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An empirical Bayes model to assess deer-vehicle crash safety in urban areas in Iowa

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Abstract

Deer-vehicle crashes are a growing problem in Iowa. In 2008, deer-vehicle crashes represented 12% of all the crashes reported, which include 9 fatalities and 442 injuries. This is especially true in urban areas of Iowa, where the problem has been increasing. There has been quite a bit of research conducted on countermeasure action that could help solve this problem. However, there has been little previous work that attempted to model deer-vehicle crashes in urban areas using the two data sources available: deer carcass salvage reports and deer-vehicle crash reports. The objective of this thesis is to assess the safety of roadway segments using both deer-vehicle crash and deer carcass salvage data in an empirical Bayes model to predict crashes in select urban areas of Iowa.

In this thesis, three cities were selected with long-running deer management programs for evaluation. Data were collected from both the deer-vehicle crash and carcass salvage data bases. Records were reconciled to help eliminate double counting. Count data models were estimated that examined crash frequency as a function of roadway and environmental factors. The count model estimates were used to develop safety performance functions as part of an empirical Bayes analysis to assess the safety of sections of state-maintained roadway. Results were discussed, limitations were examined, and recommendations were made for future work.

Chapter 1: Introduction

1.1 Background Summary and Problem Statement

In the United States, 1.5 million deer-vehicle crashes occur every year that result in 150 fatalities and cost $1.1 billion (Hedlund et al. 2004). According to State Farm Insurance (2009), the nationwide average insurance claim for a deer-vehicle crash was $3,050. From past research, it has also been found that the cost of deer-fatality alone has been estimated between $23 million and $1 billion per year (Schwabe and Schuhmann 2002). Specifically, Iowa ranks among the top four states where drivers are most likely to be involved in a deer-vehicle crash within a year following the study release (probability of 1 in 104). In 2008, deer-vehicle crashes in Iowa accounted for approximately 12% of all the crashes that occurred and resulted in 9 fatalities and 442 injuries. During the period of 2000-2007, the number of fatalities in deer-vehicle collisions in Iowa increased from 1 to 12 (Iowa Department of Transportation 2008). Further, there has been an increasing problem with crashes occurring in urban areas because of factors such as increases in vehicle miles traveled, a higher deer population, and human migration into deer habitats.

Different countermeasures with varying degrees of success have been implemented over time to reduce the number of deer-related vehicle crashes (Knapp 2005). Many of these countermeasures can be expensive to implement. Resources for roadway improvements are in short supply in the current funding environment, so these countermeasures must be implemented where they will be the most effective in solving the problem. Frequently, crash numbers alone will not be enough to reveal if a section of road has a crash problem compared to other sections (Hauer et al. 2002). Therefore, a model needs to be developed to assess the crash risk in urban areas using carcass salvage data and deer-vehicle crash data with both roadway and environmental factors as criteria for ranking sections of roadway. The following section will outline the major research objectives and tasks of this thesis.

1.2 Research Objectives and Tasks

The main objective of this thesis is to assess the safety of segments of roadways in select urban areas in Iowa by developing a model using empirical Bayes (EB) to predict crashes using both deer-vehicle crash and deer carcass salvage data. The study period was 2002-2008. Results from this thesis can be used to better assess safety on these roadway sections and identify sections of roadway that are potential candidates for countermeasure action. The model could then be transferred to different areas by recalibrating the model to the new area's conditions.

The thesis reports on the following tasks:

Task 1: Literature Review

Past research on deer-vehicle crashes was reviewed and synthesized. Two major areas were examined in this review. The first area included studies on the effectiveness of countermeasures that have been undertaken to reduce the number of deer-vehicle crashes that occur. In the second area, various data collection and analysis techniques were reviewed and discussed. The techniques reviewed include different methods of collecting deer-vehicle crash and deer carcass salvage data, different ways of identifying high-crash areas, the examination of factors influencing deer-vehicle crashes, and analysis of crash and/or carcass data.

Task 2: Selection of Study Sites and Data Collection

Candidate cities were selected from those that have an urban deer management program in place. Those that were selected have had a long running program that was continuous through the study period. Three databases were used in this data: deer population counts from 1994-2010 acquired from the Iowa Department of Natural Resources (DNR), deer carcass salvage data from 2002-2008 obtained from the Iowa Department of Transportation (DOT), and deer-vehicle crash data from 2002-2008 were gathered from DOT through the Iowa Traffic Safety Data Service (ITSDS).

Task 3: Descriptive Data Analysis

A descriptive data analysis was conducted to quantify trends in the deer population, deer carcass salvage, and deer-vehicle crashes along state-maintained highways in the study area during the analysis period. In addition, the magnitude of underreporting of deer-vehicle crashes was examined using the deer carcass salvage and deer-vehicle crash data.

Task 4: Statistical Data Analysis

A model was developed to predict crashes along sufficiency segments from the Iowa DOT's Geographic Information Management System (GIMS). Crashes and carcasses were assigned to each segment based on geographic location. Then, crash and carcass records were examined to eliminate any double counting between the two databases. Next, count data models were examined to develop a safety performance function (SPF) for deer-vehicle crashes on state-maintained roadways during the study period. This SPF was then used in an EB model to develop the final model to assess the safety of and rank these segments.

Task 5: Conclusions, Recommendations, and Limitations

Based on the work conducted in this thesis, recommendations were made based on the findings to the appropriate agencies. Recommendations were made in the areas of data collection, data reporting, the empirical Bayes model developed, and on roadway segmentations. Limitations of the study and recommendations for additional research are also discussed.

Chapter 2: Literature Review

2.1 Overview

In this chapter, the past research in the area of deer-vehicle crashes is critically reviewed and synthesized. There are two major areas of deer-vehicle interaction that are examined. The first area includes studies on countermeasures, which have been implemented to reduce the number of deer-vehicle crashes that occur. These studies have evaluated the effectiveness of these countermeasures and identified future research needs. The second area includes studies on improving data collection and analysis techniques. Different techniques of collecting and comparing carcass and crash data are presented. The review concludes with a discussion on different methods and tools for identifying high crash areas or hot spots and different analysis techniques that have been used in the past.

2.2 Countermeasures

2.2.1 Categories

There are various countermeasures that have been implemented in order to reduce the growing number of deer-vehicle crashes throughout the world. These countermeasures have been applied with varying degrees of success. Following Knapp et al. (2004), deer-vehicle countermeasures can be grouped into three categories: i) driver-focused, ii) animal-focused, and iii) driver and animal focused measures. This section discusses the different types of countermeasures, while section 2.2.2 presents the findings of evaluation studies on the effectiveness of different countermeasures.

2.2.1.1 Driver-Focused Countermeasures

Some deer-vehicle crash countermeasures are targeted at drivers only. *Driver* *education* and *public service campaigns* are examples of driver-focused countermeasures. For example, the Iowa Department of Transportation issues newsletters that advise drivers what they should do in the case that they encounter a deer or other animal on the roadway (Iowa Department of Transportation 2009). Similar advice is offered by the Iowa Department of Public Safety (2006) through the "Don't Veer for Deer" campaign, whose main advice is to not to swerve if hitting a deer is imminent, as hitting the deer head on is normally safer than swerving off the road or into oncoming traffic. The effectiveness of these campaigns depends on drivers' perceived risk of a deer-vehicle collision and changes in their driving behavior as a result of the information they receive.

The second countermeasure in this category is *deer warning signs*. These signs are common on many roads throughout the country. However, limited research has been conducted to evaluate the effectiveness of the use of the sign in reducing crashes (Knapp et al. 2004). Possible enhancements to the existing deer warning signs have been proposed. Adding temporary signs could be more effective in areas with migratory deer species, however, in Iowa, the white-tailed deer is the only specie present. Since the white-tailed deer is not a migratory species, this temporary countermeasure might not be effective. Dynamic warning signs are a promising technology, where a beacon would turn on when an animal triggers a sensor. However, these systems are expensive and few studies have quantified their safety benefits.

The third type of countermeasure in this group includes *in-vehicle technologies*. These technologies include night vision systems that enable a driver to see an animal on the road much sooner at night than with only traditional headlights. However, these technologies are quite expensive and are only available on high-end vehicles. As such their effectiveness cannot be evaluated on a large-scale (Knapp et al., 2004).

The final countermeasure in this group is *speed limit reduction*. This countermeasure is based on the concept that drivers who are traveling slower have more time to react to hazardous situations that may arise while driving. However, the effectiveness of a speed limit reduction measure is debatable (Knapp et al. 2004). Most drivers drive at a speed that they feel is reasonable and prudent for given conditions, which is the reason for using 85th percentile speed as the baseline for setting speed limits. However, drivers will not usually follow a speed limit they feel is unjustly set too low, as it was shown with the nationwide implementation of a 55-mph speed limit in the United States from 1973 to 1995, as was evidence from a drop from 1996-1997 (when speed limits were increased in Iowa) from 71% to 35% of drivers exceeding the speed limit (Safety Management System Task Force on Speed Limits 1998). If this option is to be pursued, it has to be coupled with enforcement and public education campaigns that would explain the reasoning for implementing this measure.

2.2.1.2 Animal-Focused Countermeasures

A different set of countermeasures targets the deer population. *Herd reduction* is one such measure that is implemented mainly through deer hunting. A controllable deer population is a common factor in most approaches for deer-vehicle crash reduction. While this correlation has been generally acknowledged on the large scale, herd reduction has not been fully examined to date if this correlation hold true on a smaller area. A recent study (DeNicola and Williams 2008) examined the use of sharpshooting as a herd reduction measure and its effect on deer-vehicle collisions. Three sites were investigated: Iowa City, Iowa from 2000 to 2002; Princeton, New Jersey from 2001 to 2006; and Solon, Ohio from 2005 to 2006. The annual number of deer-vehicle crashes decreased by 49% to 78% in the three study sites. The study also found that population numbers did not rebound. While the study found sharpshooting to be an effective method of herd reduction in suburban areas, the study cautioned that sharpshooting can be a costly measure and as such, the benefit/cost ratio needs to be estimated in order to establish its cost-effectiveness.

Vegetation management addresses one of the reasons that deer travel near the roadway, as deer are looking for an easy, convenient food source. There are numerous guides available, which explain which plants are more susceptible to attract deer to an area according to Knapp et al. (2004). Deer are also attracted to sources of salt, such as deicing agents on the roads in the winter in colder climates. *Deicing salt alternatives* have been proposed as a possible countermeasure to keep deer away from roadways. In a study conducted in Canada from 1977-1979, it was found that moose were attracted to salt water pools, left from the salt used as a deicer on roadways mixing with rainwater. This study proposed that alternative deicers be examined to cut down on the number of salt water pools which would reduce moose-vehicle crashes (Fraser and Thomas 1982). While these measures have some merit, their effectiveness on a large scale is yet to be studied on deer (Knapp et al. 2004). The next countermeasure in this area is *intercept feeding*. This measure aims to keep deer from crossing the road to find food. A major drawback of this technique is that it can make the deer reliant on the feeding for a food source and could draw more deer to an area than those that are already present. In addition, there is the danger of chronic wasting disease (CWD). This is a disease that is similar to the mad cow disease. It is spread by direct contact between deer (CDC 2010). This has led states to ban feeding, such as the bordering state of Wisconsin, where CWD has been found in the deer herd in the southern part of the state (Fleener 2009). The proximity of CWD to Iowa can mean that this option might not be available in a bid to preserve the entire deer herd in Iowa. Another option for reducing the number of deer in a certain area is *repellants*. This measure involves applying a substance, normally a predator's urine, to make the deer move away from that area. However, when tested on the large scale, the results have been conflicting, as studies from different areas have had varying degrees of success in their implementation of this countermeasure due to different standards of measures used to find effectiveness. Furthermore, there is no evidence that these measures keep deer from crossing the road (Knapp et al. 2004).

Another measure in this category is *exclusionary fencing*. This involves putting up a fence around a roadway to keep the deer from attempting to cross it. These have been found to be effective in numerous studies (Hubbard et al. 2000; Clevenger et al. 2001); however the cost can be very prohibitive, especially if fencing is installed along long stretches of road (Knapp et al. 2004). Also, if fences are installed improperly without one-way gates, deer can become trapped inside the fence. These can also be effective if used with other countermeasures, such as wildlife crossings, in order to increase the overall effectiveness of the countermeasures (Hedlund et al. 2004).

Wildlife crossings involve constructing either an overpass or underpass for animals, such as deer, to safely cross a roadway. These have been found to be effective in numerous studies; however the cost can be very prohibitive. These projects rival many transportation projects in cost and can be perceived as a poor use of construction dollars. However, if these projects are planned well, the costs can be recovered with the benefits from crash reduction

(Knapp et al. 2004; Bissonette and Cramer 2008).

Deer flagging models, deer whistles, and *reflectors* are three other countermeasures that target deer. A *deer flagging model* consists of a model of a white tail deer with the tail up, which is a signal deer use for danger. *Deer whistles* are installed on a car in hopes of making a noise audible to deer that will scare them away from the car. However, it is questionable if the sound they produce can be heard by deer (Insurance Institute for Highway Safety 1993). Also, drivers may fall into a false sense of security after installing these on their car, and compensate for it by driving more aggressively (Knapp et al. 2004). The purpose of *reflectors* is to reflect a car's headlights to "freeze the deer in the headlights" off of the road. Reflectors have been installed in many places (such as Iowa City), but there have been conflicting results of effectiveness (Schafer and Penland 1985; Waring et al. 1991; Reeve and Anderson 1993; Ujvari et al. 1998; City of Iowa City 2008). This is an area where studies will be necessary in order to validate results (Knapp et al. 2004).

2.2.1.3 Driver and Animal-Focused Countermeasures

There are a few countermeasures that target both drivers and the deer population. *Roadway lighting* attempts to change deer crossing patterns and vehicle speeds. There has only been one study was done in this area (Reed et al., 1977 as cited in Knapp 2005), which did not find any reductions in vehicle speed, but found a reduction in crashes. However, one study cannot provide a precedent; more research is needed to validate the results. The other countermeasures in this area are taking deer-vehicle crash issues into r*oadway maintenance, design, and planning procedures*. The effectiveness of this countermeasure has not been fully examined to date. However, in the future, engineers and planners should evaluate the effects that certain construction or maintenance practices can have on the surrounding environment and wildlife (Knapp et al. 2004).

2.2.2 Studies on the Effectiveness of Countermeasures

In 2004, Hedlund et al. investigated the effectiveness of various countermeasures that have been implemented. Their report concluded that the effectiveness of *fencing* coupled with an overpass crossing has been scientifically proven. Some other measures that show potential of being effective but need more data in order to be fully evaluated are: herd reduction, roadside clearing, temporary signage, at-grade crossings (for migratory deer), and infrared driver vision. Countermeasures with limited effectiveness are reflectors, roadside lighting, intercept feeding, and deer repellants. Countermeasures that appear ineffective, based on evidence available, are education, passive signage, and speed limit reduction. Finally, methods that have not been claimed effective in scientific research are deer whistles and deer flagging.

A study (DeNicola et al. 2000) on urbanization and its effect on deer population was conducted throughout the United States. This study examined the effectiveness of many *lethal and nonlethal countermeasures* to combat deer population problems, including deer-vehicle crashes. General effects of these countermeasures are reported, rather than statistically proven. The authors concluded that deer population can be controlled with either lethal (hunts primarily) or non-lethal (trap and release deer elsewhere) management methods, and added that lethal methods (if administered properly) can provide better control than just moving the deer population elsewhere.

Danielson and Hubbard (1998) studied some countermeasures that can be used against deer-vehicle crashes in Iowa from a fresh approach. The authors also explained the impacts of crashes on the economy of Iowa and why countermeasure action is important. The study concluded that *fences* were the best countermeasure to reducing crashes, if they are maintained properly. They also stated that overpasses could work well with fencing on high speed facilities. Last, the authors identified driver education as an essential part of the solution to this growing problem.

A review of *dynamic warning systems* in North America and Europe is presented in (Huijser and McGowen 2003). Numerous systems that were already in place at the time, as well as some future sites were evaluated. However, it was found that more research should be done on these systems to prove them to be effective. A follow-up study (Huijser et al. 2009a) on the effectiveness of dynamic warning systems was conducted on a roadway in Yellowstone National Park in Montana to examine if dynamic warning signs could detect elk more accurately and could be attached to the system. Small reductions in speed were found as a result of these systems. These signs were also generally accepted by the public. However, Yellowstone National Park required the removal of the system at the end of the study, so additional data on their effectiveness was not possible to collect.

The effectiveness of different *detection systems* was evaluated in a pen, using horses and llamas (Huijser et al. 2009b). Reliability standards were established using input from the stakeholder groups of employees of transportation agencies, employees of natural resource agencies, and the traveling public. The authors found that direct comparison cannot be conducted due to the different ways of detecting large animals, and diverse environmental conditions. While "false positives" were not an issue, "false negatives" were a problem for some systems. When comparing the systems to the reliability standards that were established, five of the nine systems met the standards. The author pointed out as an area for future work the integration of these systems with intelligent transportation systems (ITS).

When the current Federal Highway authorization bill, SAFETEA-LU was passed in 2005, a provision was included to conduct a national study on wildlife vehicle crashes (Huijser et al. 2007a). It was found that about 5% of all crashes were animal-related. It was also found that while fatalities are low, the economic cost of these crashes is estimated to be \$8.4 billion per year. *Fences* were found to be 80-99% effective, while *wildlife crossings* were almost 100% effective, however at a higher cost for installation. This study also outlined the need for better planning of roadways to mitigate potential wildlife-vehicle crashes.

A study on the use of *repellants* in road salt to prevent caribou from using it for a salt lick conducted in Alberta, Canada (W. Brown et al. 2000). The products were tested on 14 caribou during a five day period. One repellant, Wolfin, was not effective at all. The second, Deer Away Big Game Repellent, was effective at first, but as the study moved on, the effectiveness tapered off. The third one, lithium chloride, was found to be effective. However, it was noted that lithium chloride could be potentially toxic to smaller animals, so further tests need to be carried out in order to evaluate the potential environmental impacts.

A study was conducted to investigate the future of *hunting* as a deer management program (T. Brown et al. 2000). At the time, the recreational hunt was being evaluated in terms of its effectiveness to control the white-tailed deer population. The authors argued that recreational hunting alone would not work, due to a decrease in hunting and human intrusion into deer habitat. The authors suggested that, while hunting will still be the major measure to control deer population in the near future, a combination of recreational deer hunting and other techniques, such as sharpshooting or culling, will be needed for good deer population control.

Kilpatrick and Walter (1999) led a study on the effectiveness of *urban archery hunts*. In the study, hunters in a residential community in Connecticut had to pass a rigorous proficiency test in order to hunt. During the first year of the hunts, the study found that deer population decreased by 50%, no deer-vehicle crashes were recorded, and that residents noticed a reduction in property damage caused by deer. In view of these findings, the authors concluded that bow hunts can be an effective tool for controlling urban deer populations.

Different *deer population management* programs in the Washington D.C. metropolitan area (including Maryland, Virginia, and the District of Columbia) are discussed in a report published by the Metro Washington Council of Governments (Bates et al. 2006). In Fairfax County, the City of Lynchburg, and the Town of Blacksburg in Virginia, and Montgomery County in Maryland, the number of deer-vehicle crashes decreased after deer management programs were implemented. However, the authors cautioned that the effectiveness of these programs cannot be evaluated solely on the decreasing trends of deer-vehicle crashes, but rather need to be proven by scientific testing.

A technique of *contraception* for the deer population has been something that wildlife biologists have been looking into using for years. Rutberg and Naugle (2008) studied the use of an immunocontraceptive on deer population and on deer-vehicle crashes. The immunization was administered between 1995 and 2003 on the campus of the National Institute of Standards and Technology in Gaithersburg, Maryland. The data for population and deer-vehicle crashes were examined between 1994 and 2004. An exact test was carried out for seasonal differences, and a multiple regression using Pearson Correlation coefficients was used to examine the relationship between crashes, population, and the administration of contraceptives. Within this analysis, the authors found that deer mortality resulting from a deer-vehicle crash was not affected by the administration of contraceptives (ie. if a deer was hit, the chances of it dying were not affected), but the contraceptives were effective in reducing the population, which the authors associated with the reduction of deer-vehicle crashes in the study area. However, there are additional barriers that must be addressed before the widespread use of this product is advocated, such as long-term population effects and public acceptance.

2.3 Other Studies of Interest

2.3.1 Studies on Data Collection Techniques

A study, funded by the National Cooperative Highway Research Program (NCHRP), was conducted in 2007 documenting how data on animal-vehicle collisions were collected across the States and Canada (Huijser et al. 2007b & Huijeser et al. 2007c). To achieve this, the researchers sent out surveys to the States and Canadian Provinces to gather information on the methods that were used to collect data on animal-vehicle collisions. It was found that in most states and provinces, the Departments of Transportation and/or Departments of Natural Resources (or similar agencies) keep track of these collisions. However, the data collection was found to be managed differently; little emphasis was put on the animal itself (specie identification, etc.), and the spatial data were often found to be without specific geographic coordinates. These limitations of the data prohibit further analysis of animal-vehicle collisions. Another of the concerns was that these agencies were collecting data for different reasons and had different methodologies, and for the benefit of both, this should be done in a more coordinated matter. This is not just on the collection, but on crash reporting thresholds (the dollar amount at which a crash report is legally necessary), and to get a more centralized data base.

A study conducted in Virginia documented the need for better carcass data collection (Donaldson and Lafon 2009). In this study, maintenance workers were provided with global positioning system (GPS) units to record the locations of deer carcasses. The study found that nine times as many carcasses were recorded compared to the number of deer-vehicle crashes reported to police. The authors recommended a broad implementation of this technology in Virginia, and concluded that improving the accuracy of the carcass removal data can be valuable in determining where countermeasures should be implemented.

2.3.2 Studies on High-Risk Locations (Hotspots)

A study conducted on Australia's Snowy Mountain Highway developed a model of wildlife fatality hotspots for different animals (Ramp et al. 2005). In this study, five different animals were examined. The study included the use of fatality surveys (carcass data) that was collected using GPS devices during a roadside survey. These were then plugged into GIS software to assess clustering and to assign environmental variables. A predictive model was then developed using these variables to find hotspots. In conclusion, the authors found that the best way to find high crash locations is by spatial data analysis, however, predictive models can be used with caution to find areas for possible mitigation.

A study, funded by the National Cooperative Highway Research Program, was conducted on the evaluation of *wildlife crossings* (Bissonette and Cramer 2008). A software tool was developed to help agencies select the best locations for wildlife crossings. High-risk locations were identified with the estimation of safety performance functions, which were calibrated on crash data. The authors recommended the use of global positioning system (GPS) units in the field for locating carcasses, and using these data for hotspot modeling. In addition, the study concluded that wildlife crossings should be used on roadway sections with high wildlife-vehicle crash rates, but they need to be properly spaced along the roadway so that they are not too dense that the wildlife will not use all of them or too sparse so that animals will cross the road anyway.

A wildlife and domestic animal accident toolkit was developed in Utah (West 2008). A wildlife collision hotspot was identified as a location with 10 or more crashes per mile in a three-year period, while a domestic animal collision hotspot was identified as one that has three or more such crashes in the three-year period. The author also reviewed previous literature on mitigation measures and their effectiveness, and concluded the importance of planning and designing roadways with animals in mind.

Using data on animal-vehicle collisions from 1986-2004, Crooks et al. (2008) identified animal-vehicle collision hotspots in Colorado. The authors used geographic information tools and spatial statistics (the Getis-Ord statistic in ArcMap) for the determination of hotspot locations. These statistics were then used to rank sections based on both fatality/injury and property damage only crashes and identified the top 1% and 5% sections for further study.

2.3.3 Factors Influencing Deer-Vehicle Crashes

Hubbard et al. (2000) conducted a study to identify the environmental factors that contribute to deer-vehicle crashes in Iowa. The study examined deer-vehicle crashes that occurred on state maintained roadways during the period 1990-1997. The authors observed that over 25% of the crashes occurred at about 3.4% of the mileposts on the network. The authors conducted a stepwise logistic regression model to examine which variables would contribute the most to determining a high deer-vehicle crash location. In this analysis, the authors found that the number of lanes and number of bridges influenced at a higher degree the designation of a high deer-vehicle crash location, while variables such as grass patches and tree patches had a much lower impact. Based on these results, the authors recommended that deer underpasses should be a consideration when designing a roadway with many bridges so that deer can use them to cross the roadway obstacle.

Bissonette and Kassar (2008) conducted a study in Utah to examine if average annual daily traffic (AADT) and posted speed limits had an effect on deer-vehicle crash rates. In the study, crash data, AADT, and speed data were collected for the analysis. Multiple regression analyses were conducted to explore those relationships. Surprisingly, speed or AADT were not found to have any relationship to deer-vehicle crashes on any of the roadways examined. However, the authors recommended that these factors should be still considered in future studies of deer-vehicle crashes, as these results might be attributed to the specific data used in this study.

Hussain et al. (2007) conducted a study to identify the factors that influence the probability of deer-vehicle crashes in Alabama. Crash data were collected at the county level from 1994 to 2003. The authors also collected data on the number of registered vehicles per mile, land use, deer density, hunting licenses, and metropolitan statistical areas (MSA). Using a negative binomial model, the researchers found that cropland reduced the probability of crashes, while pasture and urban use relative to woodland land use increased the probability of crashes. In addition, higher deer population density in a MSA, and higher density of vehicles per kilometer increased the probability of crashes occurring, while higher number of hunting license sales and deer harvest limits reduced the probability of crashes occurring. The authors acknowledged that these findings were limited to their data that mainly reflected major crashes.

In 2002, Schwabe et al. released a study that examined the costs of deer-vehicle crashes and the influence of different mitigation techniques. The study, conducted in Ohio at the county level, used harvest figures to assess hunting regulations. The study used a dynamic population model with the population growing logistically and taking into account the number of vehicle registrations and hunting regulations. Simulations were then carried out to model the deer population and number of crashes. It was found that as hunting regulations allowed for a larger harvest, crashes went down. The study also found that buck harvests have strong impacts in the short term while doe harvests have strong impacts in the long term. The study also found deer management to be a low cost, highly effective strategy to combating deer-human interactions.

Ng et al. (2008) conducted a study in Edmonton, Alberta, Canada for the period 2002-2004 to estimate deer vehicle crashes as a function of environmental and traffic variables. Data sources for this study included: crash data, data for landcover provided by the Canadian government through the program GeoGratis, and street network data from GeoEdmonton. Three levels of analysis were conducted: 1) high precision, where each crash was assigned to the closest intersection; 2) aggregate, where each crash was assigned to the closest intersection in the grid system for township and range; and 3) a hotspot model. The authors estimated logistic and ordinal regression models and found that speed and road density had the most effect, while specific types of land use were not as strong of a factor, except for water in the aggregate model.

Nielsen et al. (2003) conducted a study in Bloomington and Maple Grove, Minnesota during 1993-2000 to find environmental factors that influence deer vehicle crashes. This was done using buffered road segments with having two test groups: 80 sections with less than two DVCs and 80 sections with more than two DVCs in the study period. Land use variables were calculated using land use information and satellite images. Roadway factors such as curves and speeds were put into bins for analysis. A regression analysis was done to find which factors were influencing the crashes. From the analysis, the authors found that crashes are more likely to occur in areas with high amounts of forest cover. The crashes also occurred in areas with fewer buildings, meaning less human settlement. The authors concluded that reducing forest cover if practicable and accecptable would be the best option, but putting countermeasures in place like fences and wildlife crossings along with a deer management program should help to minimize the deer-human interactions.

Using data from 1988-2001 in the Soria Province of Spain, Malo et al. (2004) examined if predictive models are appropriate for finding areas to mitigate animal-vehicle crashes. The data used had 2067 records of collisions that were broken down into two sets: one kilometer long sections of high and low crash locations and one-tenth kilometer points of crash or no crash instances. A regression model was set up in the analysis, and it was found that crashes were more likely to occur in areas with high forest cover, low crop cover, low numbers of buildings, and a diverse habitat. The model was successful at both scales in finding the factors that influence high crash locations. The authors suggest use of such models in the future to help make roadway construction decisions and for crossing structure location.

2.3.4 Analysis of Crash and/or Carcass Data

Knapp et al. (2007) investigated the differences between the deer carcass and deer-vehicle crash data in Iowa during the period 2001–2003. Geographic information systems were used to visualize and compare the data spatially on two selected corridors. Crashes were not moved from the milepost assigned, while carcasses were assigned to the nearest milepost. Overall, the number of deer carcasses removed from those corridors was greater than the number of reported deer-vehicle crashes on those corridors. These differences can be attributed to a number of reasons, including variability in data reporting and data collection practices. The authors also developed negative binomial regression models to estimate the frequency of crashes and carcasses as a function of AADT and other roadway cross-section characteristics, such as shoulder width, number of lanes, median type, and pavement width on rural roadways. The estimation results were compared and it was determined that the model based on crash data had a better explanatory value than the model based on carcass data since crash data are modeled more precisely than carcass data. In addition, the models as a function of AADT and other cross-sectional variables did not have a better statistical fit than the models as a function of AADT only. The authors noted that these models could be modified as appropriate and used in an empirical Bayes approach. Last, it was concluded that preferably, both the deer carcass and deer-vehicle crash data should be used to describe the deer-vehicle interaction problem, but caution should be exercised to avoid double-counting.

The NCHRP report (Bissonette and Cramer 2008) discusses various analysis techniques for crash and carcass data analysis. The objectives of this study were to examine the differences between using crash and carcass data for identifying high crash locations; and also, examine if the two data sets have different relationships with roadway cross section characteristics. Environmental factors were not considered in this study as these are not present in most DOT databases. The researchers developed safety performance functions using an empirical Bayes method on rural roadways in California, Utah, North Carolina, and Washington. The researchers found that many of the roadway characteristics did not relate strongly to the crash data. The researchers also concluded that using crash or carcass data should be only if the data are present. The developed safety performance functions, if developed and calibrated correctly, can be used to determine high crash locations and evaluate countermeasure effectiveness.

2.4 Summary/Conclusions

This chapter summarized the previous work in the area of animal-vehicle crashes, which included countermeasures and studies on their effectiveness, data collection, hot spot identification, and critical data analysis. Many countermeasures, such as deer whistles and deer flagging models, have been proven ineffective; a few countermeasures, such as wildlife crossings and deer fencing, have been proven effective; while for some countermeasures (including herd management) more research is needed to evaluate their effectiveness. In addition, many studies have been conducted on data collection techniques and modeling. Many of these studies have led to the improvement of the data that is collected in the field, which can in turn lead to more accurate identification of problem areas and countermeasure effectiveness evaluation. In addition, past studies have provided valuable insights into appropriate modeling techniques to describe the magnitude of the deer-vehicle interaction problem. Although some studies have been conducted using empirical Bayes to evaluate crash locations, very few have attempted to use both crash and carcass data in an urban area. In addition, most models are calibrated based on only roadside or environmental variables, but not both. After evaluating these studies, the need to conduct a study within urban areas in Iowa with deer management programs in place became apparent. Deer-vehicle crash and deer carcass salvage data were therefore collected for the selected areas. These data sources were combined and carcass records would be eliminated if a corresponding crash record exists. Chapter 3 presents a description of the data available for analysis. The data are examined for major contributing factors and to examine the interaction between data sources. In Chapter 4, a model is calibrated based on these data, using empirical Bayes, to assess the safety of roadway segments in terms of deer-vehicle crashes.

Chapter 3: Data Description and Descriptive Analysis

3.1 Selection of Cities

Three cities in Iowa were selected for this study from those that had active deer management programs in place during the study period. The cities were selected for the length of the ongoing management plan, availability of deer population, deer carcass salvage, and deer-vehicle crash data, and adequate numbers of state maintained roadways that traversed the city. With the last requirement, the candidate cities were narrowed down to major urban centers in Iowa. The following cities met the requirements and are listed below with some vital statistics.

The first city is Dubuque. Dubuque is located on the Mississippi River in the northeastern part of the state and is the county seat of Dubuque County. The city has a population of 57,686 people according to the 2000 Census, making it the eighth largest city in the state. Dubuque has been conducting deer management archery hunts since 1997.

The second city is Iowa City. Iowa City is located in the east-central part of the state. The city is the county seat of Johnson County and home to the University of Iowa. Iowa City has a population of 62,220 people according to the 2000 Census, making it the sixth largest city in Iowa. The city has been hiring sharpshooters since 1999 to conduct deer management hunts.

The third "city" is the metropolitan area of Waterloo and Cedar Falls. These cities are located in the northeast part of the state. Waterloo is the county seat of Black Hawk County while Cedar Falls is the home of the University of Northern Iowa. Waterloo and Cedar Falls have a combined population of 102,807 people according to the 2000 Census (individually, Waterloo and Cedar Falls have populations of 66,662 and 36,145 people respectively). Waterloo is the fifth largest city in Iowa, while the metropolitan area is the fourth largest in the state. The cities have been conducting deer management archery hunts since 1994.

3.2 Deer Population

Deer population data were obtained from the Iowa Department of Natural Resources (DNR). These data are collected by zone in Dubuque and Iowa City. The entire zone is not necessarily within the city, nor do all zones cover the entire area of the city. These zones attempt to capture major areas of deer habitat. Waterloo-Cedar Falls data were delivered in two general areas, which are situated on parkland located near the Cedar River and Black Hawk Creek. Maps of these areas can be found in Appendix A.

Deer populations within each zone are counted by aerial surveys that are conducted in January or February each year. These surveys are not a perfect method of counting the deer population, as they are affected by weather; in some cases the survey cannot be conducted or completed because of adverse weather conditions. In the areas under examination, Dubuque does not have all zones evaluated every year, as well as no surveys were conducted in Iowa City in the years 1998, 2004, 2006, and 2009. Figures 3.1 to 3.3 show the deer density in each zone (in deer per square mile). The limit line in each graph corresponds to the limit each city has set, in consultation with the DNR, for its "optimal" deer population: 20 deer per square mile in Dubuque, 25 deer per square mile in Iowa City, and 30 deer per square mile in Waterloo/Cedar Falls. In Dubuque and Iowa City, zones are assigned letters by the DNR for identification purposes. In Waterloo-Cedar Falls, these zones are named after the surrounding landmarks for identification purposes. The points were connected with lines for visual purposes only; the lines connecting the points from year to year do not represent any trends. Then, a weighted average deer density per city is estimated by dividing the deer population by the area surveyed to enable a comparison of the three cities. This is shown in Figure 3.4.

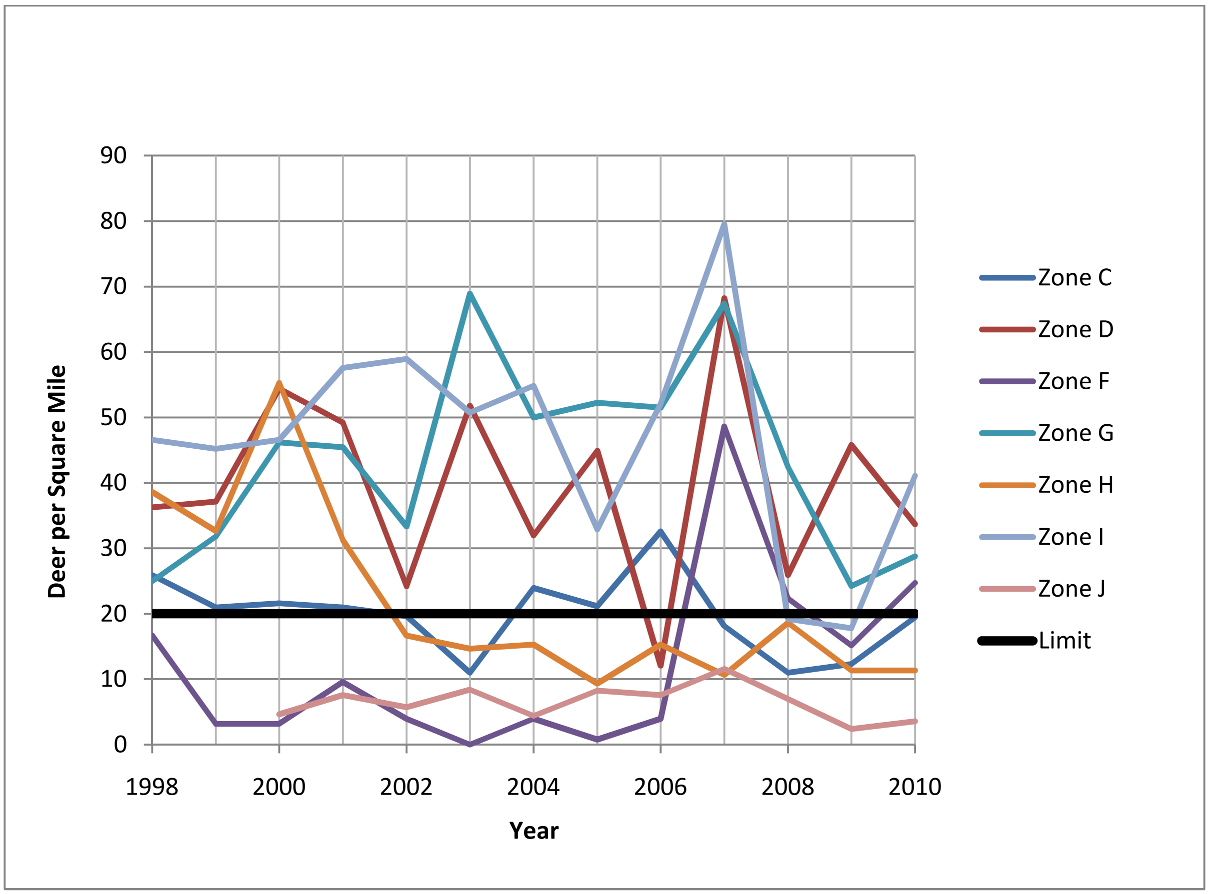

Figure 3.1. Deer density by zone in Dubuque, 1998- 2008

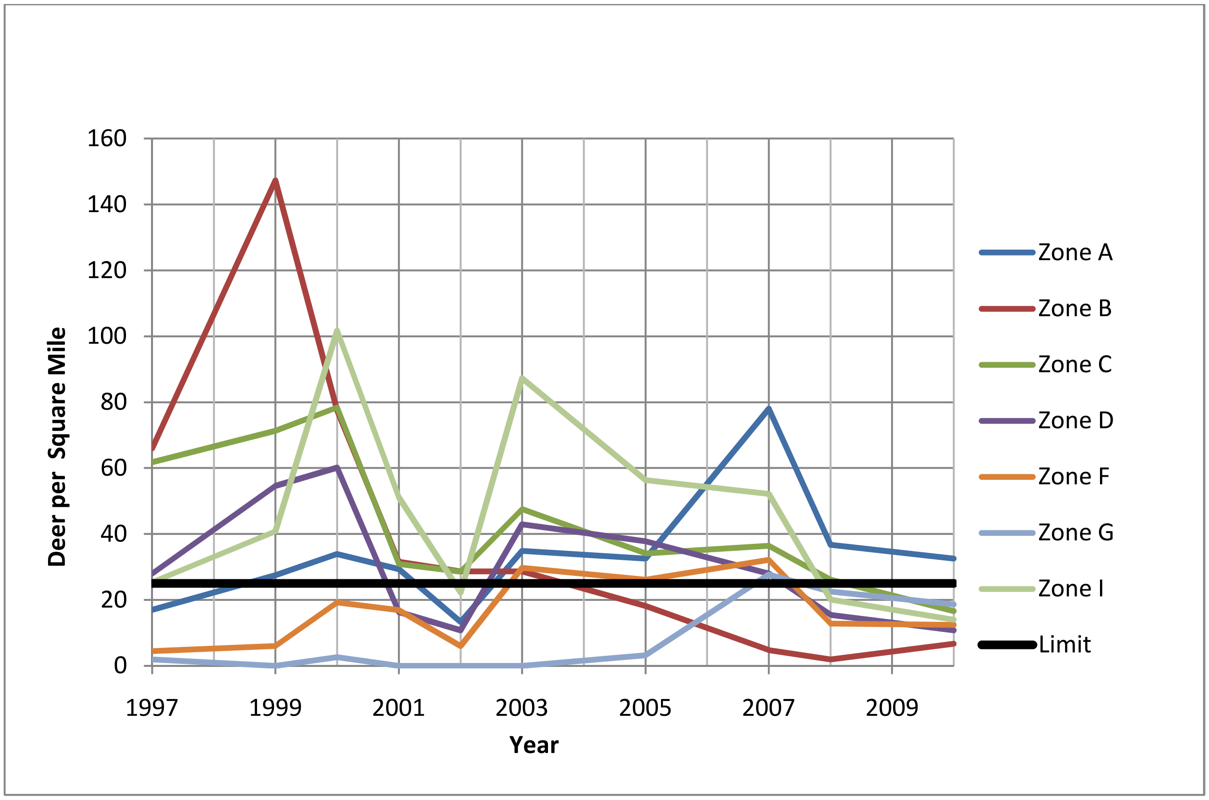

Figure 3.2. Deer density by zone in Iowa City, 1997- 2010

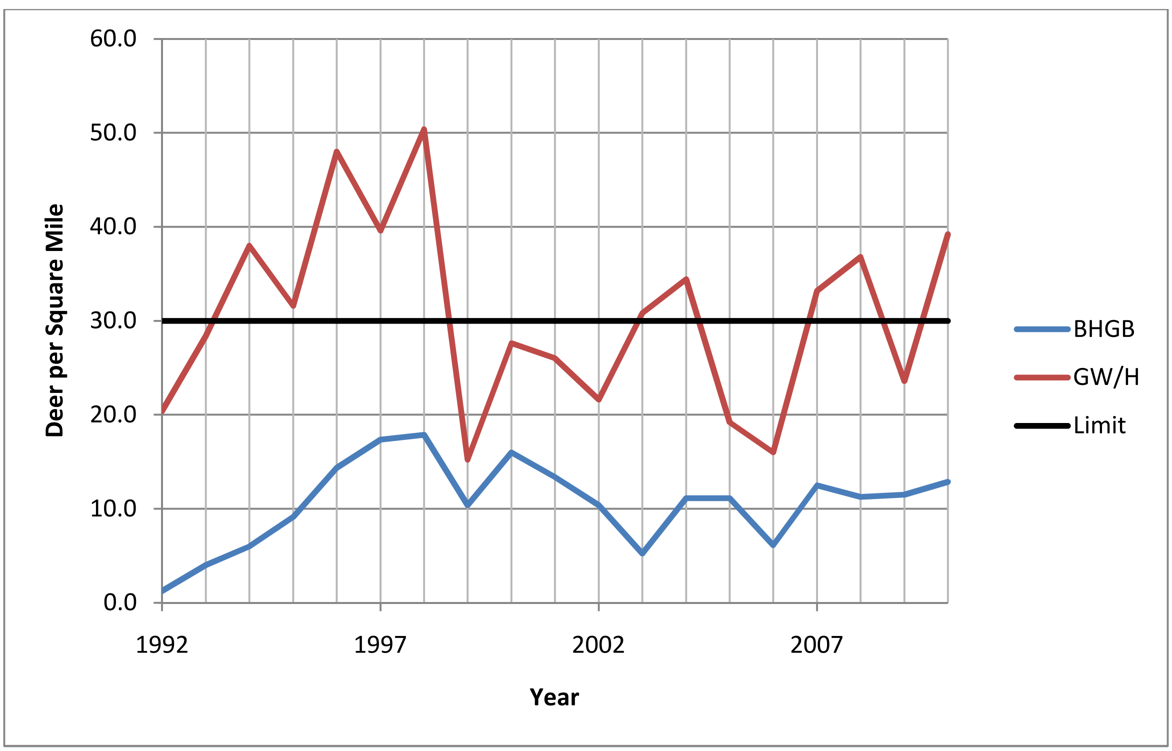

Figure 3.3. Deer density by zone in Waterloo-Cedar Falls, 1992-2010

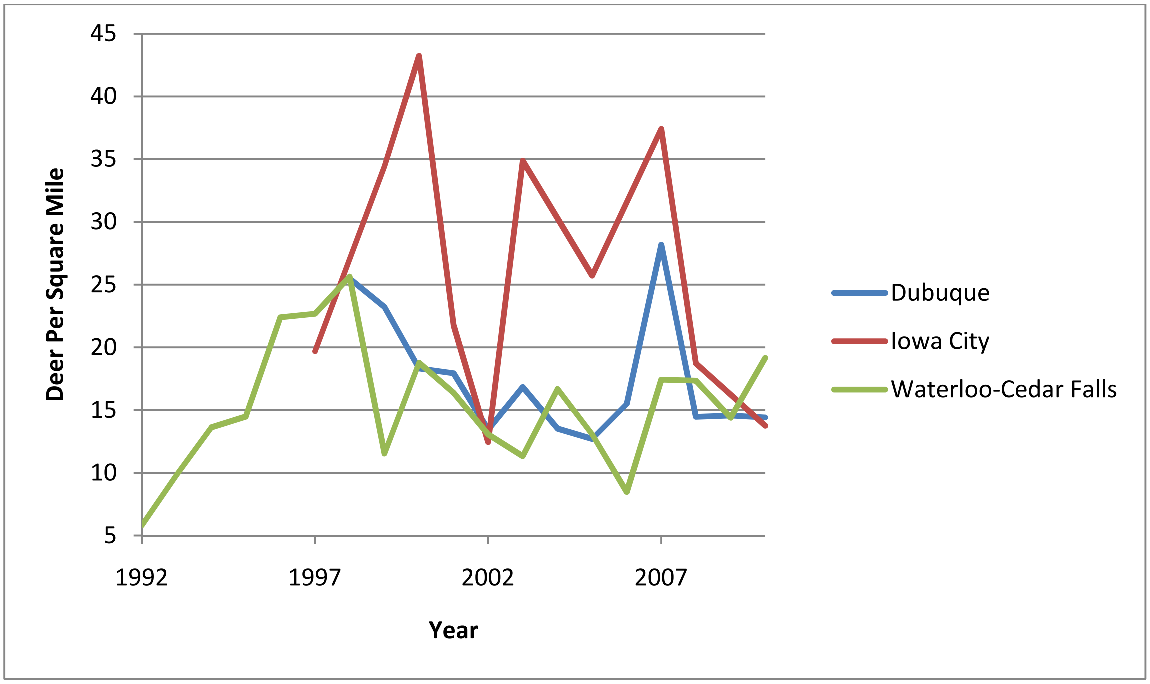

Figure 3.4. Average deer density for Dubuque, Iowa City, and Waterloo-Cedar Falls, 1992-2010

As is shown in the graphs, deer population fluctuates from year to year. Deer density has been trending downward in the last couple of years in Dubuque and Iowa City, but has been going back up in 2010 in Waterloo-Cedar Falls. A two sample t-test was conducted pairing the cities together for comparison of deer population figures. The comparison between cities showed that there were no statistically significant differences between the deer density in Waterloo-Cedar Falls and Dubuque ($p > 0.05$). However, the differences in deer density between Iowa City and the other two cities were found to be statistically significant ($p < 0.05$).

3.3 Deer Carcass Salvage Data

Deer carcass salvage locations and the corresponding carcass counts that were picked up on a state maintained roadway in a given year by maintenance crews were obtained from the Iowa Department of Transportation (DOT). These records were sorted by route number and milepost which was recorded to the nearest tenth of a milepost by the maintenance crews. A sample of a carcass report is shown in Table 3.1.

Table 3.1. Sample of Deer Carcass Salvage Report-US-20 in Black Hawk County in 2002.

Route	District	Milepost	County	Month	Day	Year	Sex
20	2	23.2	7	1	11	2002	1
20	2	64.8	7	7	2	2002	3
20	2	221.4	7	4	15	2002	2
20	2	224	7	6	4	2002	3
20	2	224	7	6	3	2002	3
20	2	224.3	7	7	30	2002	2
20	2	224.8	7	11	14	2002	1
20	2	224.8	7	11	14	2002	2
20	2	226	7	3	15	2002	2
20	2	226.3	7	11	18	2002	1
20	2	227.5	7	7	10	2002	2
20	2	231	7	10	10	2002	1
20	2	231.1	7	8	8	2002	2
20	2	231.5	7	11	4	2002	2
20	2	232	7	11	19	2002	2
20	2	232	7	7	22	2002	2
20	2	232.1	7	6	25	2002	2
20	2	239.2	7	3	7	2002	3
20	2	239.4	7	6	21	2002	3
20	2	240.2	7	3	7	2002	3
20	2	240.3	7	5	30	2002	2
20	2	241	7	6	13	2002	2
20	2	245	7	8	2	2002	1
20	2	245.8	7	5	6	2002	3

These carcass records were then assigned to a roadway segment as defined by the GIMS data provided by DOT. The GIMS system was created to document the centerline of every roadway within the state of Iowa. The data are coded for use in geographic information system (GIS) software. Each segment is given attributes such as traffic volume, pavement characteristics, and roadway characteristics. Each segment that is maintained by the state has a sufficiency code, which allows for the linking of similar segments to form longer segments, with the longest segment used for defining attributes. The number will change if roadway characteristics change drastically (for example, a lane is added) or geography changes (for example, a road crosses a county line). Sufficiency segments in urban areas vary greatly in length, with the suggested length to be 80 meters, or about 250 feet in length, although segments can be shorter if conditions warrant. Once the sufficiency segments were established, carcasses were assigned to them. Each carcass was assumed to have been killed on the segment on which it was found, and its record was therefore joined to the GIMS record with those attributes. These attributes can be used to analyze carcass data. In addition to the roadway data available in the GIMS dataset, land use data from the DNR were added spatially based on the location of the roadway segment.

Within the study area, 1,118 carcasses were collected between the years 2002 and 2008 on state-maintained roadways within the city limits of the selected cities. A breakdown by year and city is shown in Figure 3.5.

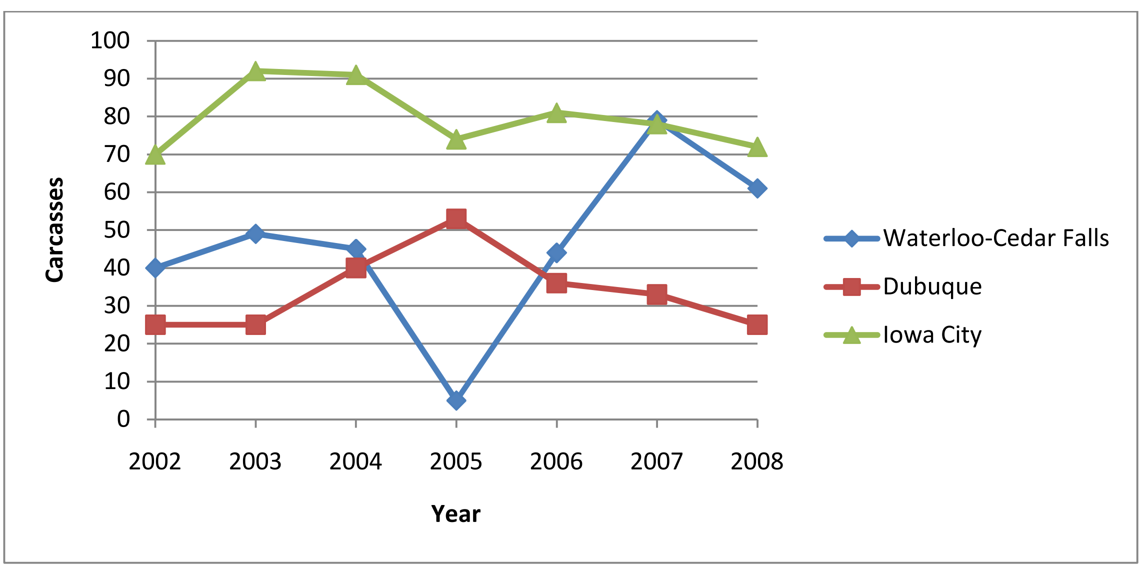

Figure 3.5. Deer carcass salvage counts on primary roadways, 2002-2008

In this chart, it is observed that carcass reports fluctuate from year to year. However, the difference in deer carcass from year to year is within a range of 20-30 carcasses. The one exception to this is Waterloo-Cedar Falls. In 2005, carcass salvage decreased, but returned to its normal numbers in 2006 before dramatically rising in 2007 and remaining high despite a decrease in 2008.

Road specific variables were examined to evaluate the carcass salvage reports. Select results are shown in Table 3.2. Most of the carcasses were found on roadways that were four lane US highways, with a speed limit of 65 mph. Most of these carcasses were found in the months of May, June, October and November. A copy of the JMP outputs can be found in Appendix B.

3.4 Deer-Vehicle Crashes

Deer-vehicle crash data were collected from crash reports. These reports are completed by state and local law enforcement agencies and aggregated by the DOT. The Iowa Traffic Safety Data Service (ITSDS) at the Institute for Transportation (InTrans) at Iowa State University (ISU) assembled all the crash data that occurred within the cities in the study area that had an animal listed as the major cause, was the first harmful event, or was in the chain of events to collect every possible crash that involved deer. While the listing of animal as a major cause does not mean that the animal is a deer, in this study, each of these crashes, the animal was assumed to be a deer. In order to be certain, every crash report would have to be obtained and the narrative would have to be read in order to know for certain. Crash data were collected from 2002 to 2008. 2002 was selected as the beginning year as it was the first full year that Iowa's standardized crash reporting form allowed for the person filling out the

Table 3.2 Summary statistics of select variables for carcass salvage in three study cities

Variables	**Mean (standard deviation) or Percentage [1]**
Month of Salvage Jan/Feb/Mar/Apr/May/Jun/Jul/Aug/Sep/Oct/Nov/Dec	5.6/2.4/5.8/6.2/13.2/11.1/3.8/2.8/3.8/ 14.3/23.3/7.5
Year of Salvage 2002/2003/2004/2005/2006/2007/2008	12.1/14.8/15.7/11.8/14.4/17.0/14.1
System Interstate/US Highway/Iowa Highway	29.6/58.6/11.8
City Waterloo-Cedar Falls/Dubuque/Iowa City	28.9/21.2/49.9
Federal Function Interstate/Other Principal Arterial/Minor Arterial	29.6/69.9/0.4
Planning Classification Interstate/Commercial-Industrial Network/Area Development/Access Route	26.6/55.7/10.5/4.2
Median Type None/Hard Surface without barrier/Grass without barrier/Grass with barrier/Barrier	7.9/0.9/81.1/4.1/6.0
Median Width-feet	41.5 (22.8)
Number of Lanes 2/3/4/5/6/7	3.4/1.0/76.0/2.8/ 16.7/0.1
Pavement Type Asphalt/Concrete	46.5/53.5
Shoulder Type-Right None/Earth/Gravel/Paved/Combined	5.8/0.4/45.3/46.8/ 1.6
Shoulder Type-Left None/Earth/Gravel/Paved/Combined	14.7/0.5/35.7/48.2/ 0.9
Shoulder Width-Right (feet)	9.3 (2.4)
Shoulder Width-Left (feet)	5.4 (2.5)
Speed Limit Below 55 mph/55 mph/65 mph	25.0/21.6/53.5
Average Annual Daily Traffic (vehicles/day)	25,566 (13,755)
Landcover (percent occurrence within) Water-Wetland/Forest/Grassland/Corn/Roadway/Commercial-Industrial/Residential	0.7/0.5/5.5/0.8/41.1/ 49.8/1.6

[1]In this table, means and standard deviations are reported for continuous variables while percentages are reported for categorical variables.

report to select animal or object in the roadway as a cause of the crash or as part of the sequence of events. 2008 was selected as the last year in the analysis because it was the last full year of data available in the system for crashes. Crashes were provided by the ITSDS in table and GIS form. Crashes that occurred on the state-maintained system were then selected as those within 250 feet of GIMS primary road centerlines. In total, 634 crashes were reported in the study area over the seven year time period. Figure 3.6 presents crashes by year and city.

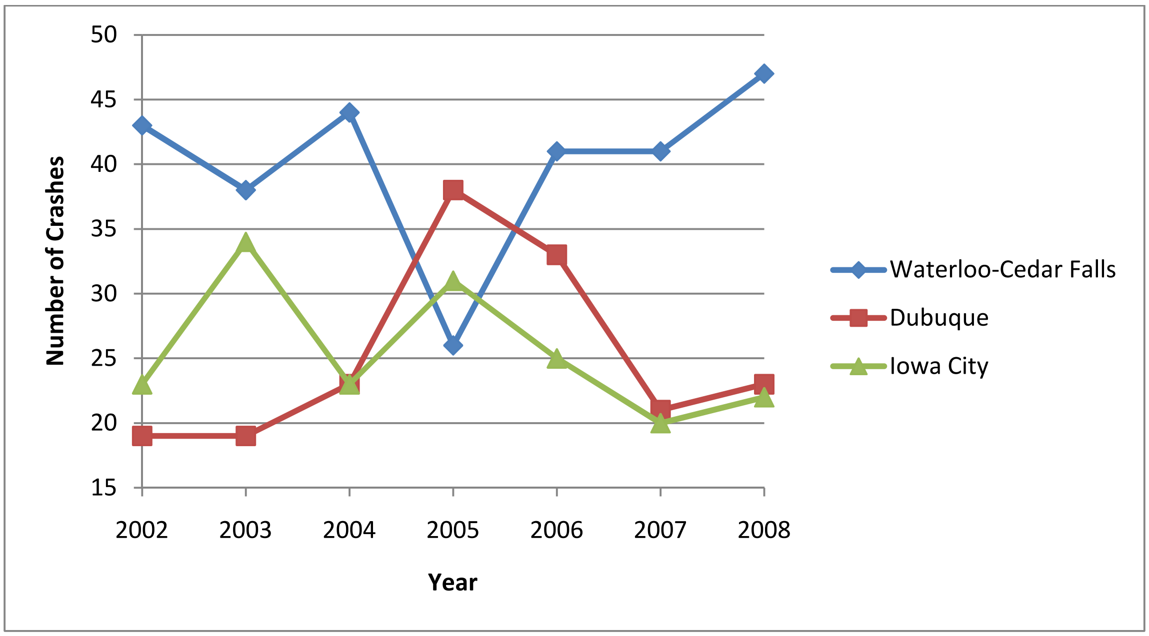

Figure 3.6. Frequency of deer-vehicle crashes by city, 2002-2008

In the chart, it can be seen that deer crashes also fluctuate from year to year. There are no observed trends between cities, although all cities had an observable increase in crashes between 2007 and 2008. There is a similar decrease in Waterloo-Cedar Falls in 2005 to that observed in the carcass report. This leads to the conclusion that there was an actual drop in crashes and that the carcass data might be more accurate than first thought.

Select road- and crash-specific variables are shown in Table 3.3. Most crashes occurred on four lane US Highways with a speed limit of 55 mph or above. Most crashes occurred in May, June, October, or November on a Monday, Friday, or Saturday. Most crashes are single vehicle-crashes that resulted in property damage only (PDO) and occurred at night under clear conditions and on dry pavement. A copy of the statistical software JMP outputs can be found in Appendix C.

Table 3.3. Summary statistics for select variables for crashes in three study cities

Variables	**Mean (standard deviation) or Percentage** [1]
Road-Specific	
System Interstate/US Highway/Iowa Highway	14.8/62.1/23.0
City Waterloo-Cedar Falls/Dubuque/Iowa City	44.2/27.8/28.1
Federal Function Interstate/Other Principal Arterial/Minor Arterial	14.8/83.9/1.3
Planning Classification Interstate/Commercial-Industrial Network/Area Development/Access Route	14.8/62.0/16.6/6.6
Median Type None/Hard Surface without barrier/Grass without barrier/Grass with barrier/Barrier	14.7/1.6/74.0/4.9/ 4.9
Median Width-feet	36.8 (25.5)
Number of Lanes 1/2/3/4/5/6/7	0.2/5.5/1.7/76.1/6.2/ 9.9/0.3
Pavement Type Asphalt/Concrete	41.8/58.2
Shoulder Type-Right None/Earth/Gravel/Paved/Combined	12.3/0.5/51.1/34.2/ 1.9
Shoulder Type-Left None/Earth/Gravel/Paved/Combined	20.7/0.6/39.1/38.5/ 1.1
Shoulder Width-Right (feet)	8.5 (3.3)
Shoulder Width-Left (feet)	4.9 (2.9)
Speed Limit Below 55 mph/55 mph/65 mph	27.9/38.8/33.2
Average Annual Daily Traffic (vehicles/day)	19,832 (11,351)
Landcover (percent occurrence within) Water-Wetland/Forest/Grassland/Corn/Roadway/Commercial-Industrial/Residential	1.4/0.6/11.2/1.4/ 29.0/50.0/6.0

Table 3.3 (continued).

Variables	**Mean (standard deviation) or Percentage**
Crash-Specific	
Month of Crash Jan/Feb/Mar/Apr/May/Jun/Jul/Aug/Sep/Oct/Nov/Dec	4.4/3.8/2.5/5.5/12.8/10.3/4.1/4.1/3.8/ 14.4/24.9/9.5
Year of Crash 2002/2003/2004/2005/2006/2007/2008	13.4/14.4/14.2/15.0/15.6/12.9/14.5
Day of Crash Sun/Mon/Tues/Wed/Thurs/Fri/Sat	13.2/15.9/12.1/13.9/12.3/17.4/15.1
Crash Severity Fatal/Major Injury/Minor Injury/Possible Injury/PDO	0.2/0.3/2.1/4.1/93.4
Number of Injuries per Crash	0.08 (0.31)
Variables	**Mean (standard deviation) or Percentage**
Number of Vehicles per Crash	1.0 (0.3)
Total Occupants	1.4 (1.0)
Single Vehicle/Multiple Vehicle	96.7/3.3
Light Condition Day/Dawn or Dusk/Night/Unknown/Not Reported	12.3/5.7/42.3/24.4/ 15.3
Weather Conditions Clear/Cloudy or Partly Cloudy/Unknown/Not Reported	32.7/21.0/24.3/16.6
Road Surface Condition Dry/Wet or Ice or Snow/Not Reported/Unknown	51.6/6.9/16.6/24.8

[1]In this table, means and standard deviations are reported for continuous variables while percentages are reported for categorical variables.

The deer-vehicle crashes and deer carcass salvage numbers were then classified into groups based on AADT. This is shown in Figure 3.7 below.

In this chart, it can be seen that most of the crashes are occurring on roadways with an AADT between 10,001 vehicles per day and 30,000 vehicles per day. However, most of the carcasses are being picked up along roadways with an AADT above 20,000 vehicles per day. This could be due to maintenance crews focusing on major routes that have a higher traffic volume, meaning that some carcasses may have been picked up before crews reached the

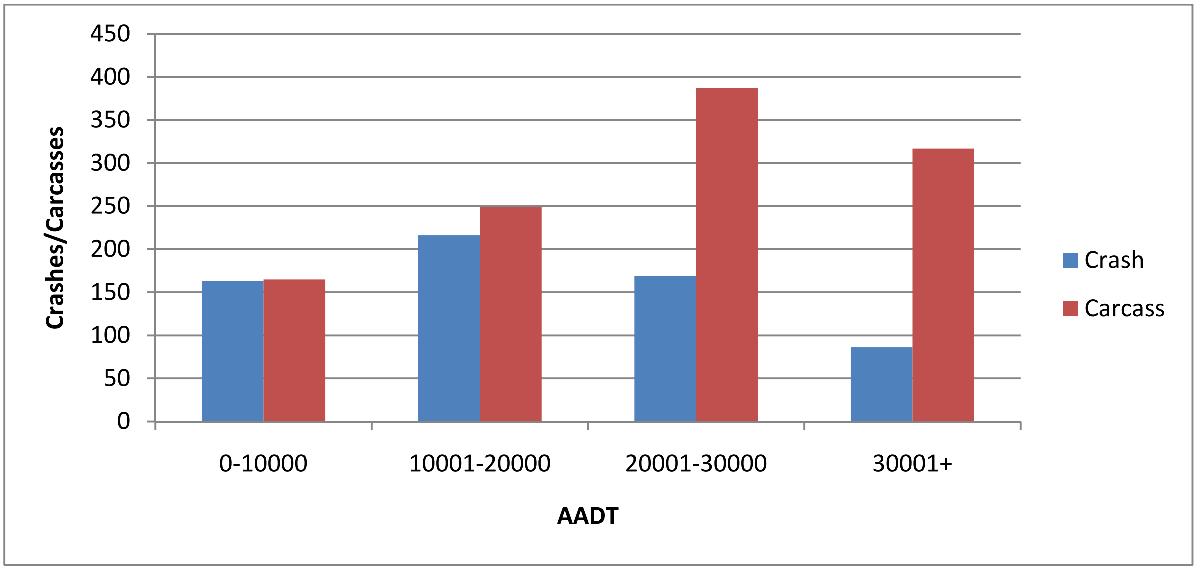

Figure 3.7. Deer-vehicle crashes and deer carcass salvage counts by AADT

lower volume roadways. In each of these groups were represented by 27.9 miles of roadway with an AADT of 10,000 vehicles per day or less, 33.9 miles of roadway with an AADT between 10,001 and 20,000 vehicles per day, 27.6 miles of roadway with an AADT between 20,001 and 30,000 vehicles per day, and 3.9 miles of roadway with an AADT of 30,001 vehicles per day or greater. This also shows that the extremely high volume roadways (those with AADT of over 30,000) are not being affected by mileage of the system, but by the number of crashes occurring.

In Figure 3.8 below, deer-vehicle crashes and deer carcass salvage counts are grouped by posted speed limit.

As shown in the chart, most carcasses and crashes are on roadways with a posted speed limit above 50 mph. This is consistent with what would be expected, as most of the state-maintained routes in these cities are high-speed facilities. 53.7 miles of the 93.3 miles of the roadway in the study area are at a posted speed limit of 50 mph or greater, meaning

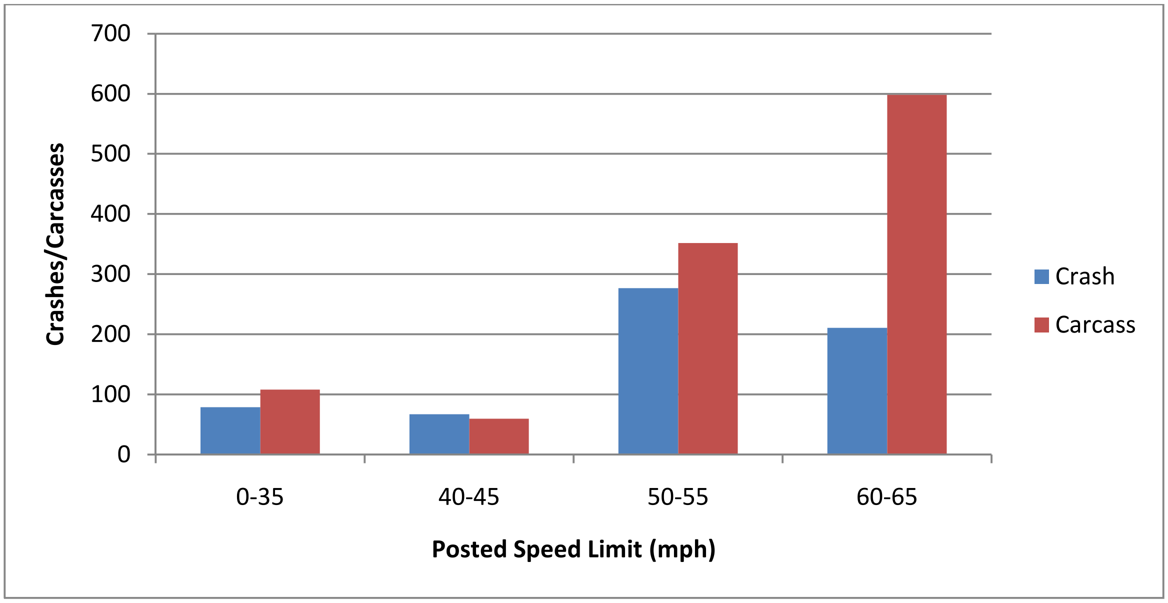

Figure 3.8. Deer-vehicle crashes and deer carcass salvage counts by posted speed limit

that the majority of crashes happen on these roadways. However, the number of crashes and carcasses found on these roadways does not line up proportionally with the number of miles of roadway that have higher speed limits. This shows that speed may be a factor in finding high deer-vehicle crash locations.

3.5 Comparison of Deer Carcass Salvage and Deer-Vehicle Crash Data

3.5.1 Comparison by City

After the summary statistics for the carcass and crash data were compiled, a comparison of these two data sources was conducted. The first was a complete city-by-city comparison. Figures 3.9, 3.10, and 3.11 show Dubuque, Iowa City, and Waterloo-Cedar Falls, respectively.

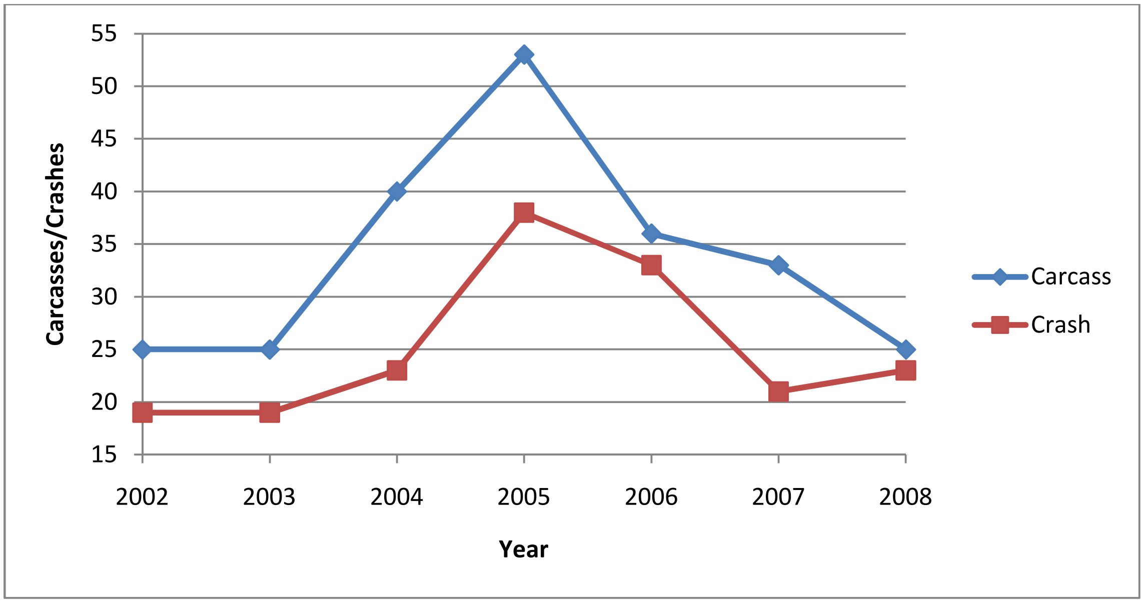

Figure 3.9. Deer carcass salvage and deer-vehicle crash counts in Dubuque

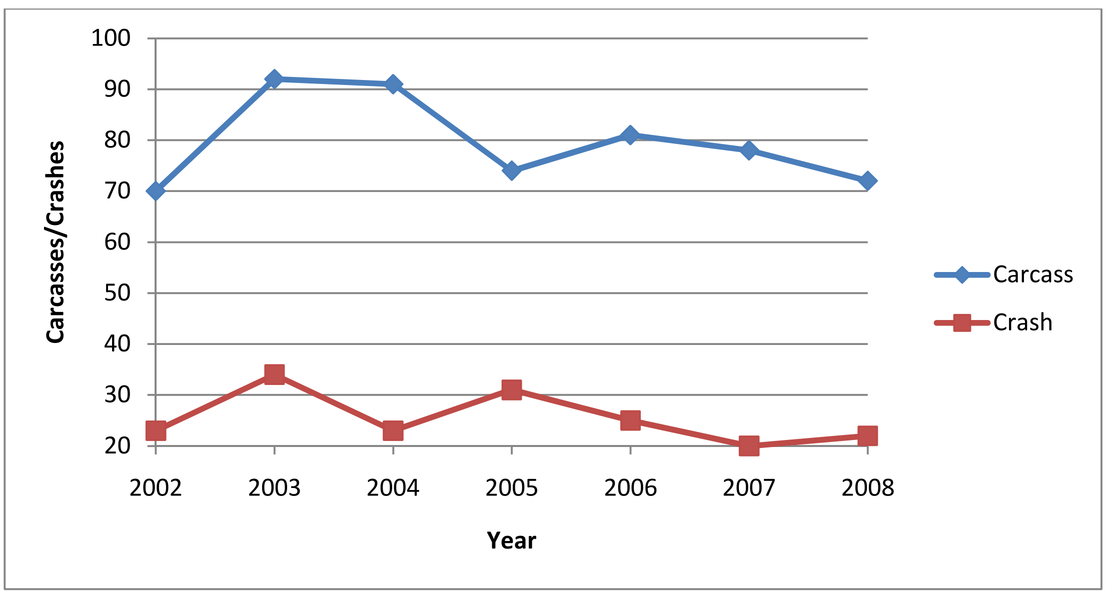

Figure 3.10. Deer carcass salvage and deer-vehicle crash counts in Iowa City

Overall, the number of deer carcasses salvaged each year exceeded the number of deer-vehicle crashes reported on each of the city's primary roadways (except for Waterloo-Cedar Falls in 2002 and 2005). This difference can be due to a number of reasons, including the variability in data reporting and data collection practices, as discussed in previous

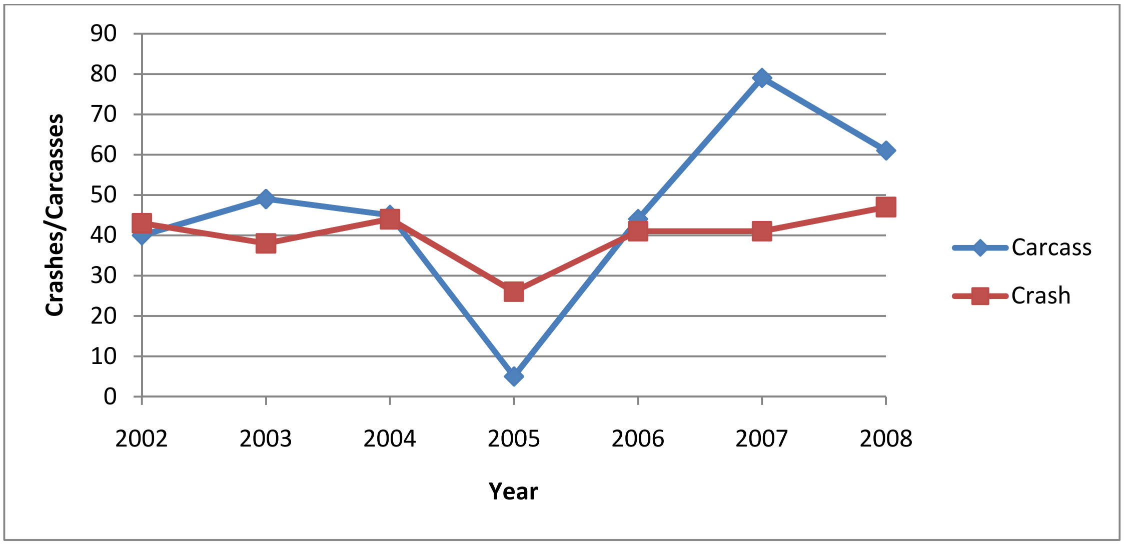

Figure 3.11. Deer carcass salvage and deer-vehicle crash counts in Waterloo-Cedar Falls

research (Knapp et al. 2007; Huijser et al. 2007b; Huijser et al. 2007c; Donaldson and Lafon 2009). However, in Dubuque and Waterloo-Cedar Falls, the differences in deer carcass salvage and deer-vehicle crash counts do not reflect the estimate that 50 percent of deer-vehicle crashes are not reported. The drop-off in Waterloo-Cedar Falls in both data sources was difficult to explain individually, but with the examination of both sources together, it can be inferred that the decrease is real (although some data may be still missing from the carcass salvage report).

A comparison of deer carcass salvage and deer-vehicle crashes was carried out using a two-factor analysis of variance. The results of this analysis are shown in Table 3.3. The analysis shows that deer carcass salvage and deer-vehicle crash counts differ significantly in Dubuque and Iowa City. However, annual differences were found to be significantly different only in Dubuque.

3.5.2 Crash and Carcass Salvage Rates by Vehicle Miles Traveled

These data were also examined by vehicle miles traveled (VMT). This analysis is

Table 3.3. Comparison of deer carcass salvage and deer-vehicle crash counts by city and year

Year	Dubuque		Iowa City		Waterloo-Cedar Falls	
	Carcass Count	Crash Count	Carcass Count	Crash Count	Carcass Count	Crash Count
2002	25	19	70	23	40	43
2003	25	19	92	34	49	38
2004	40	23	91	23	45	44
2005	53	38	74	31	5	26
2006	36	33	81	25	44	41
2007	33	21	78	20	79	41
2008	25	23	72	22	61	47

Analysis of Variance Estimation Results

	Dubuque p-value	Iowa City p-value	Waterloo-Cedar Falls p-value
Rows (years)	0.011	*ns	*ns
Columns (counts)	0.008	<0.0001	*ns

*Note: ns means no significant difference at 90% confidence interval

selected to allow for the cities to be evaluated on the basis of driver exposure. This type of analysis is useful for the general public as it brings the figures into the perspective of miles driven, and therefore individual risk. Figure 3.12 shows the crash data while Figure 3.13 shows the carcass salvage data. All of the rates are reported per 100 million VMT.

From these graphs, it can be interpreted that Dubuque, while it does not have the highest number of crashes, has the highest crash rate per 100 million VMT of the three study areas, while Iowa City has the highest carcass salvage rate per 100 million VMT as well as the highest salvage counts. While the trends follow the general shape of the count data, the normalization by VMT shows that these cities are in many cases closer to each other than raw numbers would otherwise show. This demonstrates that one should not rely on raw numbers alone for comparison of multiple areas, but should take driver exposure into account.

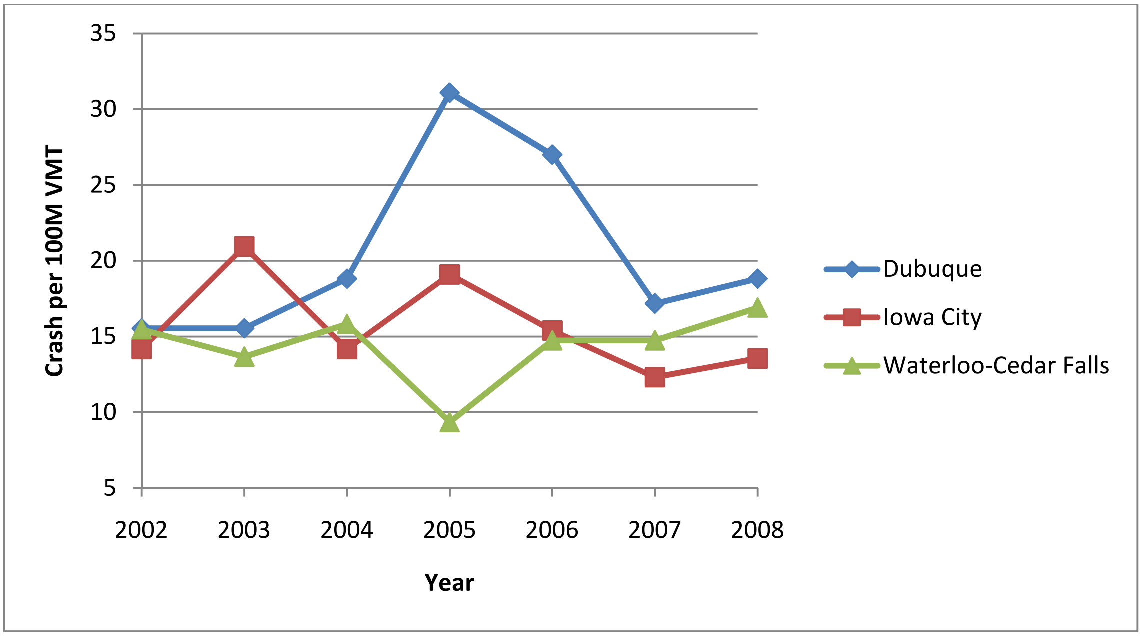

Figure 3.12. Deer-vehicle crash rate per 100 million VMT

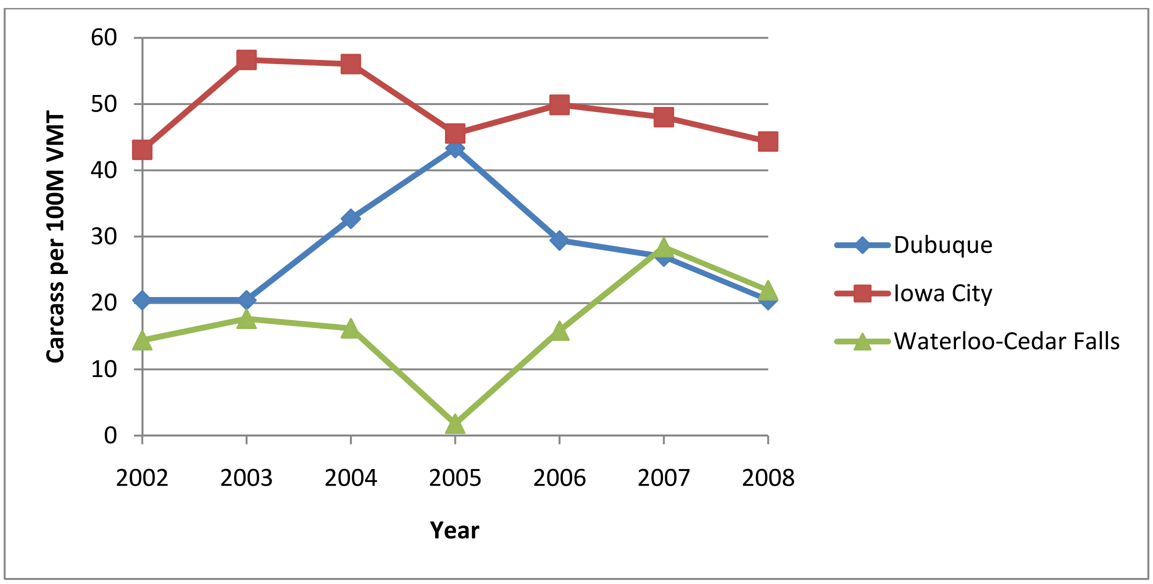

Figure 3.13. Carcass salvage rate per 100 million VMT

3.5.3 Crash and Carcass Salvage Rates by Lane Miles and Mileage

The size of the road system varies across the different candidate cities. Higher raw numbers are expected on a larger system compared to a smaller one. In order to evaluate crash and carcass numbers across these different systems, rates were calculated per lane mile of roadway. This analysis is useful to transportation decision makers, as funding decisions for projects are based on a per lane mile cost. Figure 3.14 shows the crash data, while Figure 3.15 shows the carcass salvage data.

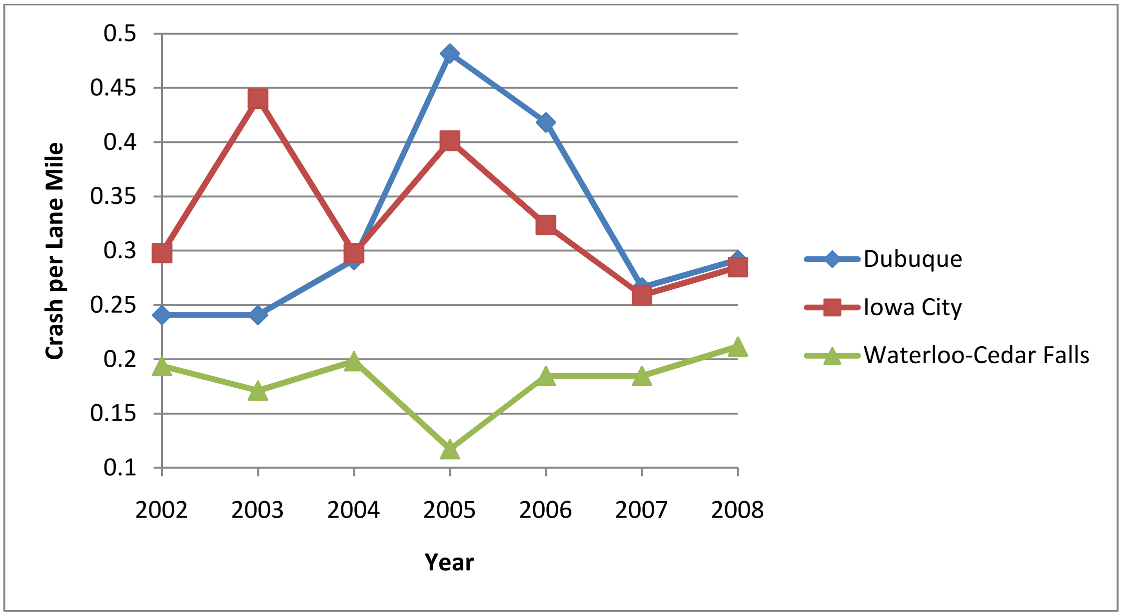

Figure 3.14. Deer-vehicle crashes per lane mile

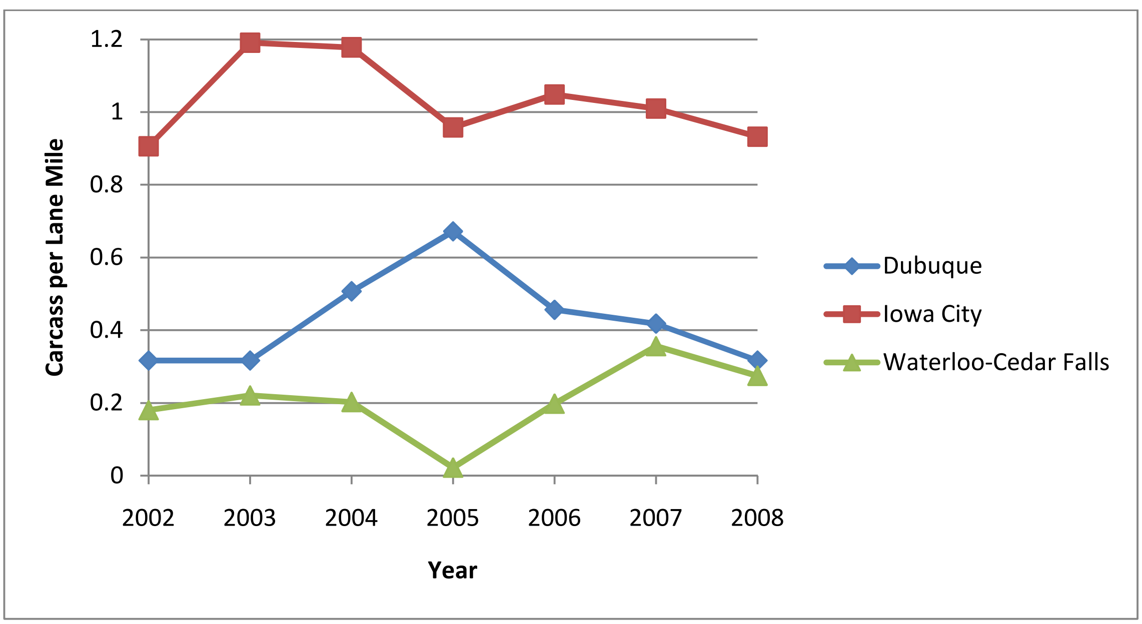

Figure 3.15. Deer carcasses salvaged per lane mile

As shown in the figures above, Iowa City had the highest crash and carcass rates per lane mile. However, caution must be exercised in evaluation of these numbers, as Waterloo-Cedar Falls has about three times the lane mileage as the other two cities. This may be one of the reasons that this city's numbers are always the lowest. Therefore, this measure may be more appropriate for examining Dubuque and Iowa City, as their lane mileage is similar. In each of the cities, the rates follow the general trend of the corresponding city's crash or carcass count; however, taking into account the lane mileage allows these numbers to be considered into perspective and indicated that these cities are more similar than the raw count data would otherwise show.

In addition, charts were produced graphing deer-vehicle crashes and carcasses per roadway mile. This was done because in past studies, the number of lanes has not had a significant impact on the number of crashes. These charts are shown in Figures 3.16 and 3.17.

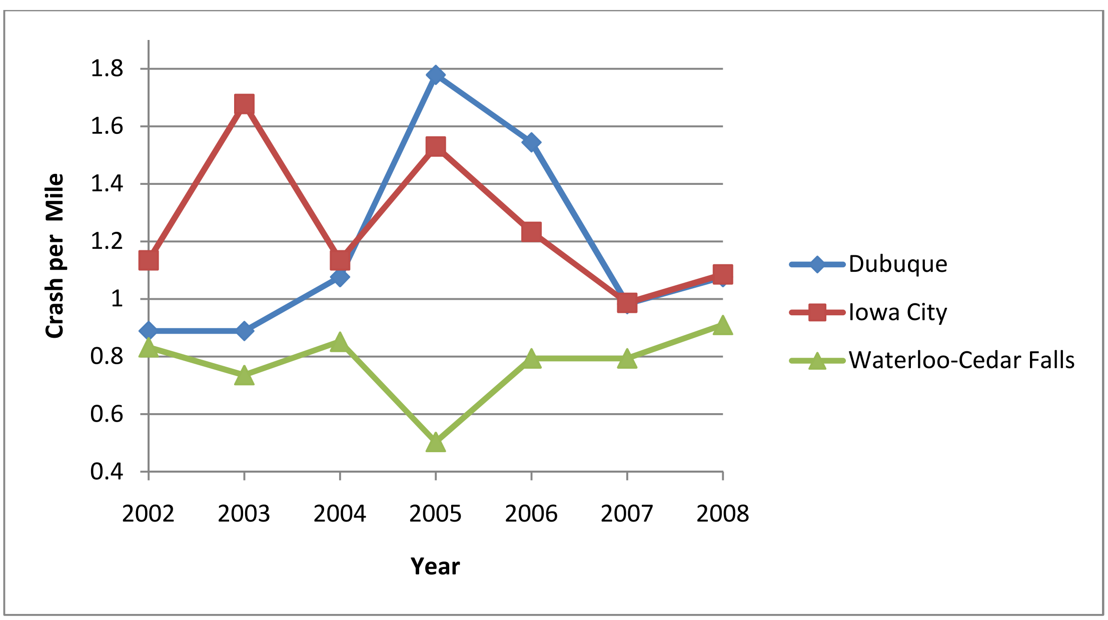

Figure 3.16. Deer-vehicle crashes per mile.

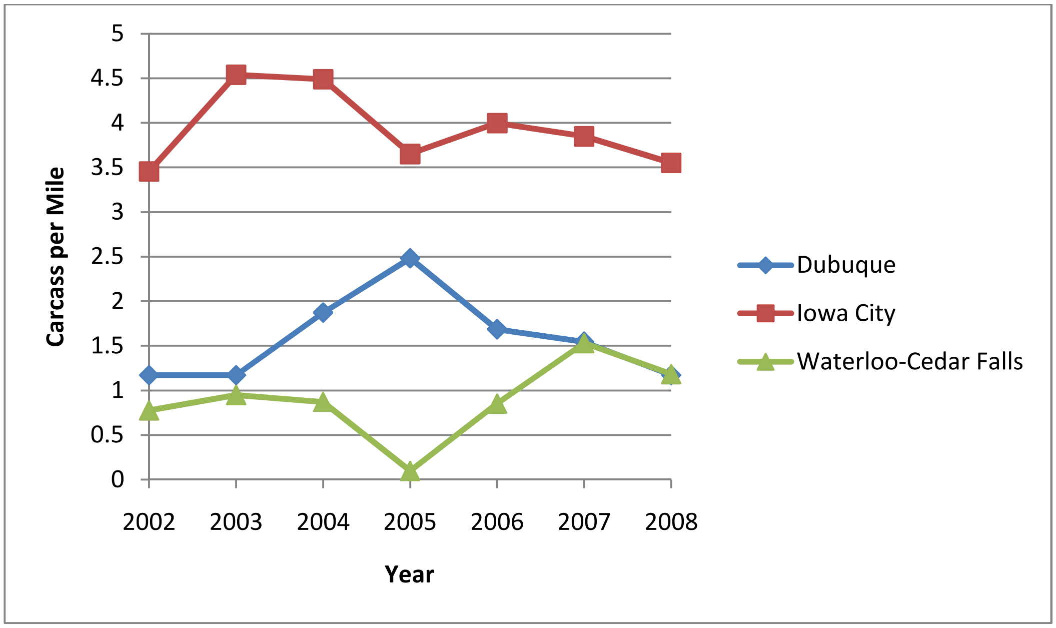

Figure 3.17. Deer carcasses salvaged per mile

As can be seen in the figures above, there is not much difference in the rates and trends per mile versus the per lane mile. This is because the number of lanes was a multiplier to the number of miles. This shows that when comparing crashes or carcasses to mileage, whether it is done in lane-miles will not make a large difference in the analysis.

3.5.4 Comparison of Deer Carcass Salvage and Deer-Vehicle Crash Counts by Route

An analysis was conducted to compare deer carcass salvage and deer-vehicle crash counts by the individual route. This is shown in Figure 3.18. This chart shows the comparison results by route in each city, with WCF denoting Waterloo-Cedar Falls, IC denoting Iowa City, and Dub denoting Dubuque.

This figure shows that there is a high underreporting of deer-vehicle crashes on major routes that carry high amounts of traffic, such as I-80 and US-218. In many cases, this shows underreporting of almost four fold in the case of I-80. However, it shows that on other

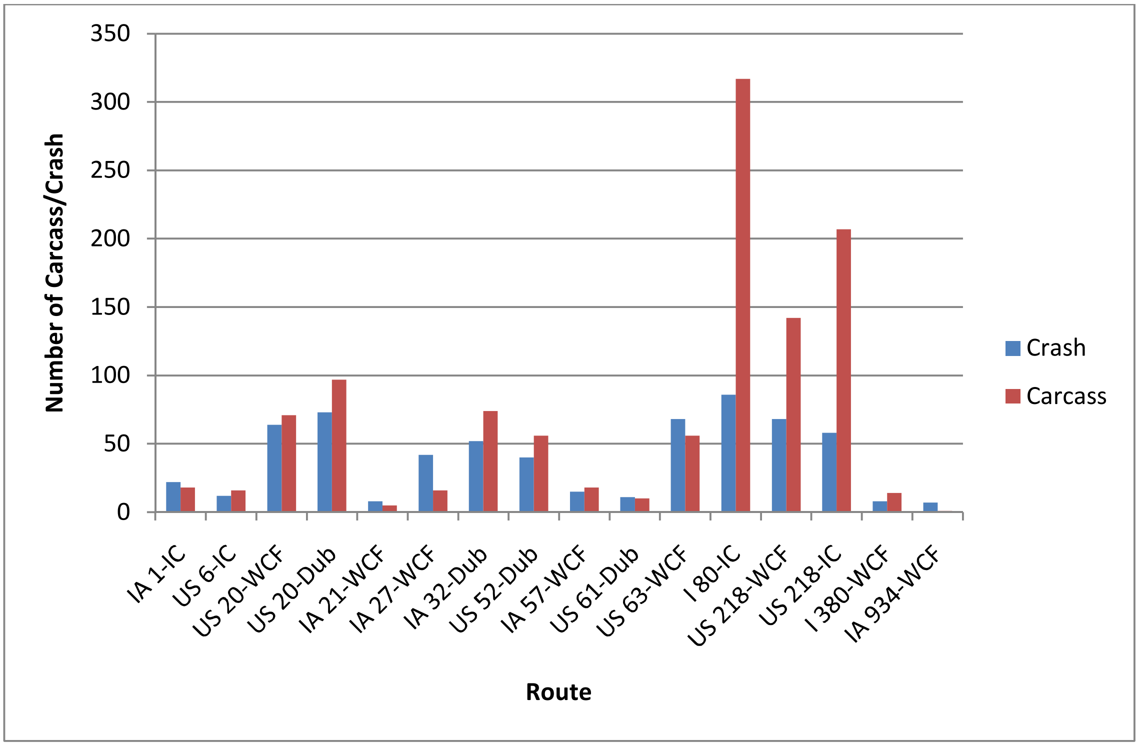

Figure 3.18. Comparison of deer-vehicle crash and deer carcass salvage counts by route

routes, the numbers are fairly close, with the carcass counts normally being slightly higher than crash counts.

3.6 Comparison of Deer-Vehicle Crash and Deer Carcass Salvage Frequency by Land Use

Lastly, the deer-vehicle crash and deer carcass salvage data were compared to the land use. A land use variable was assigned to each GIMS sufficiency segment. Next, each crash or carcass was assigned to the segment, and associated with the land use it was located within. A chart showing the frequency of crashes occurring by land use is shown in Figure 3.19.

As the chart shows, the majoring of crashes and carcasses are located on roadway or commercial-industrial areas. This is not surprising, as many of these routes are located on extensive right-of-way in non-residential developed areas in the city. The lack of cropland is

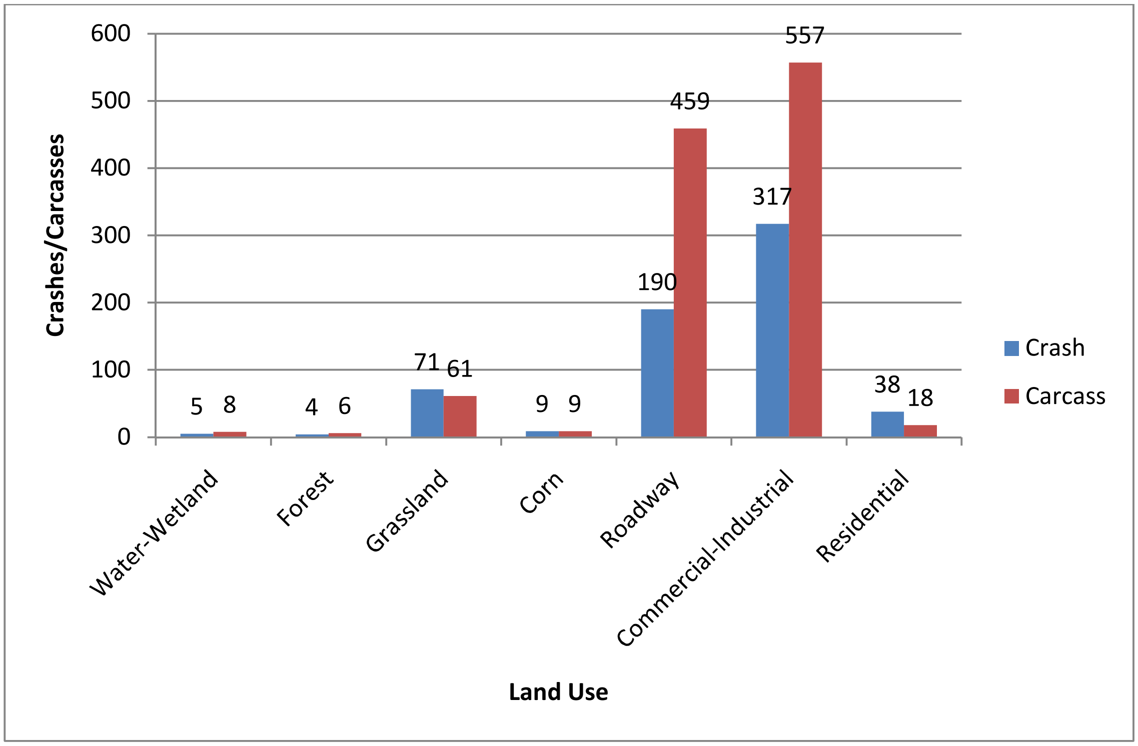

Figure 3.19. Deer-vehicle crash and deer carcass salvage frequency by land use

reasonable, as cities do not have much of cropland within their boundaries. Deer will feed on general landscaping, especially in the urban environment, which is plentiful on the roadside and in developed areas.

3.7 Summary/Conclusions

In this chapter, descriptive analysis techniques were applied to suggest the major factors that contribute to deer-vehicle crashes in the three study cities. These cities were identified and the study area was shown in visual form. Deer populations were examined with no real surprises. Deer-vehicle crash and deer carcass salvage data were evaluated and different roadway, crash, and land use factors were identified in these datasets. Cities were compared to demonstrate that the raw number of crashes is not necessary the best predictor a problem with deer and vehicle interaction. The crash and carcass figures were compared to each other to examine the magnitude of underreporting. Underreporting was found not to be as large of an issue in the cities and on minor routes, as it was first assumed but on major routes, crashes were underreported at a higher rate. In Chapter 4, an empirical Bayes model is developed using the combined crash and carcass dataset and using some of the roadway and environmental factors discussed in this chapter in order to predict deer vehicle crash frequency in urban areas.

Chapter 4: Statistical Data Analysis

4.1 Overview

In this chapter, an empirical Bayes (EB) model is developed to predict deer-vehicle crashes in urban areas using a combined data set of deer-vehicle crash and deer carcass salvage data. The datasets were combined by eliminating a carcass record when a crash record existed on the same segment and the carcass was collected within a week of the crash being reported. The deleted records, known as "double-counted" crashes are removed to improve the accuracy of these data being used. Without removing these records, areas could be seen as having up to twice as many crashes as are actually occurring. A summary table of the number of crashes, carcasses, and "double-counted" crashes per sufficiency segment is found in Appendix D. In order to estimate an EB model, first, a count data model, such as Poisson, negative binomial, or zero-inflated model is developed. The final decision on the model specification is based on tests that examine the overall goodness of fit. The estimated count-data model is an input to the EB model that predicts the number of deer-vehicle crashes on a given road segment. The EB methodology addresses the regression-to-the mean, where extreme measurements will be pulled towards the mean of the set on a later measurement, and selection biases that may be a problem when using other models or methods, such as simple before and after analysis (Hauer et al. 2002). The EB "expected" estimates can be compared to the actual number of deer-vehicle crashes during the study period. The difference indicates whether a section is likely a high crash location and can be used to rank the segments from higher-to lower risk segments.

4.2 Methodology-Count Data Models

The frequency of deer-vehicle crashes per sufficiency segment, as defined in Chapter 3, Section 3, was modeled using a count data model, of which the most popular are Poisson and negative binomial (NB) model. One requirement of the Poisson model is that mean of the count process equals its variance; if its variance is significantly larger than the mean, the data are overdispersed and are more appropriately modeled by the negative binomial (Washington et al. 2003). A zero-inflated negative binomial (ZINB) was evaluated due to the high number of zeros (50 of 150 sections examined) present in these data.

In this study, the deer-vehicle crash frequency was modeled using a negative binomial model due to the presence of overdispersion. This was confirmed by the mean being 10.85 and the variance being 464.18, and the high confidence in the overdispersion factor of the negative binomial (99.9%). In the following sections, the different count model methodology will be discussed, starting with the Poisson regression, and then moving on to the NB and the ZINB.

4.2.1 Poisson Regression

For a non-negative integer variable, Y, with observed frequencies (in this case per segment), $y_i, i = 1, \ldots, N$, the probability of y_i (deer-vehicle crashes) at *i* is given by:

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!}, \tag{1}$$

where λ_i is the Poisson parameter for i, which is equal to the expected frequency of deer-vehicle crashes at $i, E[y_i]$ (Washington et al. 2003).

The log-linear form of the model used in this study to predict the expected number of deer-vehicle crashes per sufficiency segment is shown in equation (2).

$$\ln(\lambda_i) = \beta_i * x_i, \tag{2}$$

where x_i is a vector of explanatory variables and β_i is a vector if estimable parameters by maximum likelihood estimation techniques. To assess this vector (β_i), elasticities were calculated. Elasticities measure the magnitude of a specific variable on the expected frequency. The elasticity of frequency λ_i is defined as

$$E_{x_{ik}}^{\lambda_i} = \frac{\partial \lambda_i}{\partial x_{ik}} \times \frac{x_{ik}}{\lambda_i} = \beta_k * x_{ik}, \tag{3}$$

where E represents the elasticity, x_{ik} is the value of the kth independent variable for observation I, and β_k is the estimated parameter for the kth independent variable. The definition of elasticity is the percentage effect that a one percent change in x_{ik} has on the expected frequency of λ_i. Note that elasticities cannot be estimated for indicator variables that take on the values of zero or one. The pseudoeleasticity for indicator variables represents the percent change on the expected frequency λ_i (the dependent variable) when the independent variable is changed from zero to one (Washington et al 2003). The pseudoelasticity is given as a percentage is computed as:

$$E_{x_{ik}}^{\lambda_i} = \frac{EXP(\beta_k) - 1}{EXP(\beta_k)} * 100. \tag{4}$$

4.2.2 Negative Binomial Regression

As mentioned, the negative binomial regression model is a more general case of the

Poisson regression model, which allows for the variance to be different from the mean. The negative binomial is derived by rewriting equation (1) in which λ_i is specified so that

$$\ln(\lambda_i) = \beta_i * x_i + \varepsilon_i, \tag{5}$$

where $EXP(\varepsilon_i)$ follows a gamma distribution with mean 1.0 and variance α^2. This model has an additional parameter, α, which is often referred to as the overdispersion parameter, such that

$$VAR[y_i] = E[y_i] * [1 + \alpha * E[y_i]]. \tag{6}$$

(Washington et al. 2003).

4.2.3 Zero-Inflated Negative Binomial Model

In some cases, a phenomenon can exist where an observation of zero events during the observation period may arise due to the small, but still present, likelihood of a crash occurring. This leads to two-state regimes of data (normal-count and zero-count states) that lead to overdispersion if considered in a single, normal-count state (Washington et al. 2003). The zero-inflated negative binomial (ZINB) was developed to account for this dual-state system. The ZINB model assumes that events $Y = (y_1, \ldots, y_n)$ are independent and

$$y_i = 0 \text{ with probability } p_i + (1 - p_i)\left[\frac{\frac{1}{\alpha}}{\left(\frac{1}{\alpha}\right)+\lambda_i}\right]^{1/\alpha}$$

$$y_i = y \text{ with probability } (1 - p_i)\left[\frac{\Gamma\left(\left(\frac{1}{\alpha}\right)+y\right)u_i^{1/\alpha}(1-u_i)^y}{\Gamma\left(\frac{1}{\alpha}\right)y!}\right], y = 1, 2, 3 \ldots \tag{7}$$

where $u_i = (1/\alpha)/[(1/\alpha) + \lambda_i]$. To test the appropriateness of using the ZINB model verse a traditional model, the Vuong statistic is calculated. It is calculated as, for each observation

I,

$$m_i = \ln\left(\frac{f_1(y_i|\boldsymbol{X}_i)}{f_2(y_i|\boldsymbol{X}_i)}\right), \tag{8}$$

where $f_1(y_i|\boldsymbol{X}_i)$ is the probability density function of model 1 and $f_2(y_i|\boldsymbol{X}_i)$ is the probability density function of model two. Using equation (8), Vuong's statistic for testing the two models is

$$V = \frac{\sqrt{n}\bar{m}}{S_m}, \tag{9}$$

where $\bar{m}$ is the mean $(\frac{1}{n})\sum_{i=0}^{n} m_i$, $S_m$is the standard deviation, and n is the sample size. This statistic is asymptotically normallly distributed, and if V is less than $V_{critical}$ (which is 1.96 for the 95% confidence interval), the test is inconclusive. If the statistic is greater than 1.96, the ZINB is favored, and if it is less than -1.96, the negative binomial is favored (Washington et al. 2003).

4.3 Methodology-Empirical Bayes

The EB methodology was chosen in order to assess safety of the road sections in the study urban areas. In the estimates made by traditional statistical methods, only the crashes on the study roads sections are taken into account. This inherently leads to roadways with high crash numbers being selected for treatment, leading to regression-to-the mean bias, where extreme measurements will be moved towards the mean of the set on a later measurement, if expected values of crashes are low or the amount of historical data is limited. The EB estimate allows for correction of this bias as well as providing a better estimate, because it takes other similar roadways into account (Hauer et al. 2002 & Hauer 1997). The basic procedure can be explained by

$$Estimate\ of\ Expected\ Crashes = Weight * Crashes\ expected\ on\ similar\ entities + (1 - Weight) * Count\ of\ crashes\ on\ entity\ , where\ 0 \leq Weight \leq 1\ . \quad (10)$$

The expected crash frequency is determined by safety performance functions (SPF), which are calculated using a count data model presented in Section 4.2.2. The weight is dependent on the strength of the crash record and the reliability of the SPF. In general practice, with more than three years of data, researchers should strive to use the full version of EB. However, due to lack of data, the abridged version will be used in this thesis.

The SPF is derived from the negative binomial estimation results. The SPF will follow the general format

$$\mu = L * e^{Constant} * ADT^{Coefficient_{ADT}} * e^{Variable_1 * Coefficient_1 + \cdots + Variable_n * Coefficient_n}, \quad (11)$$

where μ is the number of crashes expected for similar sections, L is the length of the segment, ADT is the average daily traffic, and $Variable_1$ to $Variable_n$ are the independent variables included in the negative binomial model, with the coefficients being those derived in the negative binomial model estimation (Hauer et al. 2002; Hauer 1997).

The next step is to estimate the weight. This can be found by

$$Weight = \frac{1}{1 + (\mu * Y)/\varphi}, \quad (12)$$

where Y is the number of years during which the crash count was taken, and φ is the overdispersion factor estimated in the negative binomial (the α parameter). After the weight is calculated, the estimate of expected crashes can be obtained using equation (10) above.

This estimate typically falls between the actual number of crashes for the study sites and the average number of crashes for similar sites. This is to correct for the regression-to-mean bias by pulling the crash count towards the mean (Hauer 1997).

Standard deviation (σ) is also calculated for the estimate, which is found by

$$\sigma(estimate) = \sqrt{(1 - Weight) * Estimate}. \tag{13}$$

(Hauer et al. 2002; Hauer 1997).

When EB was first used to assess safety, it was thought to only be a remedy for the regression-to-mean problem. Since then, EB has been widely used in different applications, such as estimating safety on individual segments or intersections (Hauer 1997). A similar application of examining deer-vehicle crashes on segments of urban state-maintained roadways is presented in this thesis.

4.4 Estimation Results-Negative Binomial Model

As stated in Section 4.2, both a negative binomial regression and a ZINB model were estimated to investigate the factors that influence the frequency of deer-vehicle crashes on the sections of roadway within the study area. In this analysis, 150 sections total from the three study cities were examined. The models were estimated using the statistical program Limdep (Greene 2007). The dependent variable is the number of crash and carcass records per segment during the study period 2002-2008. When the ZINB model was run, the Vuong statistic was found to be -0.6510. This value suggests that the test is inconclusive as to whether a ZINB model is superior to the NB. As such, the negative binomial model was selected. Table 4.1 below shows the estimated results of this model, while the model outputs can be found in Appendix E.

Table 4.1. Negative binomial regression model for frequency of deer-vehicle crashes on sections of roadway in the study area.

Variable	Estimated Coefficient	Elasticity	t-Statistic
Constant	-4.835		-2.013
Natural Log of Segment Length	1.000	FIXED	FIXED
Natural Log of Average Daily Traffic	0.689	6.502	2.731
Speed Limit: 50 mph or Higher	0.820	56.0	2.712
Land Use: Grass	0.670	48.8	1.912
Two-Lane Roadway	-0.849	-133.7	-2.042
Gravel Right Shoulder	1.438	76.6	5.113
Overdispersion Parameter α	1.451		6.018
Number of Observations		150	
Log-Likelihood at Zero		-900.106	
Log-Likelihood at Convergence		-402.522	

The variable, the natural log of average daily traffic (ADT), did not have a surprising sign, but rather a surprisingly large impact. A 1% increase in the natural log of ADT is predicted to raise the frequency of deer-vehicle crashes by 6.5%. The length parameter was added as a fixed variable with its coefficient set at one. This was included in the model so that the segment length would be taken into account without assigning any weight to its parameter.

Interestingly, the estimation results show that deer-vehicle crashes are predicted to be lower on two-lane roadways as opposed to their larger counterparts. The large pseudoelasticity (-133.7%) means that the effect of this variable on the frequency of deer-vehicle crashes is elastic and important (Washington et al. 2003). This means that of all the indicator variables (all of the variables but the natural log of average daily traffic) this is the most significant factor in the model, with the value of the pseudoelacticity representing the percent change (-133.7) in the frequency of deer-vehicle crashes when the variable is changed from zero to one (when a section has only two lanes) (Washington et al. 2003). This could be due to the fact that in urban areas, the speed limits on two lane roads are lower and therefore, the driver would have more time to react and avoid a crash with a deer.

The impact of the presence of right shoulders that are gravel on crash frequency was surprising. In most cases, the presence of shoulders decreases crashes. However, when a gravel shoulder is present, it is predicted that there will be more deer-vehicle crashes on this section. This could be due to the fact, however, that drivers sometimes overreact when they see a deer on the roadway. These drivers could swerve and drive onto the gravel, and then overcorrect and get involved in a crash. The frequency of deer-vehicle crashes was found to be higher on road segments with land use defined as grass and higher speed limits. Of these three factors (grass land use, speed limit over 50 mph, and gravel right shoulders), the presence of a right gravel shoulder has the largest impact (pseudoelasticity of 76.6%) followed by speed limit and grass land use (pseudoelasticities of 56.0% and 48.8% respectively).

The goodness of fit of this model can be found by estimating the ρ^2 statistic. This statistic is defined as

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)}, \tag{14}$$

where $LL(\beta)$ is the log likelihood at convergence with parameter β and $LL(0)$ is the log likelihood with all parameters set to zero. The perfect model would have a ρ^2 statistic equal to one, so the closer the value is to one, the more variance the model is explaining (Washington et al. 2003). The estimated model has a ρ^2 statistic of 0.551, which shows that the model explains 55.1% of the variance in the model.

In addition, the adjusted ρ^2 statistic was calculated. This statistic corrects for the number of parameters in the model, as the ρ^2 statistic increases in value as variables are added in the model. This statistic is defined as

$$\rho^2_{adjusted} = 1 - \frac{LL(\beta) - k}{LL(0)}, \tag{15}$$

where k is the number of parameters, which is seven in this model. The same boundaries are placed on the adjusted ρ^2 statistic as the regular ρ^2 statistic (Washington et al. 2003). The value of the adjusted ρ^2 statistic is 0.455, which shows that the model explains almost half of the variance in the model.

4.5 Estimation Results-Empirical Bayes

As discussed in section 4.3, the negative binomial estimation results are used to derive the SPF (shown in Equation 11). The estimated equation is then used to determine the estimate of the expected number of crashes on a similar section. The estimated SPF is:

$$\mu = L * e^{-4.835} * ADT^{0.688} * e^{HSpeed*0.820+Grass*0.670+TwoLnRd*-0.849+RShldG*1.438}. \tag{16}$$

Equation (16) was used along with the weight equation (equation 12) to solve for the expected crashes equation (equation 10). Once this was done, this estimate and the total number of crashes and carcasses (combined as crashes in the spreadsheet) were converted to a per mile-year basis for comparison. The segments were then ranked by the number of crashes, the EB estimates, and the difference between the two on a per mile-year basis. In the difference, a positive value means that the actual crashes and carcasses are larger than the corresponding estimate for that section, while a negative number means that the estimate is larger than the reported crashes. Table 4.2 shows the top 25 segments as ranked by the difference between the actual and expected number of crashes per mile-year. The full table of all the rankings can be found in Appendix F.

Table 4.2. Selection of rankings of segments by crashes/carcasses per mile, EB estimate per mile, and difference between crash/carcass and EB estimate per mile.

Sufficiency Segment	Route	City	Length	Crash	Estimate	Crash/mi-yr	Estimate/ mi-yr	Difference	Deviation /mi-yr	Rank Crash	Rank Estimate	Rank Difference
311500032	32	Dubuque	0.042	24	22.113	81.633	75.215	6.418	15.333	1	1	1
312500052	52	Dubuque	0.709	55	50.754	11.082	10.227	0.855	1.366	8	8	2
77900218	218	Waterloo-Cedar Falls	0.479	10	7.222	2.982	2.154	0.828	0.655	21	34	3
3121400052	52	Dubuque	0.131	1	0.247	1.091	0.269	0.821	0.221	70	100	4
3122550052	52	Dubuque	0.563	25	21.822	6.344	5.537	0.806	1.089	13	15	5
52103800080	80	Iowa City	0.61	85	82.170	19.906	19.244	0.663	2.076	3	3	6
52105400080	80	Iowa City	0.634	64	61.562	14.421	13.872	0.549	1.721	5	5	7
765400063	63	Waterloo-Cedar Falls	1.005	17	13.214	2.416	1.878	0.538	0.435	29	43	8
52104900080	80	Iowa City	1.463	150	144.730	14.647	14.132	0.515	1.146	4	4	9
5253500001	1	Iowa City	1.14	14	10.688	1.754	1.339	0.415	0.336	50	64	10
719400020	20	Waterloo-Cedar Falls	0.523	16	14.750	4.370	4.029	0.342	0.983	17	17	11
311600032	32	Dubuque	0.396	17	16.165	6.133	5.832	0.301	1.390	14	13	12
763400063	63	Waterloo-Cedar Falls	0.117	1	0.755	1.221	0.922	0.299	0.841	66	76	13
52105950080	80	Iowa City	0.87	48	46.386	7.882	7.617	0.265	1.085	11	11	14
5252150001	1	Iowa City	0.106	1	0.809	1.348	1.090	0.258	1.005	61	70	15
52103900080	80	Iowa City	0.285	18	17.490	9.023	8.767	0.256	2.043	9	9	16
31251230020	20	Dubuque	0.367	61	60.368	23.745	23.499	0.246	2.996	2	2	17
75600057	57	Waterloo-Cedar Falls	0.555	8	7.049	2.059	1.815	0.245	0.609	37	49	18
31251270020	20	Dubuque	0.264	5	4.565	2.706	2.470	0.235	1.063	26	26	19
52101600006	6	Iowa City	0.989	14	12.818	2.022	1.852	0.171	0.470	40	45	20
5253800001	1	Iowa City	0.479	8	7.577	2.386	2.260	0.126	0.765	30	30	21
75450057	57	Waterloo-Cedar Falls	0.112	1	0.913	1.276	1.164	0.111	1.073	63	66	22
765600063	63	Waterloo-Cedar Falls	1.459	20	18.896	1.958	1.850	0.108	0.392	42	46	23
52102100006	6	Iowa City	0.305	4	3.787	1.874	1.774	0.100	0.839	45	50	24
781200027	27	Waterloo-Cedar Falls	0.19	3	2.905	2.256	2.184	0.071	1.205	32	32	25

From this analysis, it can be observed that the EB estimate for some segments is quite different than the actual number of crashes, while both values are similar for some other segments. This is due to the fact that less weight is assigned on the average segment when more years of data are present (Hauer et al. 2002) or the model variability is high. However, with this difference being ranked, the rankings show that it is not the longest or the sections with the highest number of crashes that rank first for improvement. The difference is also finding sections that have greater room for improvement than the raw crash and carcass numbers or the EB estimate alone would find. The majority of the top 25 segments ranked by the difference between the actual and expected number of crashes per mile are less than half a mile in length and these segments are located throughout the study cities. The first ranked site in this list appears to be an outlier compared to the rest of the dataset. The estimated difference (6.418) in the crash rate and the estimate far exceeds that estimated for the other 149 segments evaluated. The rest of the segments in the top 25 are within one crash of the EB estimate, which is expected with seven years of crash and carcass data. The difference that is positive highlights that these sections have the most room for improvement by implementing possible countermeasure action to reduce the crash number, as fewer crashes are expected than are occurring. However, most of these sections have their difference within one standard deviation of the EB estimate. With this, the entire difference could disappear or grow substantially larger due to the deviance. In reality, the actual deviation from the estimate would be somewhere in the middle, however, this may cast some doubt on the findings. However, it should be noted that past work in Utah (Bissonette and Cramer 2008) did not take the deviation into account when interpreting the findings. They compared segments based on the EB predictive values against the rank that was based on the proportion of deer-vehicle crashes to all crashes. From this past research, one can infer that the deviation might not be that important to the calculation when it comes to EB estimates.

The Spearman's r correlation was also calculated, which resulted in a coefficient of 0.97, which means these ranks are highly correlated. This is not a surprise, as the estimates rely heavily on crash history with the seven years of data that were used. Whatever the final verdict is on the use of deviation, this thesis presents the first attempt to apply the EB methodology on a combined dataset that includes both deer-vehicle crash and deer carcass salvage data for urban road sections in Iowa. This model can then be used to identify areas for further study for potential countermeasure action in a bid to reduce the number of deer-vehicle crashes.

4.6 Summary/Conclusions

In this chapter, a negative binomial model and EB model were developed to examine the frequency of deer-vehicle crashes in three urban areas. The negative binomial model was estimated using a combined dataset of deer-vehicle crash and carcass data on road segments. From this model, it was found that the frequency of crashes increases as ADT increases, as expected. Also from this model, it was also found that the presence of right gravel shoulder, speed limit above 50 mph, and grass land use along the segments also increased the frequency of crashes. The elasticity estimation further revealed that the effect of the natural logarithm of ADT and the indicator variable for two-lane roads were both highly elastic. However, the direction of the effects was opposite. The frequency of deer-vehicle crashes is lower on a two-lane roadway than otherwise. This was surprising, as two lane roads are perceived as more dangerous. However, this difference may be attributable to characteristics of these types of roads in urban areas that are not explicitly captured in the model. The estimation results also may suggest that paved shoulders could replace gravel shoulders to increase safety. These estimation results also points out that multilane, high-speed roadways would have high crash occurrence. Turning to land-use variables, not many of the land uses related to development proved to be significant, but the presence of grassland increases the frequency of deer-vehicle crashes.

Based on the NB estimation results, an EB model was developed to predict the number of expected crashes on the study road sections. The sections were then ranked by crashes per mile-year, EB estimate per mile-year, and the difference between those two values. Due to the amount of data being used, EB estimates were close to the actual crash numbers. However, using these rankings, it was found that ranking the sites by the difference between the actual and expected number of crashes per mile identified sites that would otherwise have been overlooked as not having a deer-vehicle crash problem. In most cases, the deviation of the EB estimate is greater than the difference in most cases, which might be a limitation of this study. With this in mind, this model can be recalibrated (compare actual counts to what the model predicts to calculate a multiplier (Bissonette and Cramer 2008)) and used for assessing safety in terms of deer-vehicle crashes in other urban areas in Iowa.

Chapter 5: Conclusions, Limitations, and Recommendations

5.1 Summary

Deer-vehicle crashes are an increasing problem in the urban areas of Iowa. Many cities have implemented plans to reduce deer population counts in order to improve the quality of life in their cities, which includes traffic safety. While this is a good plan, other countermeasures may be appropriate at certain locations in order to reduce crashes. In order to assess the safety of segments of highways in this area, an empirical Bayes model was developed to predict deer-vehicle crashes on urban roadway segments. Three cities with long established deer management programs were selected as study areas: Dubuque, Iowa City, and Waterloo-Cedar Falls. First, deer population data from 1994-2010 were collected from the Iowa DNR. However, due to complications with how data are collected and compiled, these data were not able to be used in the final analysis. Second, deer carcass salvage reports on state maintained roadways from 2002 to 2008 were acquired from the Iowa DOT. Lastly, deer-vehicle crash data from 2002 to 2008 were acquired through the Iowa Traffic Safety Data Service from the Iowa DOT. Results from this study can allow for better identification of high deer-vehicle crash locations and could be of interest to transportation, ecology, and deer management communities.

A comparison of deer-vehicle crash counts and deer carcass salvage data was conducted across the cities. The comparison within cities confirmed the statewide trend documented by Knapp et al. (2007) and a county-trend documented by Gkritza et al. (2010) that the number of deer carcasses salvaged exceeded the number of deer-vehicle crashes reported. This comparison found that in Dubuque and Iowa City, the difference was statistically significant. This comparison also found that high cases of underreporting were found on major routes, such as I-80 and US-218. The study also looked at characteristics of roadways where carcasses were salvaged or crashes were reported. It was found that most of the carcasses were salvaged on four-lane US highways, with a speed limit of 65 mph, and were collected in the months of May, June, October and November. The crash records showed that most crashes occurred on four-lane US highways with a speed limit of 55 mph or above, in May, June, October, or November on a Monday, Friday, or Saturday. Most deer-vehicle crashes were single vehicle-crashes that resulted in property damage only (PDO) and occurred at night under clear conditions and on dry pavement. These findings are consistent with previous studies (Huijser et al. 2007a).

In this thesis, crashes and carcasses were assigned to roadway segments that had similar characteristics. In the past, researchers assigned crashes to mileposts on roadways (Knapp et al. 2007). However, due to the number of zeros in the data, segments that were classified as similar through the GIMS data (created by Iowa DOT) were selected for the crash analysis. Crash and carcass data were combined to provide a better picture of the occurrence of crashes as it was called for in previous literature (Knapp et al. 2007; Bissonette and Cramer 2008). In this process, 124 carcass and crash records were reconciled as double counts. A count data model was then calibrated based on the combined data. The negative binomial model ADT and speed were found to have a significant and positive effect on predicting crash frequency, which is contrary to past work (Bissonette and Kassar 2008). However, this may be due to the fact that in this thesis, data were limited to urban areas where past work considered all roadways. The count model also found that the frequency of deer-vehicle crashes on two-lane roadways is lower than larger facilities. This is contrary to the popular belief that two-lane roads are more dangerous, but it can be attributed to the fact that these roadways generally have lower speed limits in urban areas that allow more time for drivers to react. In addition, gravel shoulders and grassland around the roadways increased the frequency of deer-vehicle crashes. This could advocate for the greater use of paved shoulders, as not only a way to reduce deer-vehicle crashes, but to make roadways safer in general.

The negative binomial model estimation results were then used to develop EB estimates for the expected number of crashes on each segment. From this model, segments were ranked by crashes per mile-year, EB estimate per mile-year, and the difference between the two. The difference shows sections that can benefit from the implementation of countermeasures because the number of crashes is higher than what is expected. This analysis has shown that there are many sections that have greater room for improvement to reduce deer-vehicle crashes than their crash numbers alone would indicate. However, the difference between these numbers is almost always within the standard deviation of the EB estimate. This is due to the amount of data being used (more weight is being placed on observed crash data) and the variability in the data (Hauer et al. 2002). In past research (Bissonette and Cramer 2008), deviations were not considered in analysis. However, in that study, the researchers had similar results in identifying sections that would not have been indicated as high crash locations without EB analysis on the statewide basis.

This thesis shows that multiple factors affect deer-vehicle crashes on urban roadways. Some of these factors are not in line with conventional thinking, but many are shown to be common predictors. The EB model shows that examining deer-vehicle crash and carcass salvage data alone will not identify the areas with the most potential for improvement and for countermeasure action. Improving the accuracy of deer population data and land use figures is desirable. These additional data could lead to a more accurate view of deer population and the surrounding habitat and a predictive model of deer-vehicle crashes.

5.2 Limitations and Recommendations for Future Research

In this thesis, an EB model was developed to predict the number of deer-vehicle crashes on state-maintained roadways in urban areas in Iowa. This model is able to identify high-crash sections as a function of land-use and roadway characteristics and is able to identify locations that may have a crash problem that is not necessarily apparent by crash numbers alone. In the future, as more data become available, this model can be easily adapted to changing conditions. This can be done by rerunning the NB model with the updated data and putting those results into the EB model. This model can also be transferred to other cities by recalibrating it by checking the results against known points in the new city to develop a multiplier (Bissonette and Cramer 2008). This recalibration will adapt the model to local conditions. The estimated model and results from these analyses can assist decision makers in the transportation area to allocate funds on safety improvements that could have the most benefit (in terms of deer-vehicle crash reduction).

The accuracy of the developed models and results is subject to the assumptions adopted in this thesis. Deer-crash data were compiled from crash reports that had reported animal on the roadway as a cause or in the sequence of events. It was assumed that all animals reported were deer which is not likely but could be inaccurate as crash reports were not reviewed. Based on this, the Iowa DOT could study the number of animal hits reported were deer-vehicle interactions. Based on the results of this study, a possible change that could be done if the number of animals being hit are deer are significant is adding a crash element for reporting these interactions. Second, the location where the carcass data were picked up could be inaccurate as these were not geocoded by the Iowa DOT. These records were recorded by maintenance crews that may have rounded some of them to the nearest milepost for ease of recordkeeping. The accuracy of these data is important as it can reveal the magnitude of unreported crash locations. These data could be improved by using GPS units to record carcass locations so that deer carcasses could more easily be reconciled with deer-vehicle crash records. In addition, carcasses appear to be underrepresented on lower volume state roadways. An evaluation of the regular schedule for routes for maintenance crews and reporting requirements could be reviewed to make sure that crews are covering these roadways on a regular basis.

Third, the EB model is only valid for the study area and is subject to variability. This model cannot be transferred to another area or used on other roadway systems within the study area without recalibrating it to the conditions in that area. In addition, with the use of multiple years of data, the EB estimate is close to the actual crash data, and any difference is within the standard deviation of the EB estimate. While former studies have not considered the standard deviation of the EB estimate, the deviations should not be discarded. Additional study should confirm the findings before these numbers should be used in assessing where to place countermeasures. Fourth, segmentation should be re-examined. Some of the higher-ranked segments in the analysis were the shortest segments examined. This may be causing these sections to appear to have an inflated crash rate or estimate due to their short length. Future work is needed to standardize the length of the sufficiency segments in the GIMS system in urban areas in order to have a better way to estimate crashes on segments and identify high crash locations. The benefits from standardizing the length of the sufficiency segments would not only apply to analyzing deer-vehicle crashes, but any type of crashes on these segments.

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Appendix A: Maps of Deer Management Zones

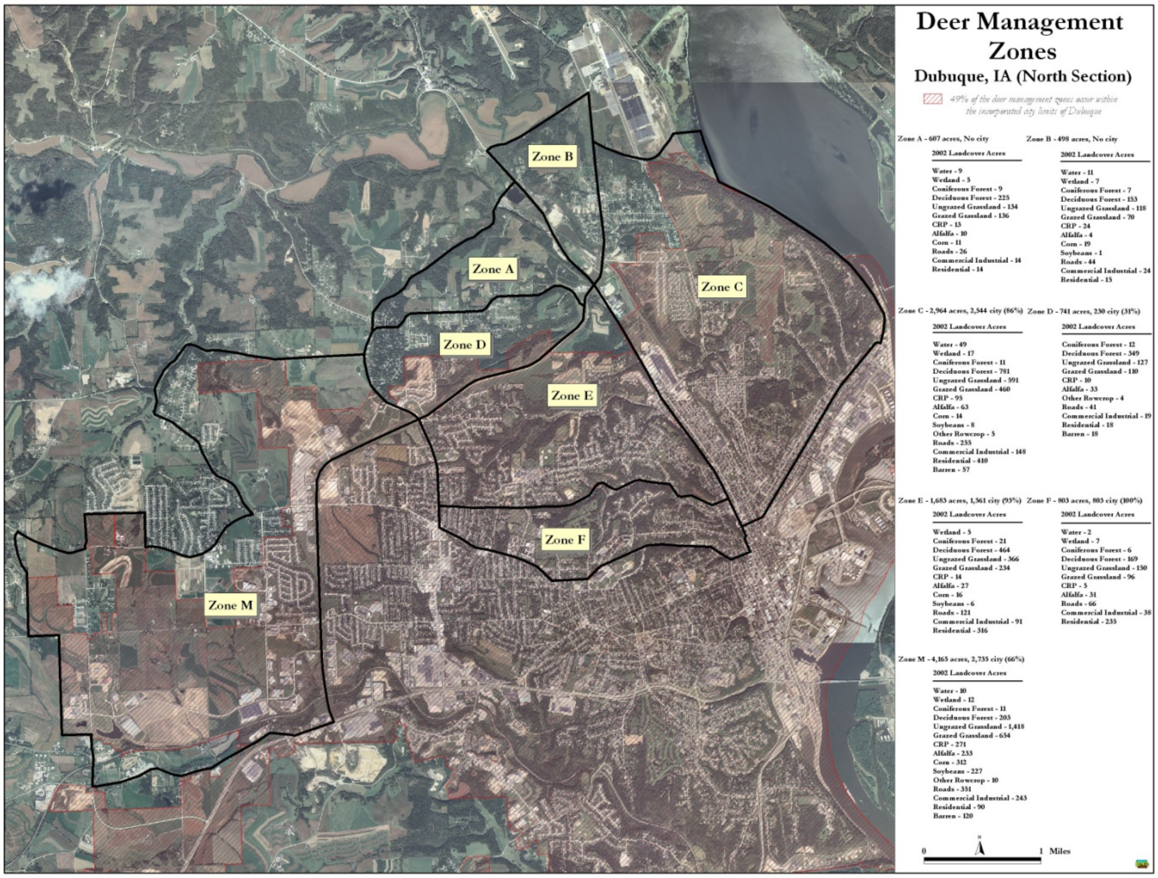


Figure A.1. Map of Dubuque deer management zones-north section

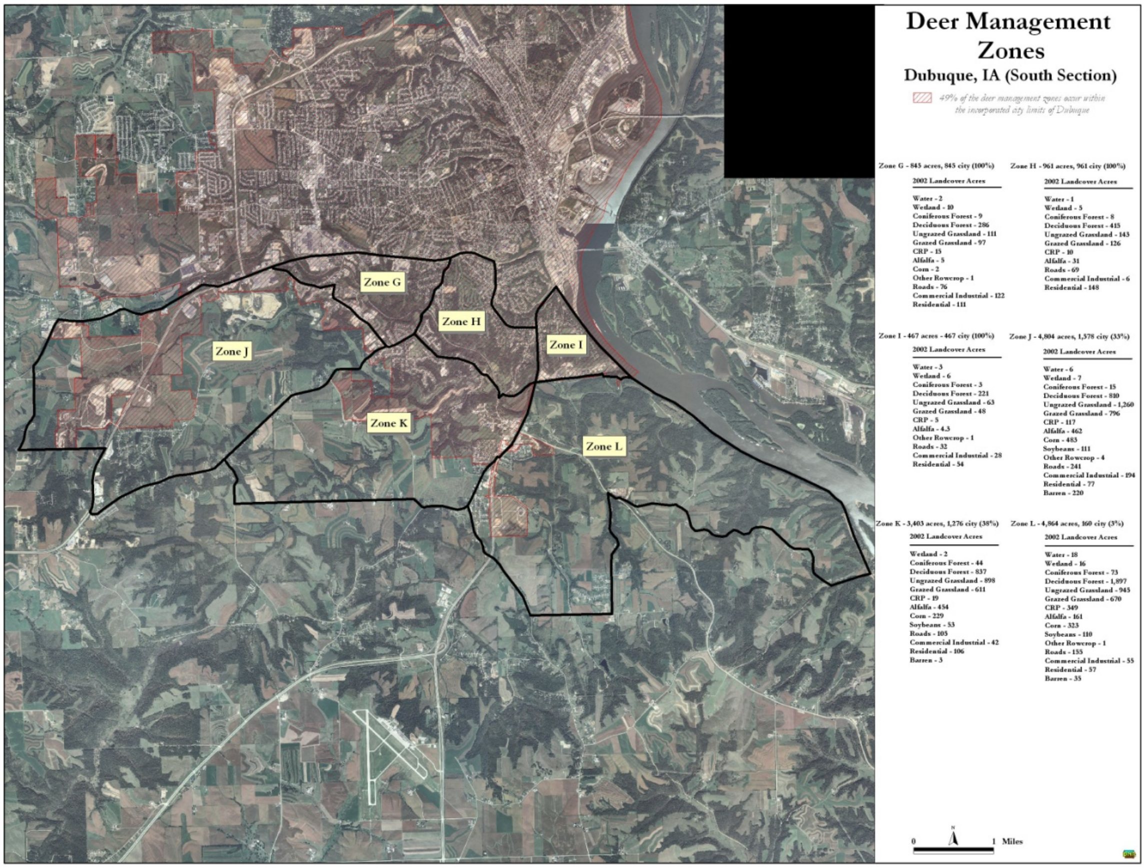


Figure A.2. Map of Dubuque deer management zones-south section

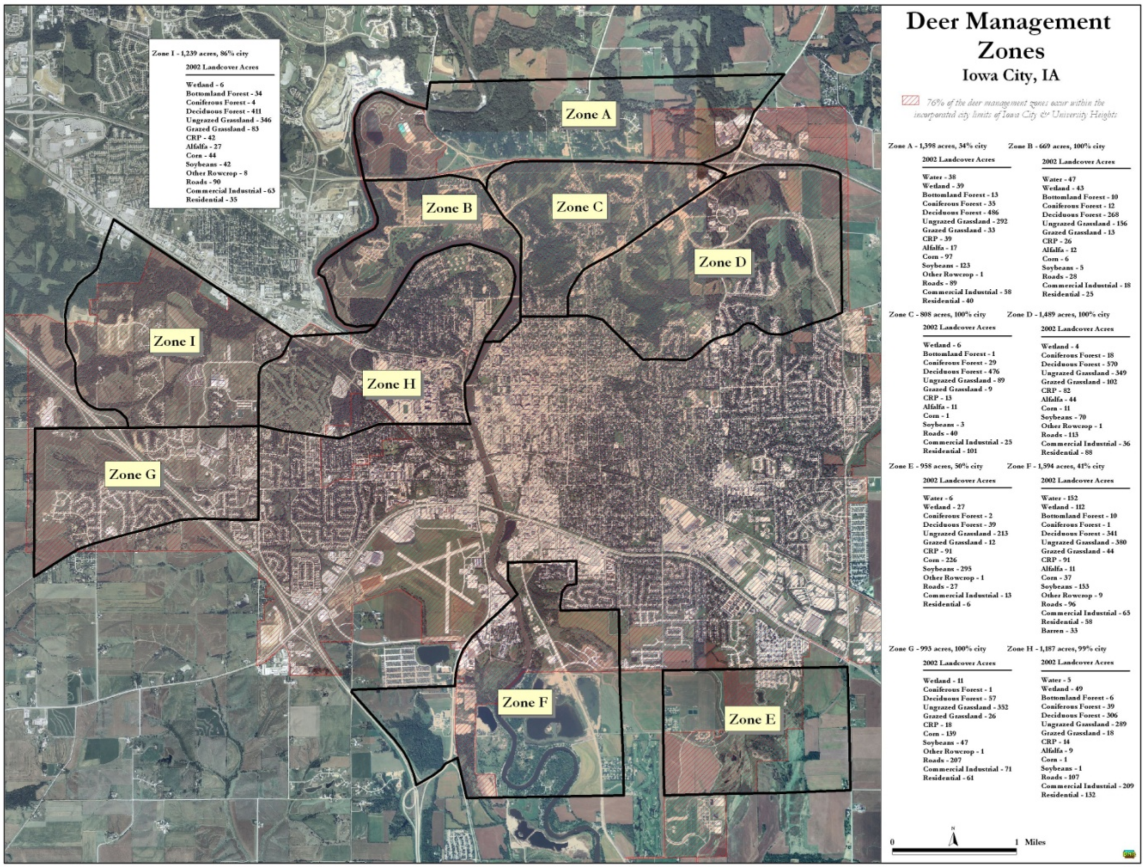


Figure A.3. Map of Iowa City deer management zones

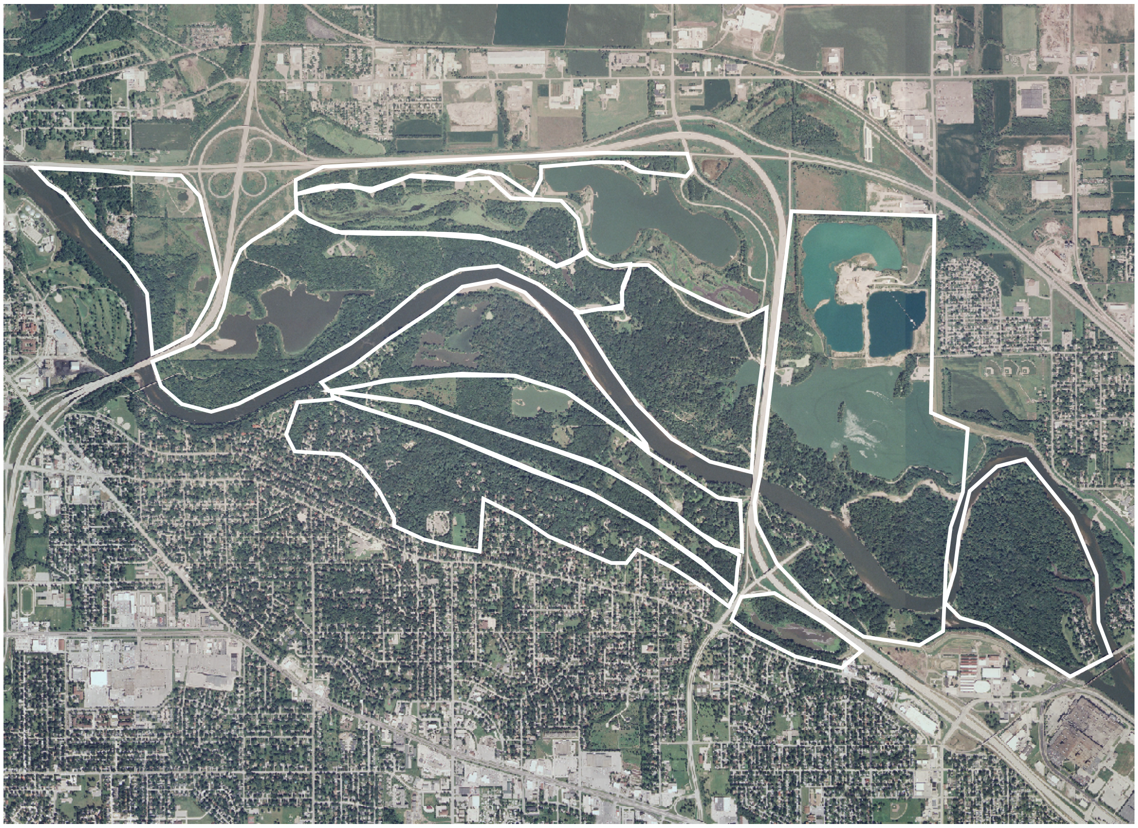


Figure A.4. Map of Waterloo-Cedar Falls deer management zones-George Wyth/Hartman (GW/H) Section

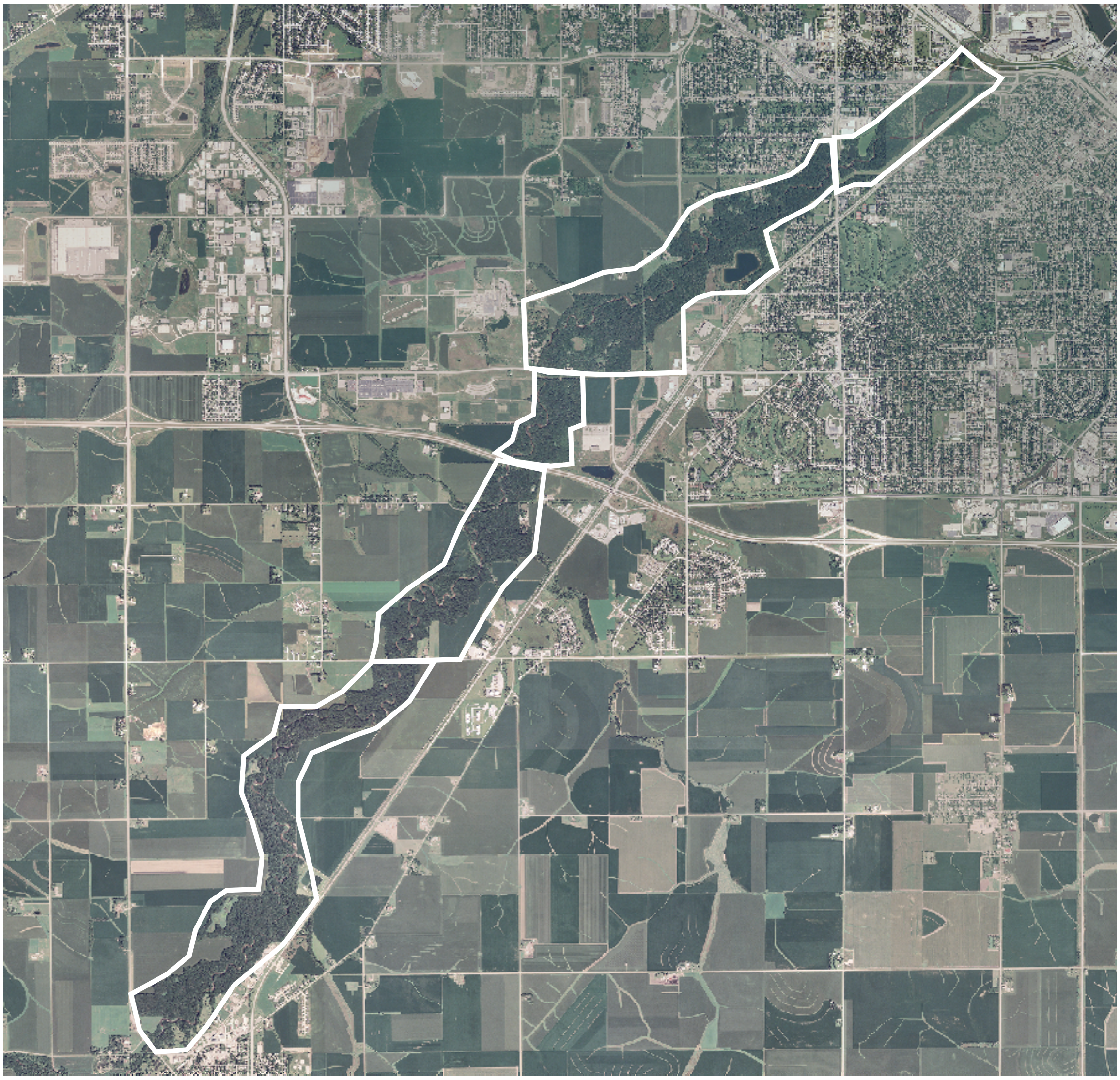
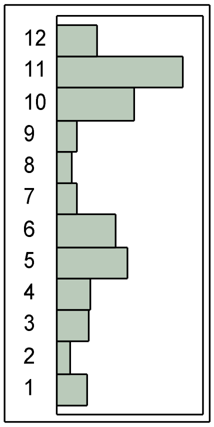


Figure A.5. Map of Waterloo-Cedar Falls deer management zones-Black Hawk County Greenbelt (BHGB) Section

Appendix B: Carcass Data Descriptive Analysis

Month



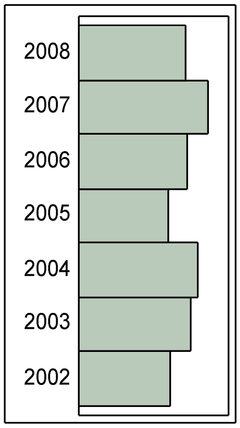
Frequencies

Level	Count	Prob
1	63	0.05635
2	27	0.02415
3	65	0.05814
4	70	0.06261
5	148	0.13238
6	124	0.11091
7	42	0.03757
8	31	0.02773
9	43	0.03846
10	160	0.14311
11	261	0.23345
12	84	0.07513
Total	1118	1.00000

N Missing
0
12 Levels

May, June, October, November

Distributions
Year

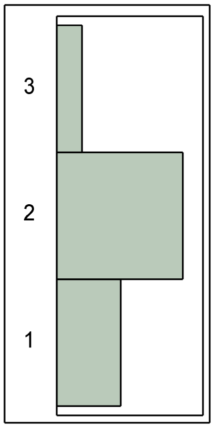


Frequencies

Level	Count	Prob
2002	135	0.12075
2003	166	0.14848
2004	176	0.15742
2005	132	0.11807
2006	161	0.14401
2007	190	0.16995
2008	158	0.14132
Total	1118	1.00000

N Missing
0
7 Levels

Distributions
SYSCODE

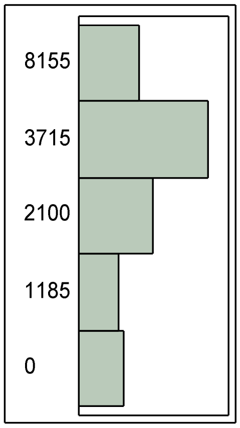


Frequencies

Level	Count	Prob	
1	331	0.29606	Interstate
2	655	0.58587	US
3	132	0.11807	Iowa
Total	1118	1.00000	

N Missing
0
3 Levels

Distributions
CITYNUM

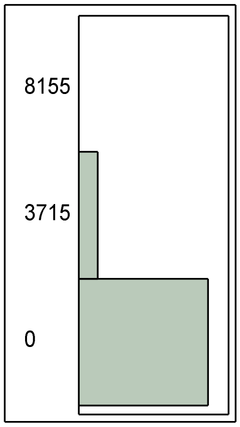


Frequencies

Level	**Count**	**Prob**	
0	144	0.12880	None
1185	127	0.11360	Cedar Falls
2100	237	0.21199	Dubuque
3715	415	0.37120	Iowa City
8155	195	0.17442	Waterloo
Total	1118	1.00000	

N Missing
0
5 Levels

CORPCITY

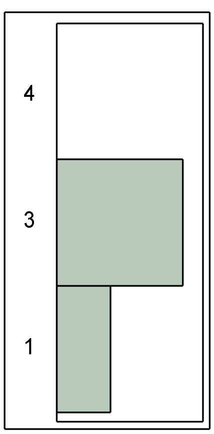


Frequencies

Level	Count	Prob	
0	974	0.87120	None
3715	143	0.12791	Iowa City
8155	1	0.00089	Waterloo
Total	1118	1.00000	

N Missing
0
3 Levels

FEDFUNC

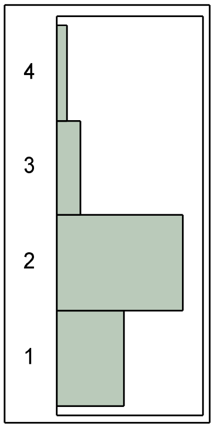


Frequencies

Level	Count	Prob	
1	331	0.29606	Interstate
3	782	0.69946	Other Principal Arterial
4	5	0.00447	Minor Arterial
Total	1118	1.00000	

N Missing
0
3 Levels

Distributions
PLANCLASS

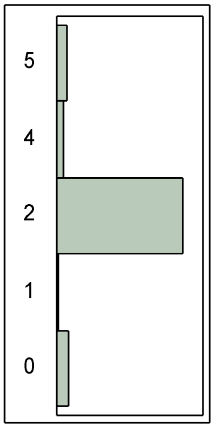


Frequencies

Level	Count	Prob	
1	331	0.29606	Interstate
2	623	0.55725	Comm/Ind Network
3	117	0.10465	Area Development
4	47	0.04204	Access Route
Total	1118	1.00000	

N Missing
0
4 Levels

Distributions
MEDTYPE

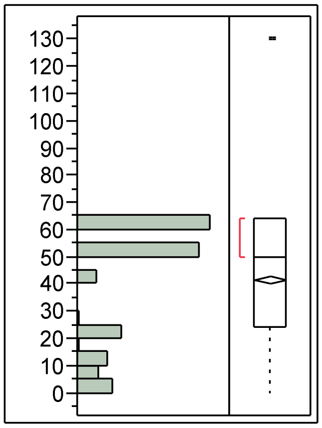


Frequencies

Level	Count	Prob	
0	88	0.07871	None
1	10	0.00894	Hard Surface w/o barrier
2	907	0.81127	Grass surface w/o barrier
4	46	0.04114	Grass surface w/ barrier
5	67	0.05993	Barrier
Total	1118	1.00000	

N Missing
0
5 Levels

Distributions
MEDWIDTH



Quantiles

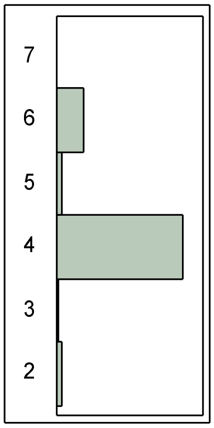
100.0%	maximum	130
99.5%		64
97.5%		64
90.0%		64
75.0%	quartile	64
50.0%	median	50
25.0%	quartile	24
10.0%		5
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	41.541145
Std Dev	22.808408
Std Err Mean	0.6821409
Upper 95% Mean	42.879567
Lower 95% Mean	40.202723
N	1118

(Median width measured to nearest foot)

Distributions
NUMLANES

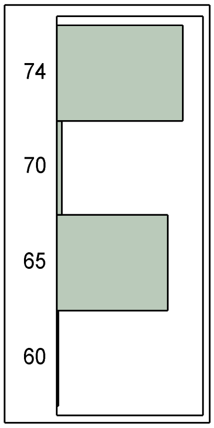


Frequencies

Level	Count	Prob
2	38	0.03399
3	11	0.00984
4	850	0.76029
5	31	0.02773
6	187	0.16726
7	1	0.00089
Total	1118	1.00000

N Missing
0
6 Levels

Distributions
SURFTYPE

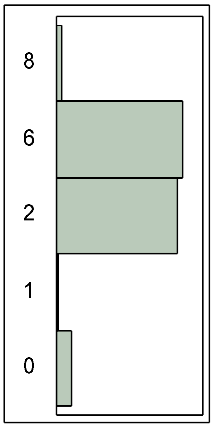


Frequencies

Level	Count	Prob	
60	6	0.00537	Generic asphalt
65	514	0.45975	Asphalt on old PCC
70	20	0.01789	Generic Concrete
74	578	0.51699	New Type PCC (not Reinforced)
Total	1118	1.00000	

N Missing
0
4 Levels

Distributions
SHDTYPER-Right Shoulder

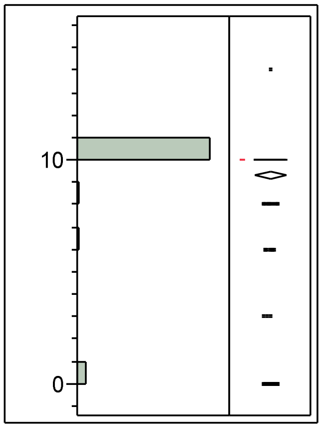


Frequencies

Level	Count	Prob	
0	65	0.05814	None
1	5	0.00447	Earth
2	507	0.45349	Gravel
6	523	0.46780	Paved
8	18	0.01610	Combined-paved & gravel
Total	1118	1.00000	

N Missing
0
5 Levels

Distributions
SHDWIDTHR-Right Shoulder



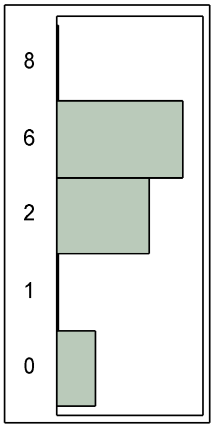
Quantiles

100.0%	maximum	14
99.5%		10
97.5%		10
90.0%		10
75.0%	quartile	10
50.0%	median	10
25.0%	quartile	10
10.0%		10
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	9.3461538
Std Dev	2.392363
Std Err Mean	0.0715494
Upper 95% Mean	9.4865403
Lower 95% Mean	9.2057674
N	1118

Distributions
SHDTYPEL-Left Shoulder

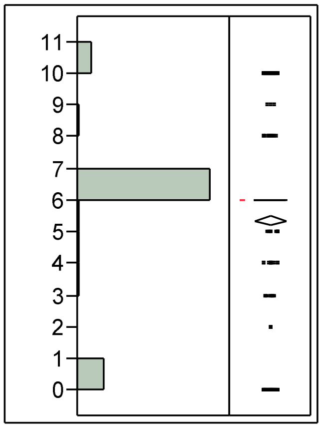


Frequencies

Level	Count	Prob	
0	164	0.14669	None
1	6	0.00537	Earth
2	399	0.35689	Gravel
6	539	0.48211	Paved
8	10	0.00894	Combo-paved & gravel
Total	1118	1.00000	

N Missing
0
5 Levels

Distributions
SHDWIDTHL-Left Shoulder



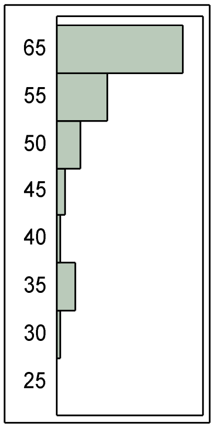
Quantiles

100.0%	maximum	10
99.5%		10
97.5%		10
90.0%		6
75.0%	quartile	6
50.0%	median	6
25.0%	quartile	6
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	5.3837209
Std Dev	2.5148411
Std Err Mean	0.0752124
Upper 95% Mean	5.5312945
Lower 95% Mean	5.2361474
N	1118

Distributions
LIMITMPH

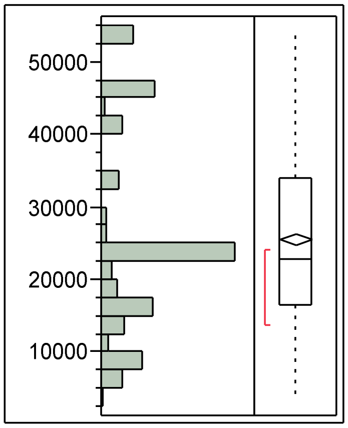


Frequencies

Level	Count	Prob
25	3	0.00268
30	13	0.01163
35	92	0.08229
40	16	0.01431
45	44	0.03936
50	111	0.09928
55	241	0.21556
65	598	0.53488
Total	1118	1.00000

N Missing
0
8 Levels

Distributions
SuffAADT



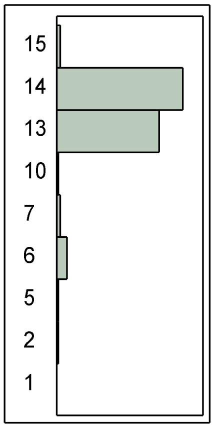
Quantiles

100.0%	maximum	53800
99.5%		53800
97.5%		53800
90.0%		45088
75.0%	quartile	33982
50.0%	median	22787
25.0%	quartile	16399
10.0%		8527
2.5%		6404
0.5%		4786.76
0.0%	minimum	3996

Moments

Mean	25566.26
Std Dev	13754.888
Std Err Mean	411.37335
Upper 95% Mean	26373.412
Lower 95% Mean	24759.109
N	1118

Distributions
GRIDCODE-Land Cover



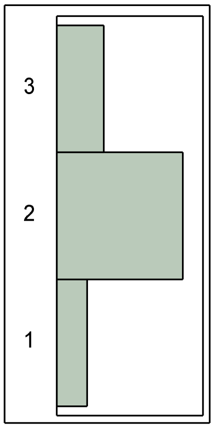
Frequencies

Level	Count	Prob	
1	3	0.00268	Open Water
2	5	0.00447	Wetland
5	6	0.00537	Deciduous Forest
6	47	0.04204	Ungrazed Grassland
7	14	0.01252	Grazed Grassland
10	9	0.00805	Corn
13	459	0.41055	Roads
14	557	0.49821	Commercial/Industrial
15	18	0.01610	Residential
Total	1118	1.00000	

N Missing
0
9 Levels

Appendix C: Crash Data Descriptive Analysis

Distributions
SYSCODE

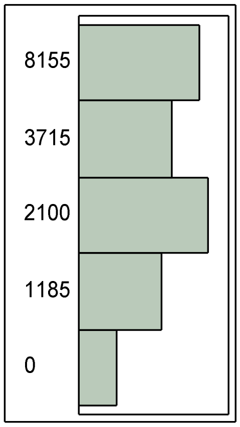


Frequencies

Level	Count	Prob	
1	94	0.14826	Interstate
2	394	0.62145	US
3	146	0.23028	Iowa
Total	634	1.00000	

N Missing
1
3 Levels

CITYNUM

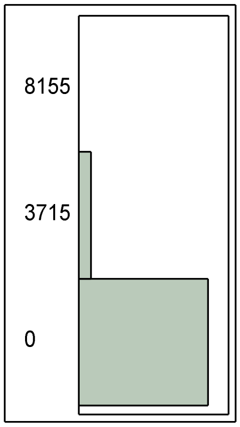


Frequencies

Level	Count	Prob	
0	52	0.08202	None
1185	113	0.17823	Cedar Falls
2100	176	0.27760	Dubuque
3715	127	0.20032	Iowa City
8155	166	0.26183	Waterloo
Total	634	1.00000	

N Missing
1
5 Levels

CORPCITY

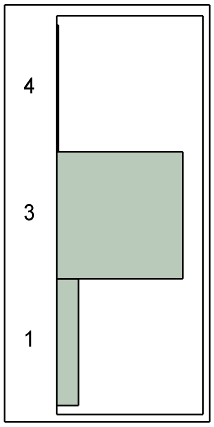


Frequencies

Level	Count	Prob	
0	582	0.91798	None
3715	51	0.08044	Iowa City
8155	1	0.00158	Waterloo
Total	634	1.00000	

N Missing
1
3 Levels

FEDFUNC

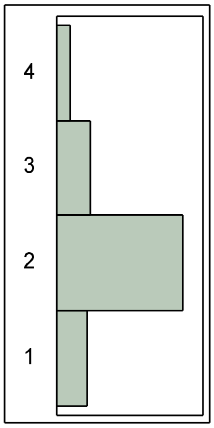


Frequencies

Level	Count	Prob	
1	94	0.14826	Interstate
3	532	0.83912	Other Principal Arterial
4	8	0.01262	Minor Arterial
Total	634	1.00000	

N Missing
1
3 Levels

PLANCLASS

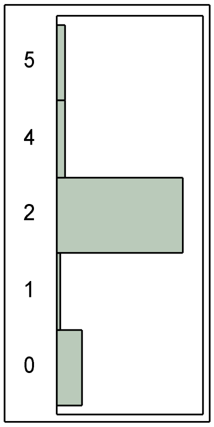


Frequencies

Level	Count	Prob	
1	94	0.14826	Interstate
2	393	0.61987	Comm/Ind Network
3	105	0.16562	Area Development
4	42	0.06625	Access Route
Total	634	1.00000	

N Missing
1
4 Levels

MEDTYPE

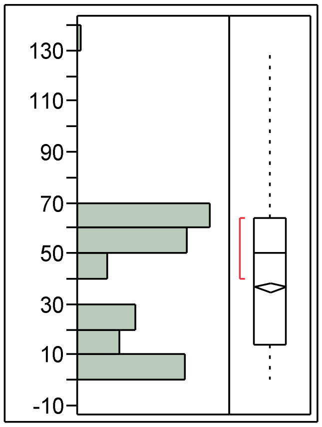


Frequencies

Level	Count	Prob	
0	93	0.14669	None
1	10	0.01577	Hard Surface w/o barrier
2	469	0.73975	Grass Surface w/o barrier
4	31	0.04890	Grass surface w/ barrier
5	31	0.04890	Barrier
Total	634	1.00000	

N Missing
1
5 Levels

MEDWIDTH



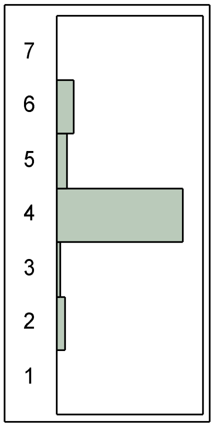
Quantiles

100.0%	maximum	130
99.5%		130
97.5%		64
90.0%		64
75.0%	quartile	64
50.0%	median	50
25.0%	quartile	14
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	36.788644
Std Dev	25.506177
Std Err Mean	1.0129797
Upper 95% Mean	38.777851
Lower 95% Mean	34.799436
N	634

NUMLANES

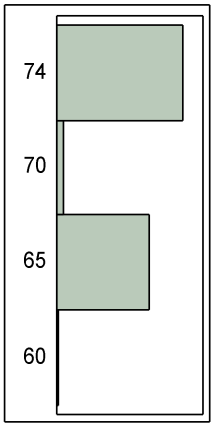


Frequencies

Level	Count	Prob
1	1	0.00158
2	35	0.05521
3	11	0.01735
4	483	0.76183
5	39	0.06151
6	63	0.09937
7	2	0.00315
Total	634	1.00000

N Missing
1
7 Levels

SURFTYPE

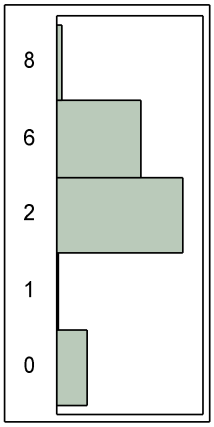


Frequencies

Level	Count	Prob	
60	7	0.01104	Generic asphalt
65	258	0.40694	Asphalt on old PCC
70	17	0.02681	Generic Concrete
74	352	0.55521	New Type PCC (not Reinforced)
Total	634	1.00000	

N Missing
1
4 Levels

SHDTYPER-Right Shoulder

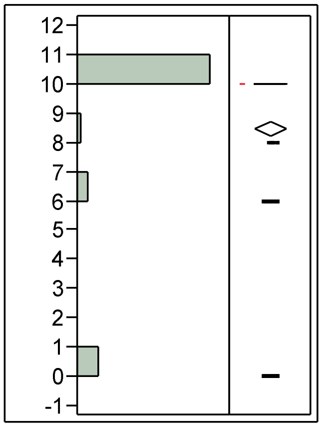


Frequencies

Level	Count	Prob	
0	78	0.12303	None
1	3	0.00473	Earth
2	324	0.51104	Gravel
6	217	0.34227	Paved
8	12	0.01893	Combined-paved & gravel
Total	634	1.00000	

N Missing
1
5 Levels

SHDWIDTHR-Right Shoulder



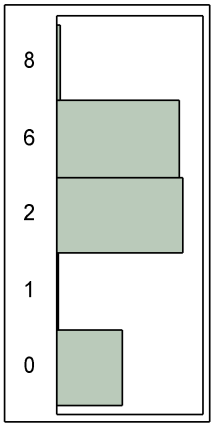
Quantiles

100.0%	maximum	10
99.5%		10
97.5%		10
90.0%		10
75.0%	quartile	10
50.0%	median	10
25.0%	quartile	10
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	8.4637224
Std Dev	3.33199
Std Err Mean	0.1323302
Upper 95% Mean	8.7235817
Lower 95% Mean	8.2038631
N	634

SHDTYPEL-Left Shoulder

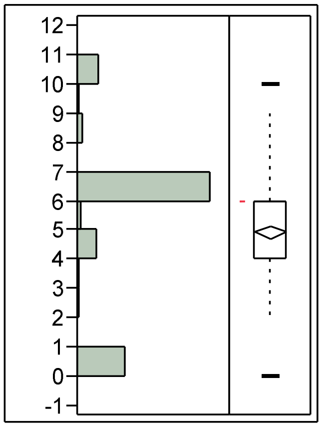


Frequencies

Level	Count	Prob	
0	131	0.20662	None
1	4	0.00631	Earth
2	248	0.39117	Gravel
6	244	0.38486	Paved
8	7	0.01104	Combo-paved & gravel
Total	634	1.00000	

N Missing
1
5 Levels

SHDWIDTHL-Left Shoulder



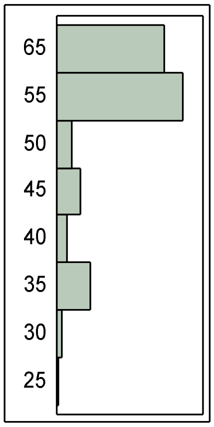
Quantiles

100.0%	maximum	10
99.5%		10
97.5%		10
90.0%		8
75.0%	quartile	6
50.0%	median	6
25.0%	quartile	4
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	4.9369085
Std Dev	2.9032521
Std Err Mean	0.1153029
Upper 95% Mean	5.1633309
Lower 95% Mean	4.7104861
N	634

LIMITMPH

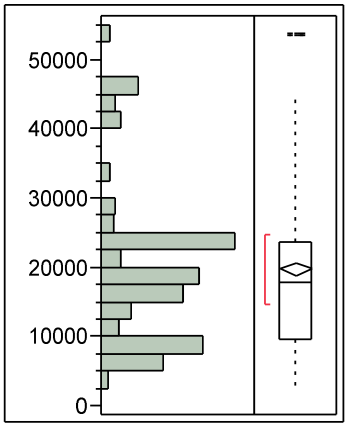


Frequencies

Level	Count	Prob
25	3	0.00473
30	9	0.01420
35	67	0.10568
40	20	0.03155
45	47	0.07413
50	31	0.04890
55	246	0.38801
65	211	0.33281
Total	634	1.00000

N Missing
1
8 Levels

SuffAADT



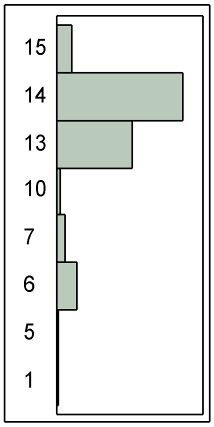
Quantiles

100.0%	maximum	53800
99.5%		53800
97.5%		45088
90.0%		41044
75.0%	quartile	23769
50.0%	median	17721
25.0%	quartile	9500
10.0%		7385
2.5%		5987
0.5%		3996
0.0%	minimum	2500

Moments

Mean	19831.897
Std Dev	11351.336
Std Err Mean	450.81915
Upper 95% Mean	20717.179
Lower 95% Mean	18946.615
N	634

GRIDCODE

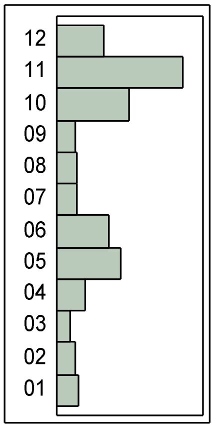


Frequencies

Level	Count	Prob	
1	5	0.00789	Open Water
5	4	0.00631	Deciduous Forest
6	50	0.07886	Ungrazed Grassland
7	21	0.03312	Grazed Grassland
10	9	0.01420	Corn
13	190	0.29968	Roads
14	317	0.50000	Commercial/Industrial
15	38	0.05994	Residential
Total	634	1.00000	

N Missing
1
8 Levels

Distributions
Month

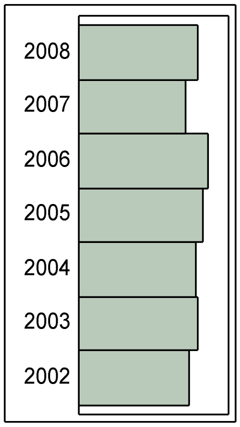


Frequencies

Level	Count	Prob
01	28	0.04416
02	24	0.03785
03	16	0.02524
04	35	0.05521
05	81	0.12776
06	65	0.10252
07	26	0.04101
08	26	0.04101
09	24	0.03785
10	91	0.14353
11	158	0.24921
12	60	0.09464
Total	634	1.00000

N Missing
0
12 Levels

Year

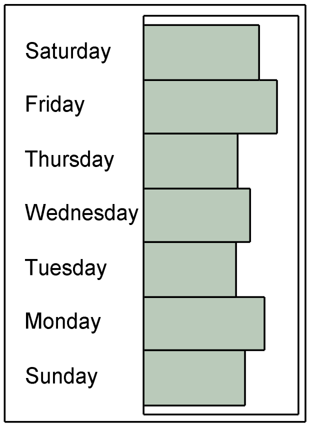


Frequencies

Level	Count	Prob
2002	85	0.13407
2003	91	0.14353
2004	90	0.14196
2005	95	0.14984
2006	99	0.15615
2007	82	0.12934
2008	92	0.14511
Total	634	1.00000

N Missing
0
7 Levels

DAY

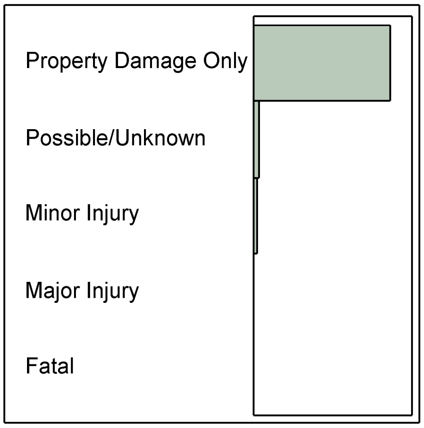


Frequencies

Level	Count	Prob
Sunday	84	0.13249
Monday	101	0.15931
Tuesday	77	0.12145
Wednesday	88	0.13880
Thursday	78	0.12303
Friday	110	0.17350
Saturday	96	0.15142
Total	634	1.00000

N Missing
0
7 Levels

Distributions
CSEVERITY

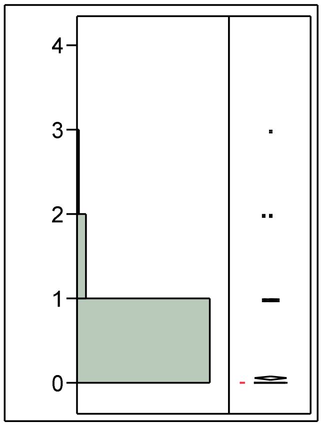


Frequencies

Level	Count	Prob
Fatal	1	0.00158
Major Injury	2	0.00315
Minor Injury	13	0.02050
Possible/Unknown	26	0.04101
Property Damage Only	592	0.93375
Total	634	1.00000

N Missing
0
5 Levels

Distributions
INJURIES



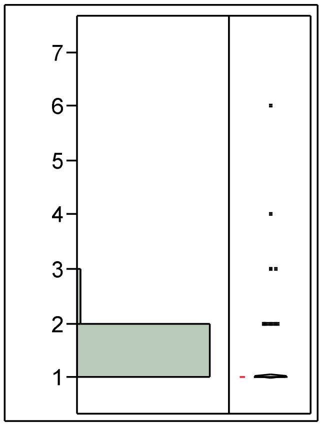
Quantiles

100.0%	maximum	3
99.5%		2
97.5%		1
90.0%		0
75.0%	quartile	0
50.0%	median	0
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	0.0772871
Std Dev	0.3109709
Std Err Mean	0.0123502
Upper 95% Mean	0.1015394
Lower 95% Mean	0.0530347
N	634

VEHICLES-Number of Vehicles



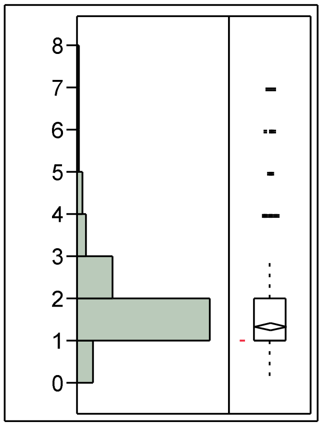
Quantiles

100.0%	maximum	6
99.5%		3
97.5%		2
90.0%		1
75.0%	quartile	1
50.0%	median	1
25.0%	quartile	1
10.0%		1
2.5%		1
0.5%		1
0.0%	minimum	1

Moments

Mean	1.0473186
Std Dev	0.3093601
Std Err Mean	0.0122863
Upper 95% Mean	1.0714454
Lower 95% Mean	1.0231919
N	634

Distributions
TOCCUPANTS-Total Occupants



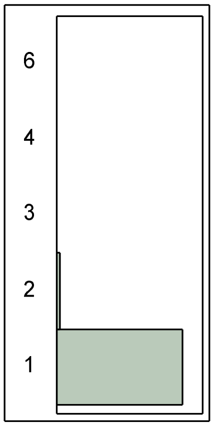
Quantiles

100.0%	maximum	7
99.5%		7
97.5%		4
90.0%		2
75.0%	quartile	2
50.0%	median	1
25.0%	quartile	1
10.0%		1
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	1.3673469
Std Dev	1.0199484
Std Err Mean	0.042062
Upper 95% Mean	1.4499572
Lower 95% Mean	1.2847367
N	588

Distributions
VEHICLES-Percentages

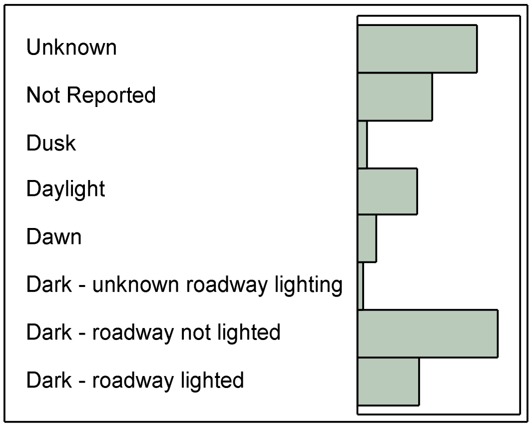


Frequencies

Level	Count	Prob
1	613	0.96688
2	16	0.02524
3	3	0.00473
4	1	0.00158
6	1	0.00158
Total	634	1.00000

N Missing
0
5 Levels

LIGHT

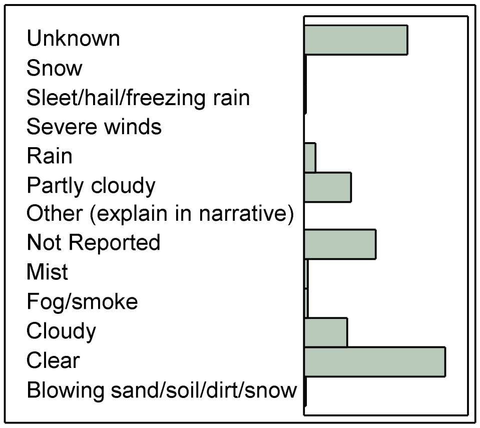


Frequencies

Level	Count	Prob
Dark - roadway lighted	79	0.12461
Dark - roadway not lighted	181	0.28549
Dark - unknown roadway lighting	8	0.01262
Dawn	24	0.03785
Daylight	78	0.12303
Dusk	12	0.01893
Not Reported	97	0.15300
Unknown	155	0.24448
Total	634	1.00000

N Missing
0
8 Levels

Distributions
WEATHER1

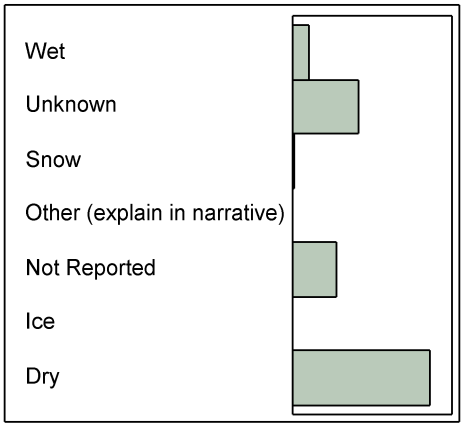


Frequencies

Level	Count	Prob
Blowing sand/soil/dirt/snow	2	0.00315
Clear	207	0.32650
Cloudy	63	0.09937
Fog/smoke	5	0.00789
Mist	5	0.00789
Not Reported	105	0.16562
Other (explain in narrative)	1	0.00158
Partly cloudy	70	0.11041
Rain	17	0.02681
Severe winds	1	0.00158
Sleet/hail/freezing rain	2	0.00315
Snow	2	0.00315
Unknown	154	0.24290
Total	634	1.00000

N Missing
0
13 Levels

SURF_COND-Road Surface Conditions



Frequencies

Level	Count	Prob
Dry	327	0.51577
Ice	2	0.00315
Not Reported	105	0.16562
Other (explain in narrative)	1	0.00158
Snow	3	0.00473
Unknown	157	0.24763
Wet	39	0.06151
Total	634	1.00000

N Missing
0
7 Levels

Appendix D: Crash and Carcass Data Combination and Double Count Elimination

Table D.1. Summary of Crash, Carcass, and Double Counted Records for Combination of Data Sources.

Sufficiency Segment	Crash	Carcass	Double Count	Total (exclude double)	Grand Total	Zero (1 Yes, 0 No)
71100934	0	0	0	0	0	1
71200934	3	0	0	3	3	0
71300934	1	0	0	1	1	0
71400934	2	1	1	2	3	0
71500934	0	0	0	0	0	1
71600934	0	0	0	0	0	1
71700934	1	0	0	1	1	0
75350057	9	9	1	17	18	0
75370057	0	0	0	0	0	1
75400057	0	0	0	0	0	1
75450057	1	0	0	1	1	0
75500057	0	1	0	1	1	0
75550057	0	0	0	0	0	1
75600057	5	3	0	8	8	0
75700057	0	5	0	5	5	0
76200021	6	5	1	10	11	0
76300021	2	0	0	2	2	0
77850218	1	1	0	2	2	0
77900218	3	7	0	10	10	0
77950218	0	0	0	0	0	1
78950027	0	0	0	0	0	1
311100032	8	4	1	11	12	0
311200032	3	7	0	10	10	0
311300032	10	17	2	25	27	0
311400032	21	14	2	33	35	0
311500032	0	24	0	24	24	0
311600032	10	8	1	17	18	0
312500052	23	41	9	55	64	0
312550052	2	3	1	4	5	0
312600052	0	0	0	0	0	1
312650052	0	0	0	0	0	1
312700052	0	0	0	0	0	1
312800052	0	0	0	0	0	1

Table D.1 (continued).

Sufficiency Segment	Crash	Carcass	Double Count	Total (exclude double)	Grand Total	Zero (1 Yes, 0 No)
312900052	0	0	0	0	0	1
312950052	0	0	0	0	0	1
525120001	0	0	0	0	0	1
525150001	2	2	0	4	4	0
525400001	9	3	0	12	12	0
719400020	9	7	0	16	16	0
719600020	6	5	1	10	11	0
719800020	17	22	3	36	39	0
754550380	3	3	0	6	6	0
754600380	2	6	0	8	8	0
754700380	3	5	0	8	8	0
761000063	15	17	1	31	32	0
761300063	7	2	0	9	9	0
761600063	13	6	2	17	19	0
761900063	5	5	0	10	10	0
762200063	1	0	0	1	1	0
762300063	1	1	0	2	2	0
762500063	1	1	0	2	2	0
762800063	0	3	0	3	3	0
763000063	1	1	0	2	2	0
763100063	0	2	0	2	2	0
763200063	0	0	0	0	0	1
763300063	0	0	0	0	0	1
763400063	0	1	0	1	1	0
763500063	0	0	0	0	0	1
763600063	0	0	0	0	0	1
764100063	0	0	0	0	0	1
764400063	0	0	0	0	0	1
764600063	0	0	0	0	0	1
764700063	0	0	0	0	0	1
765300063	0	0	0	0	0	1
765350063	1	2	0	3	3	0
765400063	12	5	0	17	17	0
765600063	11	10	1	20	21	0
771000218	8	5	0	13	13	0
771050218	5	2	0	7	7	0
771070218	1	0	0	1	1	0
771100218	0	2	0	2	2	0
771200218	0	0	0	0	0	1

Table D.1 (continued).

Sufficiency Segment	Crash	Carcass	Double Count	Total (exclude double)	Grand Total	Zero (1 Yes, 0 No)
771300218	0	1	0	1	1	0
771400218	0	6	0	6	6	0
771500218	2	11	0	13	13	0
774400218	7	20	4	23	27	0
774500218	3	6	0	9	9	0
774600218	0	0	0	0	0	1
774620218	0	5	0	5	5	0
774650218	0	0	0	0	0	1
774700218	15	53	4	64	68	0
774800218	23	23	4	42	46	0
781000027	39	7	3	43	46	0
781100027	1	4	0	5	5	0
781200027	1	2	0	3	3	0
781300027	1	1	0	2	2	0
781400027	0	2	0	2	2	0
3121000052	0	0	0	0	0	1
3121050052	0	0	0	0	0	1
3121100052	0	0	0	0	0	1
3121200052	0	0	0	0	0	1
3121300052	0	0	0	0	0	1
3121400052	1	0	0	1	1	0
3122400052	0	0	0	0	0	1
3122550052	14	12	1	25	26	0
3181650061	8	8	0	16	16	0
3181700061	0	0	0	0	0	1
3181750061	2	0	0	2	2	0
3183000061	0	0	0	0	0	1
3183100061	0	0	0	0	0	1
3183600061	1	2	0	3	3	0
3183650061	0	0	0	0	0	1
3183700061	0	0	0	0	0	1
3184000061	0	0	0	0	0	1
5241200218	7	23	2	28	30	0
5242000218	2	6	1	7	8	0
5245000218	27	111	17	121	138	0
5246000218	22	67	10	79	89	0
5251100001	0	0	0	0	0	1
5251300001	0	0	0	0	0	1
5251400001	0	0	0	0	0	1

Table D.1 (continued).

Sufficiency Segment	Crash	Carcass	Double Count	Total (exclude double)	Grand Total	Zero (1 Yes, 0 No)
5251500001	0	0	0	0	0	1
5251600001	0	1	0	1	1	0
5251700001	0	0	0	0	0	1
5251800001	0	0	0	0	0	1
5251900001	0	0	0	0	0	1
5252000001	0	0	0	0	0	1
5252100001	0	0	0	0	0	1
5252150001	1	0	0	1	1	0
5253300001	0	0	0	0	0	1
5253500001	7	7	0	14	14	0
5253800001	3	5	0	8	8	0
7194000020	16	13	2	27	29	0
7194200020	16	24	3	37	40	0
31251150020	9	0	0	9	9	0
31251200020	36	0	0	36	36	0
31251230020	2	61	2	61	63	0
31251250020	4	6	1	9	10	0
31251270020	2	4	1	5	6	0
31251300020	11	14	3	22	25	0
31251650020	0	3	0	3	3	0
31251700020	1	3	0	4	4	0
31251800020	2	0	0	2	2	0
31251900020	5	5	2	8	10	0
31252000020	1	0	0	1	1	0
31252700020	0	0	0	0	0	1
31252800020	0	1	0	1	1	0
52101600006	6	8	0	14	14	0
52102100006	1	3	0	4	4	0
52102500006	1	1	0	2	2	0
52102700006	0	1	0	1	1	0
52102900006	1	1	0	2	2	0
52102950006	1	0	0	1	1	0
52103000006	2	2	0	4	4	0
52103800080	9	80	4	85	89	0
52103900080	13	7	2	18	20	0
52104900080	36	134	20	150	170	0
52105400080	19	52	7	64	71	0
52105950080	9	43	4	48	52	0
52105970080	0	1	0	1	1	0

Table D.1 (continued).

Sufficiency Segment	Crash	Carcass	Double Count	Total (exclude double)	Grand Total	Zero (1 Yes, 0 No)
Total	634	1118	124	1628	1752	50

Appendix E: Count Model Data Outputs from Limdep

E.1 Zero Inflated Negative Binomial

```
-->
negbin;lhs=x4;rhs=one,logADT,HSpeed,grass,logLen,twolnrd,rshldg;rst=b0,b1..
.
+---------------------------------------------+
| Poisson Regression                          |
| Maximum Likelihood Estimates                |
| Model estimated: Jun 13, 2010 at 11:18:34PM.|
| Dependent variable                  X4      |
| Weighting variable                None      |
| Number of observations             150      |
| Iterations completed                 7      |
| Log likelihood function      -900.1056      |
| Number of parameters                 7      |
| Info. Criterion: AIC =        12.09474      |
|   Finite Sample: AIC =        12.10000      |
| Info. Criterion: BIC =        12.23524      |
| Info. Criterion:HQIC =        12.15182      |
| Restricted log likelihood    -2059.908      |
| McFadden Pseudo R-squared     .5630360      |
| Chi squared                   2319.605      |
| Degrees of freedom                   6      |
| Prob[ChiSqd > value] =        .0000000      |
+---------------------------------------------+

+---------------------------------------------+
| Poisson Regression                          |
| Chi- squared =  2365.33749  RsqP=   .6288   |
| G  - squared =  1418.88021  RsqD=   .6205   |
| Overdispersion tests: g=mu(i)  :  2.541     |
| Overdispersion tests: g=mu(i)^2:  1.833     |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|   -10.0526367       .60917517   -16.502   .0000
 LOGADT  |    1.21036391       .06049479    20.008   .0000   9.43742853
 HSPEED  |    1.06760746       .06907251    15.456   .0000    .42666667
 GRASS   |     .33826364       .10035005     3.371   .0007    .12000000
 LOGLEN  |     .65414189       .03416650    19.146   .0000   -.91651482
 TWOLNRD |     .06964840       .13786415      .505   .6134    .18000000
 RSHLDG  |     .72101808       .05447277    13.236   .0000    .26666667

Warning   141: Iterations:current or start estimate of sigma is nonpositiv
Normal exit from iterations. Exit status=0.



+---------------------------------------------+
| Negative Binomial Regression                |
| Maximum Likelihood Estimates                |
| Model estimated: Jun 13, 2010 at 11:18:34PM.|
| Dependent variable                  X4      |
| Weighting variable                None      |
| Number of observations             150      |
```

```
| Iterations completed                 15      |
| Log likelihood function       -399.1547      |
| Number of parameters                  8      |
| Info. Criterion: AIC =          5.42873      |
|   Finite Sample: AIC =          5.43554      |
| Info. Criterion: BIC =          5.58930      |
| Info. Criterion:HQIC =          5.49396      |
| Restricted log likelihood     -900.1056      |
| McFadden Pseudo R-squared      .5565469      |
| Chi squared                    1001.902      |
| Degrees of freedom                    1      |
| Prob[ChiSqd > value] =         .0000000      |
| NegBin form 2; Psi(i) = theta               |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|   -5.65061877      2.20899949    -2.558   .0105
 LOGADT  |     .73755717       .23249610     3.172   .0015   9.43742853
 HSPEED  |    1.06541302       .28624450     3.722   .0002    .42666667
 GRASS   |     .82704953       .31858155     2.596   .0094    .12000000
 LOGLEN  |     .68947648       .11618601     5.934   .0000   -.91651482
 TWOLNRD |   -.81367900        .37128629    -2.192   .0284    .18000000
 RSHLDG  |    1.31653347       .31355047     4.199   .0000    .26666667
---------+Dispersion parameter for count data model
 Alpha   |    1.37655220       .23022819     5.979   .0000

Normal exit from iterations. Exit status=0.
```

```
+-----------------------------------------------------------------------+
| Zero Altered Neg.Binomial Regression Model                            |
| Logistic distribution used for splitting model.                       |
| ZAP term in probability is F[tau x ln LAMBDA]                         |
| Comparison of estimated models                                        |
|             Pr[0|means]       Number of zeros        Log-likelihood |
| Poisson          .01283   Act.=    50 Prd.=     1.9      -900.10561 |
| Neg. Bin.        .14554   Act.=    50 Prd.=    21.8      -399.15465 |
| Z.I.Neg_Bin      .28008   Act.=    50 Prd.=    42.0      -403.35991 |
| Note, the ZIP log-likelihood is not directly comparable.              |
| ZIP model with nonzero Q does not encompass the others.               |
| Vuong statistic for testing ZIP vs. unaltered model is      -.6510    |
| Distributed as standard normal. A value greater than                  |
| +1.96 favors the zero altered Z.I.Neg_Bin model.                      |
| A value less than -1.96 rejects the ZIP model.                        |
```

```
+---------------------------------------------------------------------+
+---------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient   | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+---------+--------------+----------------+--------+--------+----------+
---------+Poisson/NB/Gamma regression model
 Constant|   -3.47885077      1.96391042    -1.771   .0765
 LOGADT  |     .58198228       .20698684     2.812   .0049   9.43742853
 HSPEED  |     .63625895       .25078549     2.537   .0112    .42666667
 GRASS   |     .49796600       .31177464     1.597   .1102    .12000000
 LOGLEN  |    1.00000000    ......(Fixed Parameter).......
 TWOLNRD |    -.59967435       .36487531    -1.644   .1003    .18000000
 RSHLDG  |    1.20004401       .20739176     5.786   .0000    .26666667
---------+Dispersion parameter
 Alpha   |    1.24217493       .11953921    10.391   .0000
---------+Zero inflation model
 Tau     |   -1.33510769       .36274282    -3.681   .0002
```

E.2 Negative Binomial Model

negbin;lhs=x4;rhs=one,logADT,HSpeed,grass,logLen,twolnrd,rshldg;rst=b0,b1..
.

```
+----------------------------------------------+
| Poisson Regression                           |
| Maximum Likelihood Estimates                 |
| Model estimated: Jun 13, 2010 at 11:19:38PM.|
| Dependent variable                  X4       |
| Weighting variable                None       |
| Number of observations             150       |
| Iterations completed                 7       |
| Log likelihood function      -900.1056       |
| Number of parameters                 7       |
| Info. Criterion: AIC =        12.09474       |
|   Finite Sample: AIC =        12.10000       |
| Info. Criterion: BIC =        12.23524       |
| Info. Criterion:HQIC =        12.15182       |
| Restricted log likelihood    -2059.908       |
| McFadden Pseudo R-squared     .5630360       |
```

```
| Chi squared                      2319.605      |
| Degrees of freedom                      6      |
| Prob[ChiSqd > value] =           .0000000      |
+------------------------------------------------+

+------------------------------------------------+
| Poisson Regression                             |
| Chi- squared =  2365.33749  RsqP=   .6288      |
| G  - squared =  1418.88021  RsqD=   .6205      |
| Overdispersion tests: g=mu(i)  :  2.541        |
| Overdispersion tests: g=mu(i)^2:  1.833        |
+------------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|   -10.0526367       .60917517   -16.502   .0000
 LOGADT  |    1.21036391       .06049479    20.008   .0000   9.43742853
 HSPEED  |    1.06760746       .06907251    15.456   .0000    .42666667
 GRASS   |     .33826364       .10035005     3.371   .0007    .12000000
 LOGLEN  |     .65414189       .03416650    19.146   .0000   -.91651482
 TWOLNRD |     .06964840       .13786415      .505   .6134    .18000000
 RSHLDG  |     .72101808       .05447277    13.236   .0000    .26666667

Warning   141: Iterations:current or start estimate of sigma is nonpositiv
Normal exit from iterations. Exit status=0.
```

```
+------------------------------------------------+
| Negative Binomial Regression                   |
| Maximum Likelihood Estimates                   |
| Model estimated: Jun 13, 2010 at 11:19:38PM.|
| Dependent variable                      X4     |
| Weighting variable                    None     |
| Number of observations                 150     |
| Iterations completed                    14     |
| Log likelihood function          -402.5223     |
| Number of parameters                     7     |
| Info. Criterion: AIC =             5.46030     |
|   Finite Sample: AIC =             5.46556     |
| Info. Criterion: BIC =             5.60079     |
| Info. Criterion:HQIC =             5.51738     |
| Restricted log likelihood        -900.1056     |
| McFadden Pseudo R-squared         .5528055     |
| Chi squared                       995.1666     |
| Degrees of freedom                       1     |
| Prob[ChiSqd > value] =            .0000000     |
| NegBin form 2; Psi(i) = theta                  |
+------------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|    -4.83458076     2.40155830    -2.013   .0441
 LOGADT  |     .68859195       .25210521     2.731   .0063   9.43742853
 HSPEED  |     .81989021       .30236573     2.712   .0067    .42666667
 GRASS   |     .66985906       .35030343     1.912   .0558    .12000000
```

```
 LOGLEN  |    1.00000000    ......(Fixed Parameter).......
 TWOLNRD |    -.84901624       .41579781    -2.042   .0412    .18000000
 RSHLDG  |    1.43763603       .28115219     5.113   .0000    .26666667
---------+Dispersion parameter for count data model
 Alpha   |    1.45095143       .24108788     6.018   .0000
```

Appendix F: Empirical Bayes Output

Table F.1. Rankings of segments by crashes/carcasses per mile, EB estimate per mile, and difference between crash/carcass and EB estimate per mile.

Sufficiency Segment	Route	City	Length	Crash	Estimate	Crash/mi-yr	Estimate/mi-yr	Difference	Deviation /mi-yr	Rank Crash	Rank Estimate	Rank Difference
311500032	32	Dubuque	0.042	24	22.113	81.633	75.215	6.418	15.333	1	1	1
312500052	52	Dubuque	0.709	55	50.754	11.082	10.227	0.855	1.366	8	8	2
77900218	218	Waterloo-Cedar Falls	0.479	10	7.222	2.982	2.154	0.828	0.655	21	34	3
3121400052	52	Dubuque	0.131	1	0.247	1.091	0.269	0.821	0.221	70	100	4
3122550052	52	Dubuque	0.563	25	21.822	6.344	5.537	0.806	1.089	13	15	5
52103800080	80	Iowa City	0.61	85	82.170	19.906	19.244	0.663	2.076	3	3	6
52105400080	80	Iowa City	0.634	64	61.562	14.421	13.872	0.549	1.721	5	5	7
765400063	63	Waterloo-Cedar Falls	1.005	17	13.214	2.416	1.878	0.538	0.435	29	43	8
52104900080	80	Iowa City	1.463	150	144.730	14.647	14.132	0.515	1.146	4	4	9
5253500001	1	Iowa City	1.14	14	10.688	1.754	1.339	0.415	0.336	50	64	10
719400020	20	Waterloo-Cedar Falls	0.523	16	14.750	4.370	4.029	0.342	0.983	17	17	11
311600032	32	Dubuque	0.396	17	16.165	6.133	5.832	0.301	1.390	14	13	12
763400063	63	Waterloo-Cedar Falls	0.117	1	0.755	1.221	0.922	0.299	0.841	66	76	13
52105950080	80	Iowa City	0.87	48	46.386	7.882	7.617	0.265	1.085	11	11	14
5252150001	1	Iowa City	0.106	1	0.809	1.348	1.090	0.258	1.005	61	70	15
52103900080	80	Iowa City	0.285	18	17.490	9.023	8.767	0.256	2.043	9	9	16
31251230020	20	Dubuque	0.367	61	60.368	23.745	23.499	0.246	2.996	2	2	17
75600057	57	Waterloo-Cedar Falls	0.555	8	7.049	2.059	1.815	0.245	0.609	37	49	18
31251270020	20	Dubuque	0.264	5	4.565	2.706	2.470	0.235	1.063	26	26	19
52101600006	6	Iowa City	0.989	14	12.818	2.022	1.852	0.171	0.470	40	45	20
5253800001	1	Iowa City	0.479	8	7.577	2.386	2.260	0.126	0.765	30	30	21
75450057	57	Waterloo-Cedar Falls	0.112	1	0.913	1.276	1.164	0.111	1.073	63	66	22
765600063	63	Waterloo-Cedar Falls	1.459	20	18.896	1.958	1.850	0.108	0.392	42	46	23
52102100006	6	Iowa City	0.305	4	3.787	1.874	1.774	0.100	0.839	45	50	24
781200027	27	Waterloo-Cedar Falls	0.19	3	2.905	2.256	2.184	0.071	1.205	32	32	25
75350057	57	Waterloo-Cedar Falls	1.706	17	16.150	1.424	1.352	0.071	0.305	59	62	26
761000063	63	Waterloo-Cedar Falls	1.793	31	30.355	2.470	2.419	0.051	0.417	27	27	27
5251600001	1	Iowa City	0.151	1	0.951	0.946	0.900	0.046	0.808	74	78	28
31252000020	20	Dubuque	0.088	1	0.972	1.623	1.578	0.045	1.482	54	56	29
77850218	218	Waterloo-Cedar Falls	0.257	2	1.922	1.112	1.069	0.043	0.690	69	71	30
719800020	20	Waterloo-Cedar Falls	1.675	36	35.549	3.070	3.032	0.038	0.489	20	20	31

Table F.1 (continued).

Sufficiency Segment	Route	City	Length	Crash	Estimate	Crash/mi-yr	Estimate/ mi-yr	Difference	Deviation /mi-yr	Rank Crash	Rank Estimate	Rank Difference
5246000218	218	Iowa City	0.869	79	78.792	12.987	12.953	0.034	1.446	6	6	32
7194200020	20	Waterloo-Cedar Falls	1.782	37	36.614	2.966	2.935	0.031	0.466	22	21	33
771000218	218	Waterloo-Cedar Falls	1.154	13	12.765	1.609	1.580	0.029	0.411	55	55	34
311400032	32	Dubuque	0.886	33	32.844	5.321	5.296	0.025	0.904	16	16	35
311300032	32	Dubuque	1.228	25	24.805	2.908	2.886	0.023	0.557	23	22	36
5245000218	218	Iowa City	1.465	121	120.808	11.799	11.780	0.019	1.062	7	7	37
5241200218	218	Iowa City	0.494	28	27.949	8.097	8.083	0.015	1.508	10	10	38
75700057	57	Waterloo-Cedar Falls	0.395	5	5.032	1.808	1.820	-0.011	0.769	48	48	39
765350063	63	Waterloo-Cedar Falls	0.635	3	3.067	0.675	0.690	-0.015	0.345	83	87	40
52105970080	80	Iowa City	0.046	1	1.006	3.106	3.124	-0.019	3.023	19	19	41
31251650020	20	Dubuque	0.401	3	3.082	1.069	1.098	-0.029	0.578	72	69	42
75500057	57	Waterloo-Cedar Falls	0.214	1	1.047	0.668	0.699	-0.031	0.604	85	86	43
774500218	218	Waterloo-Cedar Falls	0.625	9	9.142	2.057	2.090	-0.033	0.663	38	37	44
771500218	218	Waterloo-Cedar Falls	0.874	13	13.203	2.125	2.158	-0.033	0.571	34	33	45
31252800020	20	Dubuque	0.457	1	1.131	0.313	0.354	-0.041	0.265	96	95	46
762800063	63	Waterloo-Cedar Falls	0.303	3	3.090	1.414	1.457	-0.042	0.784	60	58	47
774400218	218	Waterloo-Cedar Falls	1.81	23	23.544	1.815	1.858	-0.043	0.367	46	44	48
312550052	52	Dubuque	0.369	4	4.113	1.549	1.592	-0.044	0.746	57	54	49
754550380	380	Waterloo-Cedar Falls	0.408	6	6.125	2.101	2.145	-0.044	0.834	35	35	50
754700380	380	Waterloo-Cedar Falls	0.581	8	8.188	1.967	2.013	-0.046	0.676	41	39	51
774800218	218	Waterloo-Cedar Falls	0.898	42	42.292	6.682	6.728	-0.046	1.022	12	12	52
3183600061	61	Dubuque	0.639	3	3.210	0.671	0.718	-0.047	0.359	84	84	53
31251900020	20	Dubuque	0.605	8	8.203	1.889	1.937	-0.048	0.649	44	40	54
774620218	218	Waterloo-Cedar Falls	0.426	5	5.154	1.677	1.728	-0.052	0.728	52	51	55
31251800020	20	Dubuque	0.299	2	2.109	0.956	1.008	-0.052	0.643	73	72	56
719600020	20	Waterloo-Cedar Falls	1.091	10	10.425	1.309	1.365	-0.056	0.400	62	61	57
771100218	218	Waterloo-Cedar Falls	0.173	2	2.070	1.652	1.709	-0.058	1.138	53	52	58
774700218	218	Waterloo-Cedar Falls	1.592	64	64.799	5.743	5.815	-0.072	0.714	15	14	59
52103000006	6	Iowa City	0.36	4	4.183	1.587	1.660	-0.073	0.779	56	53	60
3181750061	61	Dubuque	0.14	2	2.077	2.041	2.119	-0.078	1.427	39	36	61
312900052	52	Dubuque	0.161	0	0.094	0.000	0.084	-0.084	0.100	113	150	62
3121050052	52	Dubuque	0.108	0	0.063	0.000	0.084	-0.084	0.123	129	149	63
3121000052	52	Dubuque	0.224	0	0.132	0.000	0.084	-0.084	0.086	128	148	64

Table F.1 (continued).

Sufficiency Segment	Route	City	Length	Crash	Estimate	Crash/mi-yr	Estimate/ mi-yr	Difference	Deviation /mi-yr	Rank Crash	Rank Estimate	Rank Difference
312950052	52	Dubuque	0.13	0	0.079	0.000	0.087	-0.087	0.122	114	147	65
761300063	63	Waterloo-Cedar Falls	0.468	9	9.296	2.747	2.838	-0.090	0.912	25	24	66
754600380	380	Waterloo-Cedar Falls	1.067	8	8.684	1.071	1.163	-0.092	0.375	71	67	67
31251700020	20	Dubuque	0.469	4	4.301	1.218	1.310	-0.092	0.604	67	65	68
761600063	63	Waterloo-Cedar Falls	0.992	17	17.639	2.448	2.540	-0.092	0.591	28	25	69
71700934	934	Waterloo-Cedar Falls	0.651	1	1.422	0.219	0.312	-0.093	0.216	97	99	70
3121300052	52	Dubuque	0.226	0	0.155	0.000	0.098	-0.098	0.121	132	146	71
31251300020	20	Dubuque	1.135	22	22.808	2.769	2.871	-0.102	0.590	24	23	72
761900063	63	Waterloo-Cedar Falls	0.626	10	10.449	2.282	2.385	-0.103	0.722	31	28	73
7194000020	20	Waterloo-Cedar Falls	3.04	27	29.236	1.269	1.374	-0.105	0.245	64	60	74
5251900001	1	Iowa City	0.31	0	0.236	0.000	0.109	-0.109	0.125	146	145	75
5251800001	1	Iowa City	0.377	0	0.302	0.000	0.114	-0.114	0.123	145	144	76
763200063	63	Waterloo-Cedar Falls	0.186	0	0.150	0.000	0.115	-0.115	0.177	116	143	77
311200032	32	Dubuque	0.99	10	10.812	1.443	1.560	-0.117	0.461	58	57	78
311100032	32	Dubuque	0.867	11	11.713	1.812	1.930	-0.117	0.551	47	41	79
764100063	63	Waterloo-Cedar Falls	0.079	0	0.066	0.000	0.119	-0.119	0.285	120	142	80
5251700001	1	Iowa City	0.456	0	0.380	0.000	0.119	-0.119	0.119	144	141	81
762500063	63	Waterloo-Cedar Falls	0.415	2	2.346	0.688	0.808	-0.119	0.499	82	81	82
781300027	27	Waterloo-Cedar Falls	0.407	2	2.342	0.702	0.822	-0.120	0.509	81	80	83
5252000001	1	Iowa City	0.722	0	0.611	0.000	0.121	-0.121	0.097	147	140	84
3121100052	52	Dubuque	0.647	0	0.558	0.000	0.123	-0.123	0.106	130	139	85
52102500006	6	Iowa City	0.74	2	2.642	0.386	0.510	-0.124	0.288	91	92	86
5252100001	1	Iowa City	0.455	0	0.405	0.000	0.127	-0.127	0.132	148	138	87
71400934	934	Waterloo-Cedar Falls	0.495	2	2.442	0.577	0.705	-0.128	0.425	88	85	88
31251200020	20	Dubuque	1.511	36	37.372	3.404	3.533	-0.130	0.572	18	18	89
3121200052	52	Dubuque	0.741	0	0.675	0.000	0.130	-0.130	0.107	131	137	90
762300063	63	Waterloo-Cedar Falls	0.44	2	2.408	0.649	0.782	-0.132	0.479	86	82	91
5253300001	1	Iowa City	0.266	0	0.249	0.000	0.134	-0.134	0.187	149	136	92
3122400052	52	Dubuque	1.4	0	1.338	0.000	0.137	-0.137	0.084	133	135	93
76200021	21	Waterloo-Cedar Falls	1.71	10	11.636	0.835	0.972	-0.137	0.274	76	73	94
71300934	934	Waterloo-Cedar Falls	0.673	1	1.646	0.212	0.349	-0.137	0.244	99	97	95
71200934	934	Waterloo-Cedar Falls	2.015	3	4.942	0.213	0.350	-0.138	0.141	98	96	96
771050218	218	Waterloo-Cedar Falls	1.357	7	8.316	0.737	0.875	-0.139	0.291	80	79	97

Figure F.1 (continued).

Sufficiency Segment	Route	City	Length	Crash	Estimate	Crash/mi-yr	Estimate/ mi-yr	Difference	Deviation /mi-yr	Rank Crash	Rank Estimate	Rank Difference
3181650061	61	Dubuque	1.03	16	17.037	2.219	2.363	-0.144	0.565	33	29	98
771400218	218	Waterloo-Cedar Falls	1.36	6	7.381	0.630	0.775	-0.145	0.274	87	83	99
76300021	21	Waterloo-Cedar Falls	0.617	2	2.644	0.463	0.612	-0.149	0.358	89	88	100
763300063	63	Waterloo-Cedar Falls	0.217	0	0.234	0.000	0.154	-0.154	0.253	117	133	101
763500063	63	Waterloo-Cedar Falls	0.073	0	0.079	0.000	0.154	-0.154	0.436	118	134	102
31252700020	20	Dubuque	0.043	0	0.047	0.000	0.155	-0.155	0.572	150	132	103
763100063	63	Waterloo-Cedar Falls	0.365	2	2.397	0.783	0.938	-0.155	0.589	77	75	104
781400027	27	Waterloo-Cedar Falls	0.88	2	2.969	0.325	0.482	-0.157	0.264	95	94	105
763000063	63	Waterloo-Cedar Falls	0.383	2	2.422	0.746	0.903	-0.157	0.564	79	77	106
771300218	218	Waterloo-Cedar Falls	0.323	1	1.358	0.442	0.600	-0.158	0.493	90	89	107
764400063	63	Waterloo-Cedar Falls	0.067	0	0.074	0.000	0.159	-0.159	0.473	121	131	108
31251150020	20	Dubuque	0.674	9	9.766	1.908	2.070	-0.162	0.655	43	38	109
525150001	1	Iowa City	0.467	4	4.538	1.224	1.388	-0.164	0.641	65	59	110
763600063	63	Waterloo-Cedar Falls	0.511	0	0.589	0.000	0.165	-0.165	0.180	119	130	111
781000027	27	Waterloo-Cedar Falls	3.648	43	47.246	1.684	1.850	-0.166	0.266	51	47	112
5242000218	218	Iowa City	0.569	7	7.664	1.757	1.924	-0.167	0.688	49	42	113
31251250020	20	Dubuque	0.624	9	9.730	2.060	2.228	-0.167	0.708	36	31	114
764600063	63	Waterloo-Cedar Falls	0.609	0	0.713	0.000	0.167	-0.167	0.168	122	129	115
762200063	63	Waterloo-Cedar Falls	0.185	1	1.217	0.772	0.940	-0.168	0.833	78	74	116
764700063	63	Waterloo-Cedar Falls	0.012	0	0.014	0.000	0.169	-0.169	1.210	123	128	117
75370057	57	Waterloo-Cedar Falls	0.122	0	0.144	0.000	0.169	-0.169	0.381	104	127	118
71600934	934	Waterloo-Cedar Falls	0.501	0	0.599	0.000	0.171	-0.171	0.190	103	126	119
3183650061	61	Dubuque	0.212	0	0.256	0.000	0.172	-0.172	0.296	137	125	120
765300063	63	Waterloo-Cedar Falls	0.962	0	1.165	0.000	0.173	-0.173	0.140	124	124	121
781100027	27	Waterloo-Cedar Falls	0.606	5	5.736	1.179	1.352	-0.174	0.557	68	63	122
312650052	52	Dubuque	0.21	0	0.255	0.000	0.174	-0.174	0.300	110	123	123
75400057	57	Waterloo-Cedar Falls	0.705	0	0.864	0.000	0.175	-0.175	0.166	105	122	124
71500934	934	Waterloo-Cedar Falls	0.509	0	0.624	0.000	0.175	-0.175	0.195	102	121	125
3183700061	61	Dubuque	0.464	0	0.572	0.000	0.176	-0.176	0.206	138	120	126
52102950006	6	Iowa City	0.432	1	1.535	0.331	0.508	-0.177	0.396	94	93	127
75550057	57	Waterloo-Cedar Falls	0.041	0	0.051	0.000	0.178	-0.178	0.702	106	119	128

Figure F.1 (continued).

Sufficiency Segment	Route	City	Length	Crash	Estimate	Crash/mi-yr	Estimate/ mi-yr	Difference	Deviation /mi-yr	Rank Crash	Rank Estimate	Rank Difference
3183000061	61	Dubuque	0.173	0	0.216	0.000	0.179	-0.179	0.344	135	117	129
3183100061	61	Dubuque	0.113	0	0.141	0.000	0.179	-0.179	0.425	136	118	130
5251500001	1	Iowa City	0.257	0	0.324	0.000	0.180	-0.180	0.284	143	116	131
3184000061	61	Dubuque	0.272	0	0.344	0.000	0.181	-0.181	0.278	139	115	132
5251400001	1	Iowa City	0.361	0	0.461	0.000	0.182	-0.182	0.244	142	114	133
71100934	934	Waterloo-Cedar Falls	0.037	0	0.047	0.000	0.182	-0.182	0.763	101	113	134
78950027	27	Waterloo-Cedar Falls	0.05	0	0.064	0.000	0.183	-0.183	0.657	108	112	135
312800052	52	Dubuque	0.245	0	0.314	0.000	0.183	-0.183	0.297	112	111	136
5251100001	1	Iowa City	0.115	0	0.148	0.000	0.184	-0.184	0.436	140	110	137
5251300001	1	Iowa City	0.101	0	0.130	0.000	0.184	-0.184	0.465	141	109	138
312700052	52	Dubuque	0.268	0	0.349	0.000	0.186	-0.186	0.290	111	108	139
525400001	1	Iowa City	1.849	12	14.419	0.927	1.114	-0.187	0.291	75	68	140
771070218	218	Waterloo-Cedar Falls	0.391	1	1.513	0.365	0.553	-0.188	0.441	93	91	141
774650218	218	Waterloo-Cedar Falls	0.06	0	0.079	0.000	0.188	-0.188	0.623	127	107	142
312600052	52	Dubuque	0.722	0	0.953	0.000	0.189	-0.189	0.180	109	106	143
52102900006	6	Iowa City	2.138	2	4.913	0.134	0.328	-0.195	0.145	100	98	144
771200218	218	Waterloo-Cedar Falls	0.065	0	0.089	0.000	0.195	-0.195	0.627	125	105	145
52102700006	6	Iowa City	0.38	1	1.523	0.376	0.573	-0.197	0.459	92	90	146
774600218	218	Waterloo-Cedar Falls	0.547	0	0.757	0.000	0.198	-0.198	0.219	126	104	147
3181700061	61	Dubuque	0.121	0	0.169	0.000	0.199	-0.199	0.471	134	103	148
525120001	1	Iowa City	0.009	0	0.013	0.000	0.201	-0.201	1.744	115	102	149
77950218	218	Waterloo-Cedar Falls	0.356	0	0.501	0.000	0.201	-0.201	0.278	107	101	150