00**	**451.00**	**7071.00**	**8267.00**	100.00

Table 4. 3 Road Traffic Crashes for Road Users by Gender and Age Group (2013-2015)

	Age in years	**Fatal**		**severe Injury**		**slight Injury**		**Total**		**Total**	**%**
	Age in years	**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**		
Drivers	**<18**	0	0	0	0	0	0	0	0	0	0
	18-30	12	0	10	0	23	0	45	0	45	68.18
	31-50	5	0	1	0	8	0	14	0	14	21.21
	≥ 51	2	0	1	0	4	0	7	0	7	10.61
	Total	19	0	12	0	35	0	66	0	**66**	**100.00**
Pedestrians	**<17**	0	0	0	0	0	0	0	0	0	0
	7_17	6	0	4	3	6	1	16	4	20	1.97
	14_17	3	0	19	8	7	5	29	13	42	4.12
	18_30	23	9	264	41	280	36	567	86	653	64.21
	31_50	10	3	110	27	111	17	231	47	278	27.33
	>51	6	3	6	5	2	2	14	10	24	2.36
	Total	48	15	403	84	406	61	857	160	**1017**	**100.00**
Passengers	**<17**	0	0	0	0	0	0	0	0	0	0
	7_17	1	0	4	2	2	2	7	4	11	11.34
	14_17	5	0	4	1	3	0	12	1	13	13.40
	18_30	11	2	16	4	8	4	35	10	45	46.39
	31_50	6	0	4	0	6	1	16	1	17	17.53
	>51	3	2	2	0	4	0	9	2	11	11.34
	Total	26	4	30	7	23	7	79	18	**97**	**100.00**

4.1.3. Crashes by Road Environment

About 95.70% of crashes occurred in the subjected sub city is on asphalt roads and only 3.34% on gravel and earth roads. whereas the total Asphalt road length up to 2011/12 in Addis Ababa city Road length is only 1,807km (Source: Asphalt road development in Addis Ababa in km (2014) ,Addis Ababa City Road Authority).

There is the relationship between crashes and land use appears. Various types of land uses tend to generate and attract different types of trips, and trip-making behavior affects the nature and volume of traffic. As the use of land intensifies, it does not seem unreasonable to expect that the potential exposure to crashes would also increase. The analysis indicates that most fatal and injury crashes occurred in central business districts and residential areas. Table 4 shows that 57.14% fatalities and 37.59% of serious injuries occurred in central business districts and residential areas in the three year period under consideration. The high occurrence of crashes in these areas may be explained by driver's Over-speeding, rash driving, violation of rules, failure to understand signs, fatigue, alcohol and for the pedestrian Carelessness, illiteracy, crossing at wrong places moving on carriageway, Jaywalkers. Motor vehicle traffic crashes are complex events that are a culmination of various driver, vehicle or environment-related factors. Driver-related factors that contribute to motor vehicle traffic crashes are mostly behavioral in nature. These include impaired driving, aggressive driving including speeding, and distracted driving, etc.(National Techinical Information Service, SpringÞeld, VA22161,2005).

Table 4. 4 Crashes by Land Use

No	Land use	Fatal Crashes	%	Severe Injury Crashes	%	Slight Injury Crashes	%	Property Damage	%	Total
		0	0	0	0	0	0	0	0	0
1	Agriculture areas	0	0	0	0	0	0	0	0	0
2	School areas	6	5.35	120	18.95	57	12.63	1108	15.67	1291
3	Industrial	4	3.57	4	0.63	51	11.30	1825	25.81	1884
4	Church areas	5	4.46	2	0.31	4	0.88	103	1.45	114
5	Market areas	15	13.39	209	33.01	132	29.26	1927	27.25	2283
6	Recreational areas	9	8.03	56	8.84	36	7.98	418	5.911	519
7	Hospital areas	3	2.67	4	0.63	9	1.99	56	0.79	72
8	CBD	31	27.67	184	29.06	123	27.27	990	14.00	1328
9	Urban Residential	33	29.46	54	8.53	39	8.64	644	9.11	770
10	Other	6	5.35	0	0	0	0	0	0	6
	Total	112	100	633	100	451	100	7071	100	8267

There are also relations between different land use types and the occurrence of crashes. The analysis indicates that most fatal crashes in central business districts and residential areas. Table 4.4 shows that 29.46% fatalities occurred in central business districts and residential areas in the three year period under consideration.

Table 4. 5 Fatal and Injury Crashes in the Three Year Period by Lanes/Medians, Road Alignment, Junction Type and Illumination Condition

	Lanes/Medians	**Fatal Crashes**	**%**	**Severe Injury Crashes**	**%**	**Slight Injury Crashes**	**%**	**Property Damage**	**%**	**Total**
1	One way	19	16.96	284	44.86	176	39.02	1516	21.43	1995
2	Undivided Two way	31	27.68	247	39.02	223	49.44	2846	40.24	3347
3	Double carriageway (median)	36	32.14	40	6.319	49	10.86	1156	16.34	1281
4	Two-way (divided with solid lines road marking)	20	17.86	0	0	0	0	582	8.23	602
5	Two-way (divided with broken lines road marking)	6	5.36	62	9.79	3	0.66	971	13.73	1042
	Total	**112**	100.00	**633**	100	**451**	100	**7071**	100	8267
	Road Alignment									
1	Tangent road with flat terrain	60	53.57	593	93.68	419	92.90	5702	80.63	6774
2	Tangent road with mild grade and flat terrain	9	8.035	18	2.84	8	1.77	1270	17.96	1305
3	Tangent road with mountainous terrain and escarpments	3	2.676	0	0	0	0	0	0	3
4	Tangent road with rolling terrain	5	4.464	2	0.31	6	1.33	8	0.11	21
5	Gentle horizontal curve	10	8.92	4	0.63	0	0	10	0.14	24
6	Sharp reverse curve	3	2.67	0	0	0	0	6	0.08	9
7	Steep grade upward with mountainous terrain	6	5.35	14	2.21	14	3.10	64	0.90	98
8	Steep grade downward with mountainous terrain	10	8.92	2	0.31	4	0.88	11	0.15	27
9	Other	6	5.35	0	0	0	0	0	0	6
	Total	112	100	633	100	451	100	7071	100	8267

Median barriers are longitudinal barriers most commonly used to separate opposing directions of traffic on a divided highway. While these systems may not reduce the frequency of crashes due to roadway departure, they can definitely help prevent a median crash from becoming a median crossover head-on collision. In the time it takes for the driver to yawn, a vehicle traveling at highway speeds can cross a highway median and strike opposing traffic head-on. Head-on crashes at highway speed are generally more severe than other types of highway crashes (Safer Roads in America, October, 2014).

According to the three years of data considered, 40.49% of crashes occurred on undivided roadways with two lanes. Dual carriageway and one-way roads accounted for 39.62% of the crashes. Barrier design and placement needs to effectively protect motorists traveling in opposing lanes, while also considering the safety of the occupants of the errant vehicle.

Table 4. 6 Fatal and Injury Crashes in the Three Year Period by Lanes/Medians, Road Illumination Condition

	Illumination conditions	Fatal	%	Severe Injury	%	Slight Injury	%	PDO	%	Total
1	Daytime with sufficient daylight	57	50.89	360	56.872	338	74.9446	4962	70.17	5717
2	Twilight	12	10.71	179	28.278	61	13.5255	1347	19.04	1599
3	Sun rising	13	11.60	4	0.6319	6	1.33038	61	0.86	84
4	Night with sufficient light	16	14.28	90	14.218	46	10.1996	701	9.913	853
5	Night with insufficient light	5	4.46	0	0	0	0	0	0	5
6	Night without light	4	3.57	0	0	0	0	0	0	4
7	Other	5	4.46	0	0	0	0	0	0	5
	Total	**112**	100	**633**	100	**451**	100	**7071**	100	8267
	Road junction type									
1	Midblock	41	36.60	373	58.92	288	63.85	4569	64.61	5271
2	Y-junction	11	9.82	47	7.42	82	18.181	409	5.78	549
3	T-junction	18	16.07	34	5.37	2	0.443	104	1.47	158
4	Roundabout	22	19.64	178	28.12	77	17.073	1859	26.29	2136
5	Four leg junction	8	7.14	1	0.15	2	0.443	81	1.14	92
6	Five leg junction	4	3.57	0	0	0	0	47	0.66	51
7	Rail crossing	0	0	0	0	0	0	0	0	0
8	Other	8	7.14	0	0	0	0	0	0	8
	Total	**112**	100	**633**	100	**451**	100	**7071**	100	8267

With respect to road alignment, 53.57% of fatal and 82.33% of injury crashes occurred on tangent (straight) road segments with flat terrain. Tangent roads with mild grade and steep grade downward with mountainous terrain contributed to 16.97% of the crashes.

It appears that road lighting contributes to the reduction of the number of crashes and their severity and that this influence increases with the increase of the severity of the crashes.

The absence of street lighting during nighttime has the highest impact on the number of fatalities and serious injuries. The results show that nighttime lighting has great potential in improving traffic safety and reducing the crash severity, especially for persons killed and seriously injured. (Most crashes occurred in daytime with sufficient lighting conditions. Table 5 shows that 50.89% of fatal crashes and 69.40% of injury crashes occurred in daylight most crashes occurred in daytime with sufficient lighting conditions.

Light conditions are known to affect the number of vehicle accidents and fatalities but the relationship between light conditions and vehicle speed is not fully understood. It is needed to study to examine whether vehicle speed on roads is higher in daylight and under road lighting than in darkness, and determine the combined effects of light conditions, posted speed limit and weather conditions on driving speed to check the conditions in Ethiopia and the Identification of the effect of lighting on road safety may benefit road safety policy decision makers in designing and implementing appropriate road safety measures.

Midblock road sections had a major share of fatal and non-fatal crashes in the three years, because much pedestrian crossing takes place in these sections many people do not go out of their way to cross at established intersections.

Instead, they choose to cross the street using the most direct route, even if that means crossing several lanes of busy traffic and may Mid-block pedestrian crossings decrease random and unpredictable crossings associated with a high risk of collisions, especially in areas that are heavily travelled by pedestrians or where block lengths are long. Overall, 36.61% of fatalities and 64.13% of non-fatal injury crashes occurred on midblock road sections, as shown in Table 5.The number of injuries increased over time from crossing at midblock locations, but decreased from crossing at intersections. This differential trend between midblock and intersection crossings is true for both fatal and non-fatal injuries. Specifically, fatal injuries increased by 5.9 percent at midblock locations but decreased by 20.4 percent at intersections. At the same time, non-fatal injuries increased by 12.1 percent at midblock locations, but decreased by 4.8 percent at intersections. This differential trend does not necessarily mean that crossing at midblock locations is getting more dangerous relative to crossing at intersections. It could have resulted from the suburbanization of population and employment and a behavioral shift toward crossing more at midblock locations than at intersections (XuehaoChu, Center for Urban Transportation Research, September 2006).

4.1.4. Crashes by Collision Type

During the three years of consideration most fatal crashes occurred Collision with pedestrians (36.61% of fatal crashes) pedestrians account for a much greater proportion of road traffic injury deaths increased vehicle speeds are associated with increased injury severity and death for Pedestriansin low- and middle-income countries(D.C.RichardsTransport Research Laboratory,2010).

4.1.5. Involvement of Vehicle Types in Crashes

Crashes were analyzed in terms of vehicle type, and findings indicated that Automobile and Land Cruiser vehicles were involved in 50.24% of severe injuries in the three-year period. Minibus taxis and buses were also involved in 32.84% of severe injuries.

Table 4. 7 Crashes by Collision and Vehicle Type

	Collision Types	**Fatal Crashes**	**%**	**Severe Injury Crashes**	**%**	**Slight Injury Crashes**	**%**	**Property Damage**	**%**
1	Head –on collisions	6	5.36	0	0.00	0	0	248	3.51
2	Rear-end collisions	3	2.68	0	0.00	0	0	1330	18.81
3	Broadside collision	2	1.79	0	0.00	0	0	1387	19.62
4	Sideswipe collision	6	5.36	0	0.00	0	0	1653	23.38
5	Rollover	28	25.00	0	0.00	0	0	88	1.24
6	Collision with pedestrians	41	36.61	616	97.31	451	100	0	0.00
7	Fall from vehicles	5	4.46	0	0.00	0	0	11	0.16
8	Collision with animals	0	0.00	0	0.00	0	0	34	0.48
9	Collision with roadside parked vehicles	6	5.36	0	0.00	0	0	1025	14.50
10	Collision with road side objects	3	2.68	0	0.00	0	0	1295	18.31
11	With Train	0	0.00	0	0.00	0	0	0	0.00
12	Others	3	2.68	0	0.00	0	0	0	0.00
13	Unknown	9	8.04	17	2.69	0	0	0	0.00
14	Total	**112**	100.00	**633**	100.00	**451**	100	**7071**	0.00
	Type of Vehicles								
1	Cycle and Motorcycle	9	8.04	2	0.32	7	1.55	36	0.51
2	Automobile and Land Cruiser	12	10.71	318	50.24	266	58.98	1874	26.50
3	Commercial Vehicle	50	44.64	88	13.90	36	7.98	911	12.88
4	Minibuses and Buses	26	23.21	208	32.86	142	31.49	4242	59.99
5	Earth Moving	6	5.36	0	0.00	0	0.00	2	0.03
6	Rail	0	0.00	0	0.00	0	0.00	0	0.00
7	Animal Drawn Cart	0	0.00	0	0.00	0	0.00	6	0.08
8	Others	6	5.36	0	0.00	0	0.00	0	0.00
9	Unknown	3	2.68	17	2.69	0	0.00	0	0.00

4.2. Nominal regression Analysis

Base out come(#) specifies the value of dependent variable to be treated as the base outcome. The default is to choose the most frequent outcome.

An important feature of the multinomial logit model is that it estimates k-1 models, where k is the number of levels of the outcome variable. For our case, we have taken each outcome as a reference group turn by turn, and therefore estimated a model for each variable relative to the respective reference group.

Since the parameter estimates are relative to the reference group, the standard interpretation of the multinomial logit is that for a unit change in the predictor variable, the logit of outcome m relative to the referent group is expected to change by its respective parameter estimate (which is in log-odds units) given the variables in the model are held constant.

- Driver's gender is significant at 5% significant level relative probability of having **Slight injury** rather than having **PDO is 45.7%** lower (exp(-.610)=.543) for **Males** than for **Females**.
- Odds ratio or relative probability of having **Fatal** rather than having **PDO** is 45.5% higher (exp(.375)=1.455) for **Males** than for **Females**.
- The age of the driver increases, the probability of having a Fatal crash increases relative to the property damage only (at the 95% confidence level) and Relative probability of having serious injury rather than having PDO increases by 1.8% when driver's age increases by one unit. Whilst there is no effect of age in slight injury crashes relative to the PDO.
- The results indicate that the probability of having **Serious injury** and **Fatal** rather than having **PDO** decreases when education level increases by one unit.
- Driver's Experience was found to be significant in the **Serious injury** and **Fatal** crash functions at 95% confidence level. Relative probability of having **serious injury** rather

than having **PDO** decreases by 4.2% **Fatal** by 3.1% when driver's experience increases by one unit.

Parameter Estimates

status[a]		B	Std. Error	Wald	Df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Slightly injury	Intercept	-4.796	.560	73.346	1	.000			
	Age	.006	.005	1.470	1	.225	1.006	.996	1.016
	Experc	-.002	.006	.181	1	.671	.998	.986	1.009
	Educt	.036	.018	4.003	1	.045	1.036	1.001	1.073
	[sex=1]	-.610	.301	4.103	1	.043	.543	.301	.980
	[sex=2]	0[b]	.	.	0	.	.	.	.
	[owneship=1]	.189	.170	1.234	1	.267	1.208	.866	1.684
	[owneship=2]	-.390	.121	10.388	1	.001	.677	.534	.858
	[owneship=3]	0[b]	.	.	0	.	.	.	.
	[timeperiod=1]	1.357	.432	9.871	1	.002	3.886	1.666	9.064
	[timeperiod=2]	1.587	.368	18.590	1	.000	4.891	2.377	10.064
	[timeperiod=3]	1.667	.365	20.915	1	.000	5.296	2.592	10.821
	[timeperiod=4]	1.390	.375	13.742	1	.000	4.017	1.926	8.378
	[timeperiod=5]	1.420	.375	14.378	1	.000	4.139	1.986	8.625
	[timeperiod=6]	.706	.416	2.879	1	.090	2.027	.896	4.582
	[timeperiod=7]	0[b]	.	.	0	.	.	.	.
Serios injury	Intercept	-2.757	.634	18.882	1	.000			
	Age	.018	.005	11.736	1	.001	1.018	1.008	1.029
	Experc	-.043	.008	29.164	1	.000	.958	.943	.973
	Educt	-.053	.021	6.413	1	.011	.949	.911	.988
	[sex=1]	.090	.505	.031	1	.859	1.094	.407	2.941
	[sex=2]	0[b]	.	.	0	.	.	.	.
	[owneship=1]	-.147	.204	.515	1	.473	.864	.578	1.289
	[owneship=2]	-.538	.127	18.032	1	.000	.584	.455	.748
	[owneship=3]	0[b]	.	.	0	.	.	.	.

	[timeperiod=1]	-.665	.331	4.026	1	.045	.514	.269	.985
	[timeperiod=2]	-1.262	.249	25.641	1	.000	.283	.174	.461
	[timeperiod=3]	-.692	.208	11.097	1	.001	.500	.333	.752
	[timeperiod=4]	-.052	.198	.069	1	.793	.949	.644	1.400
	[timeperiod=5]	-.530	.217	5.939	1	.015	.589	.384	.901
	[timeperiod=6]	-.155	.218	.504	1	.478	.856	.558	1.314
	[timeperiod=7]	0^b	.	.	0	.	.	.	.
Fatal	Intercept	-4.453	.647	47.302	1	.000			
	Age	.012	.005	6.520	1	.011	1.012	1.003	1.022
	Experc	-.031	.007	22.247	1	.000	.969	.957	.982
	Educt	-.049	.019	6.594	1	.010	.953	.918	.989
	[sex=1 Male]	.375	.503	.556	1	.456	1.455	.543	3.899
	[sex=2 Female]	0^b	.		0	.		.	
	[owneship=1]	.049	.210	.055	1	.815	1.050	.696	1.586
	[owneship=2]	.197	.129	2.337	1	.126	1.218	.946	1.569
	[owneship=3]	0^b	.	.	0	.	.	.	.
	[timeperiod=1]	1.331	.309	18.567	1	.000	3.784	2.066	6.933
	[timeperiod=2]	.919	.273	11.341	1	.001	2.507	1.468	4.280
	[timeperiod=3]	.065	.289	.051	1	.821	1.068	.606	1.882
	[timeperiod=4]	.654	.282	5.369	1	.020	1.923	1.106	3.345
	[timeperiod=5]	1.033	.274	14.261	1	.000	2.810	1.644	4.805
	[timeperiod=6]	1.144	.281	16.587	1	.000	3.138	1.810	5.442
	[timeperiod=7]	0^b	.	.	0	.	.	.	.

a. The reference category is: PDO.

b. This parameter is set to zero because it is redundant.

Note: all other variables controlled

Table 4. 8 Regression Analysis output

4.3. Hot spot identification

Getis-OrdGi*techniques for finding crash Hot Spots is explained in detail in subsection 5.6.2 There is a tool in ArcGIS named Spatial Statistics Tools includes hot spot analysis techniques by Getis-OrdGi*. Output table from this tool returns the value of Z-score and the value of p-value for each location. The value of GiZscore represents the strength of being Hot Spots with statistical significance (represented by GiP Value The more the value of GiZ Scoreis, the more intense to be Hot Spots.

The Hot Spot Analysis tool calculates the Getis-OrdGi* statistic for each feature in a weighted set of features. The G-statistic tells us whether features with high values or features with low values tend to cluster in a study area. In this study invers distance is used for conceptualization of spatial relationship; that is when zero is entered for the "Distance Band or Threshold Distance" parameter all features are considered neighbors of all other features; when this parameter is left blank, a default threshold distance will be applied. And distance method used Euclidian distance which is the straight-line distance between two points.
This tool works by looking at each feature within the context of neighboring features, if a feature's value is high, and the values for all of its neighboring features are also high, it is a part of the crash hot spot.

The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance, a statistically significant Z score is the result. Basically the crash incidence classified in to three main parts ;High , Medium, Low depend up on their Getis-OrdGi* value that means as previously mentioned the more the negative value the more crash incident in that area and decrease negative value crash incidence is also low.

Using such parameters the research got the following crash clustering result which is categorized in to three main categories. The red one indicates very hot crash area that means crash clustering is dense. On the other hand the green color indicates that low crash clustering when compared to the red and yellow ones. Finally the yellow color indicates medium crash clustering on the area and in order to explain the pattern in terms of specific place; high car crash incidence areas like Hana

Mariam, saris, Jomo, Gotera and 58 mazoria ,Medium car crash areas recorded; Kera, Lebumeberat hail, gotera, Geremenadebabay, jomo, hana Mariam and kadisko. The rest of other car crash areas are cool spot area. The study shows that straight Road Geometry are more dangerous (hot spot) than curves and Roundabouts.

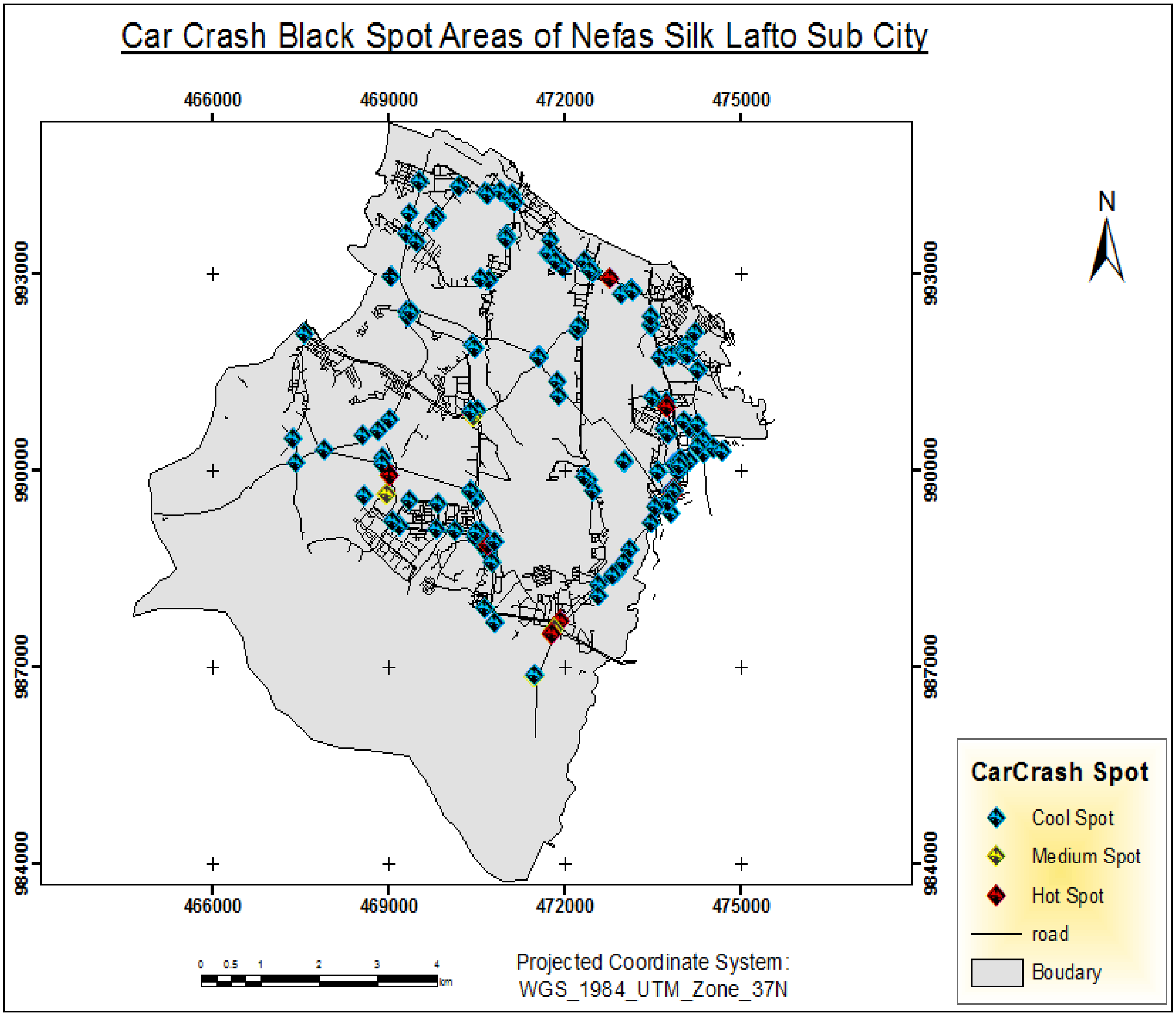

Figure 4. 2 Hot/black spot map

5. Conclusions and Recommendations

5.1. Conclusions

The objective of this study was to perform a statistical data analysis on crash data for N/silk lafto sub city and identify attributes associated with severity of crashes and identify hot spot areas. Crash Data from the Addis Ababa police commission and the respective sub city police department for the years 2013 to 2015 was used. Statistical models using Multinomial Logistic Regression were developed to analyze the influence of Driver's age, driving experience, driver experience, land use, Road and Road Profile, Road Alignment and Two-Vehicle Analysis on Severity of the crash. The model gives the descriptive statistics of the features of the crashes and a comparison of attributes of Crashes with severity slight injury relative to PDO and serious injury and Fatal relative to PDO. Differences in driving behavior between male and female

- The variation in road traffic crashes by sex reflects male drivers involve in Serious and Fatal injury than females. In a study by Storie (1977), significant differences in driving characteristics were found between the two sexes with regard to speed, skill, and attitude. Females were more likely to drive at lower speeds and overtake more carefully. Males, on the other hand, were generally more skillful, able to perform difficult maneuvers, and more likely to risk driving under the influence of alcohol.

- Analysis was carried out to investigate driver age correlation with crash trend. In the present study, drivers were categorized into four age groups. The results confirm a Highest Fatal crash injury rate was observed in age group 40-54 years. This may be attributed to overconfidence of this age group in their driving abilities.

- In terms of collision types, pedestrian crashes are the dominant types of collision, As pedestrians are the most vulnerable of all road users, they are overrepresented in crashes, especially fatal crashes, in comparison to their mode share of trips.

- Commercial vehicles, minibuses, and buses have a high involvement in crashes. Growing concern about traffic crashes is forcing some in the transportation sector to focus on crash avoiding techniques of driving, called defensive driving, and post-crash insurance mechanisms and higher training and licensing standards for professional drivers need in reducing road traffic crashes.

- Managing exposure to risk through transport and land-use policies: reducing the volume of motor vehicle traffic by means of better land use, providing efficient networks where the shortest or quickest routes coincide with the safest routes, encouraging people to switch from higher-risk to lower-risk modes of transport and placing restrictions on motor vehicle users, on vehicles, or on the road infrastructure.

- Address road safety in a holistic manner, that requires involvement from multiple sectors (transport, police, health, education) and that addresses the safety of roads, vehicles, and road users themselves.

- Designing safer infrastructure and incorporating road safety features into land-use and transport planning; improving the safety features of vehicles; and improving post-crash care for victims of road crashes. Interventions that target road user behavior are equally important, such as setting and enforcing laws relating to key risk factors, and raising public awareness. An increase in average speed is directly related both to the likelihood of a crash occurring and to the severity of the consequences of the crash. An adult pedestrian's risk of dying is less than 20% if struck by a car at 50 km/h and almost 60% if hit at 80 km/h. 30 km/h speed zones can reduce the risk of a crash and are recommended in areas where vulnerable road users are common like residential and schools areas. Apart from reducing road traffic injuries, lower average traffic speeds can have other positive effects on health outcomes (e.g. by reducing respiratory problems associated with car emissions).

- Drinking and driving increases both the risk of a crash and the likelihood that death or serious injury will result. The risk of being involved in a crash increases significantly above a blood alcohol concentration (BAC) of 0.04 g/dl. Laws that establish BACs of 0.05g/dl or below are effective at reducing the number of alcohol-related crashes. Enforcing sobriety checkpoints and random breath testing can lead to reductions in alcohol-related crashes of about 20% and have shown to be very cost-effective.

- Young and novice drivers are subject to an increased risk of road traffic crashes, when under the influence of alcohol, compared to older and more experienced drivers. Laws that establish lower BACs (≤0.02 g/dl) for young and novice drivers can lead to reductions in the number of crashes involving young people by up to 24%.

5.2. Recommendations

- Avoid distracted driving: - Anything that takes attention away from driving can be a distraction. Visual: taking eyes off the road, Manual: taking hands off the wheel; and Cognitive: taking mind off of driving. Sending a text message, talking on a cell phone, using a navigation system, and eating while driving are a few examples of distracted driving. Any of these distractions can endanger the driver and others.

- Avoid Rear-end crashes By keeping a safe following distance from the vehicle in front at all times, it will allow you time to brake gently when slowing or stopping.
- Introduce penalties offline, imprisonment, disqualification, or endorsements on licenses for careless driving.
- Traffic police has to check drivers for their drunkenness and impose suitable penalties.
- Prescribe maximum hours of work for drivers of commercial vehicles and buses to prevent them from fatigue.
- Prescribe uniform road signs throughout the country and provide for penalties for the non-observance of the same.
- Lay down rules for pedestrians when crossing streets and to impose penalties for their non-observance.
- Prescribe rules for the maximum size and weights (axle loads) of vehicles.
- Prescribe minimum standards for the design of vehicle.
- The major reason in relation to the causes of traffic crashes is the quality of training schools so it needs to inspect the training schools.
- The police department is better to use new technology for data storage and collection like GPS.
- The traffic police should record crash happening area by their relative location of specific location.
- New opening institutions should be established far from traffic crash spot areas.
- Traffic law enforcement and regulation should be strong.

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Annex 1: Data Collection Sheet

Crash hour	Date	Day of the week	year	Driver					Vehicle type	Vehicle ownership	Vehicle Service year (age)	Additional description on crash locations	Land use	Road Type	Road Geometry	3 Intersection type	Type of Road pavement	Road condition	Lighting conditions	Weather condition	Defendant Vehicle maneuvering condition	Type of crash	Type of severity
				age	Gender	education	ation wit	experience of the Drivers															