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A Study on the Relationship Between Asset Condition and Safety on Primary Roads in Iowa

Jian Gao
Iowa State University

A study on the relationship between asset condition and safety on primary roads in Iowa

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Jian Gao

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Program of Study Committee:
Konstantina Gkritza, Co-Major Professor
Omar Smadi, Co-Major Professor
Monica Haddad
Alicia Carriquiry

Iowa State University
Ames, Iowa
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ABSTRACT

Incorporating safety performance measures into asset management can assist agencies to manage their aging assets efficiently and improve system-wide safety. Past research has revealed the relationship between individual asset performance and safety, but the relationship between combined measures of operational asset condition and safety performance has not been explored.

This study investigates the effect of pavement marking retroreflectivity and pavement condition on safety in a multi-objective manner. Data on one-mile segments for all Iowa primary roads from 2004 to 2009 period were collected from the Iowa Department of Transportation and integrated by linear referencing. An Asset Condition Index (ACI), with a range of 1 to 3, was developed for the road segments by scoring and weighting individual components. Statistical models were then developed to estimate the relationship between ACI and expected number of crashes, while controlling for exposure. Finally, alternative treatment strategies for pavements and pavement markings were evaluated by benefit-cost ratio analysis, considering related treatment costs and safety benefits. Results indicated that minor rehabilitation and durable material marking have the highest B/C ratio within one year after implementation. And in terms of five years after treatments, a decision making matrix of ACI ranges versus treatment alternatives was developed. The same recommendation holds for segments with ACI higher than 2.0. For segments with ACI lower than 1.5, major rehabilitation and tape marking are recommended.

CHAPTER 1. INTRODUCTION

1.1 Problem Statement

Asset management (AM) is an efficient approach in managing the performance and investment in roadway infrastructure. AM concepts, principles, and performance measures have received increasing attention from transportation agencies and transportation leaders in the United States (U.S) and abroad in the last two decades. AM concepts and tools utilize tradeoff analysis and multi-criteria decision making by incorporating system-wide costs and benefits of alternative strategies.

The Iowa Department of Transportation (DOT) has a wide-reaching history in the implementation of infrastructure management systems, such as pavement management, bridge management, and pavement marking management systems, and, consequently, has comprehensive historic data for different assets. Recently, the Iowa DOT started developing its own asset management implementation. This decision was made not only because the economic recession, but also the desire of a systematic, efficient, and critical methodology of fiscal investment.

In addition, as a state with low crash rate but has one of the best safety databases throughout the country, the Iowa DOT is interested in assessing safety benefits or the effect on safety of any project or management system. In 2011, the total fatalities on Iowa roadways were 364, which is the lowest number of deaths since 1944, and the crash rate has been dropped less than one for every 10,000 registered vehicles (Iowa DOT, 2012), which was lower than the nationwide average (around 1.2 fatality per 10,000 registered vehicles in 2009) (NHTSA, 2009).

While past research has revealed the relationship between individual asset performance (such as pavement condition and pavement marking retroreflectivity), and safety, the relationship between combined measures of operational asset condition and safety performance has not been fully examined. Furthermore, to date the impact of alternative strategies on safety has not been included in the decision making framework. Therefore, there is a need to develop a methodology for investigating the relationship between asset performance and safety, and further investigate the feasibility of developing a methodology to prioritize safety improvements based on this relationship.

Incorporating safety performance measures into asset management can assist agencies to manage their aging assets efficiently and improve system-wide safety.

1.2 Research Objectives and Tasks

The objectives of this thesis are to

- develop a methodology for estimating an index that represent overall physical asset condition on a roadway segment;
- investigate the effect of asset condition on safety, and develop a methodology to prioritize safety improvement based on asset condition.

To achieve these objectives, the following tasks were conducted:

Task 1: Review of Literature

The literature review included the overview of asset management, the potential benefits of integrating safety into asset management, and the review of selected asset performance and safety measures.

Task 2: Descriptive Data Analysis

The datasets from different management systems, such as the Iowa DOT Pavement Management Information System (PMIS) and Iowa Pavement Marking Management System (IPMMS) are introduced, summarized, and interpreted using descriptive analysis techniques and Geographic Information System (GIS).

Task 3: Integration of different data sets

The collected datasets were integrated using both GIS system proximity method and Linear Reference System (LRS). In addition, a personalized Python GIS tool box was created for validating the integrated data through LRS method. Finally, a geodatabase for 2004 rural roads in Story County was created, as a pilot study of the feasibility of geodatabase on the Iowa DOT databases.

Task 4: Estimation of Asset Condition Index

An Asset Condition Index (ACI) was developed as a simple, convenient and understandable indicator for representing the overall physical asset condition of a roadway segment. The step-by-step methodology for calculating a unique condition index of multiple asset conditions can assist agencies in monitoring asset condition using a convenient indicator.

Task 5: Investigation of Relationship between Asset Performance and Safety Performance

The relationship between crash frequency and ACI was investigated, controlled by traffic exposure. Statistical analyses were conducted to select appropriate models to estimate the relationship between ACI, exposure, and number of crashes. Separate models were developed for ACI ranges since they were proved to be better in explaining the relationship.

Task 6: Evaluation of Different Asset Treatment Strategies

The single-year Benefit-Cost Ratio (BCR) analysis and five-year Net Present Value (NPV) analysis were conducted. Both short-term and long-term safety benefits and treatment costs were estimated for six alternative treatment strategies. Recommendations based on the analysis were presented as well.

Task 7: Conclusions and Recommendations

Based on the work conducted in the previous tasks, some concluding remarks and recommendations were offered. Additional, research needs for future studies were identified as well.

1.3 Thesis Organization

Table 1.1 Tasks for this thesis and the corresponding chapters.

Tasks	Corresponding Chapter
Introduction	1. Introduction
1. Review of Literature	2. Literature Review
2. Descriptive Data Analysis	3. Data Description
3. Integrating of Dataset by Different Approaches	4. Data Integration
4. Estimation of Asset Condition Index	5. Estimation of Asset Condition Index
5. Investigation of Relationship between Asset Performance and Safety Performance	6. Statistical Analysis of Crash Frequency
6. Evaluation of Different Asset Treatment Strategies	7.Evaluation of Asset Treatment Strategies
7. Conclusions and Recommendations	8. Conclusions and Recommendations

CHAPTER 2. LITERATURE REVIEW

2.1 Asset Management

2.1.1 Definition of Asset Management

Asset management (AM) is a systematic process of maintaining, upgrading and operating physical assets cost-effectively (Office of Asset Management 1999). AM combines engineering principles with business practice and economic rationale for resource allocation and utilization, with the objective of better decision making based on quality information and well-defined objectives. (OECD 2001). The “Asset Management Primer” by Federal Highway Administration (FHWA) indicates that AM is a decision-making framework, which is guided by goals of performance (Office of Asset Management 1999). AM should help highway agencies develop improvement plans and budget allocation policies to maintain, repair, or replace infrastructure cost effectively and at the appropriate time (Haas and Chairman 2001). Also, AM encompasses principles of engineering, engineering policies, economics and business management, and provides tools for both short-term and long-term planning and decision-making. Business practices from both the public and private-sectors are taken into account in an AM system (Falls, Hass, McNeil, & Tighe, 2001).

According to the FHWA, an AM system should include thirteen components, grouped into five blocks, such as strategic goals, inventory of assets. (Office of Asset Management 1999):

- strategic goals;

- inventory of assets;
- valuation of assets;
- quantitative condition and performance measures;
- measures of how well strategic goals are being met;
- usage information;
- performance-prediction capabilities;
- relational databases to integrate individual management systems;
- consideration of qualitative issues;
- links to the budget process;
- engineering and economic analysis tools;
- useful outputs, effectively presented; and
- continuous feedback procedures.
- These components could be grouped into five major blocks (Krugler, et al. 2006) :
- basic information,
- performance measures,
- needs analysis,

- program analysis, and

- program delivery.

The following figure shows the comprehensive relationship between the five blocks and the thirteen major procedures disparate into the five blocks. This is a simplified and recommended flow of the system, and agencies could modify it depending on their own data history and availability, resources, desired level of service, and other.

Goals, objectives, and policies as well as inventory data are considered in the basic information block. Condition assessment and desired levels of service are components of the performance measures block. Performance modeling and prediction along with action and funding analysis constitute the needs analysis block. Alternative analysis and program optimization are in the program analysis block. Program development and program implementation belong to the program delivery block. Finally, performance monitoring and feedback complete the cycle of the asset management process.

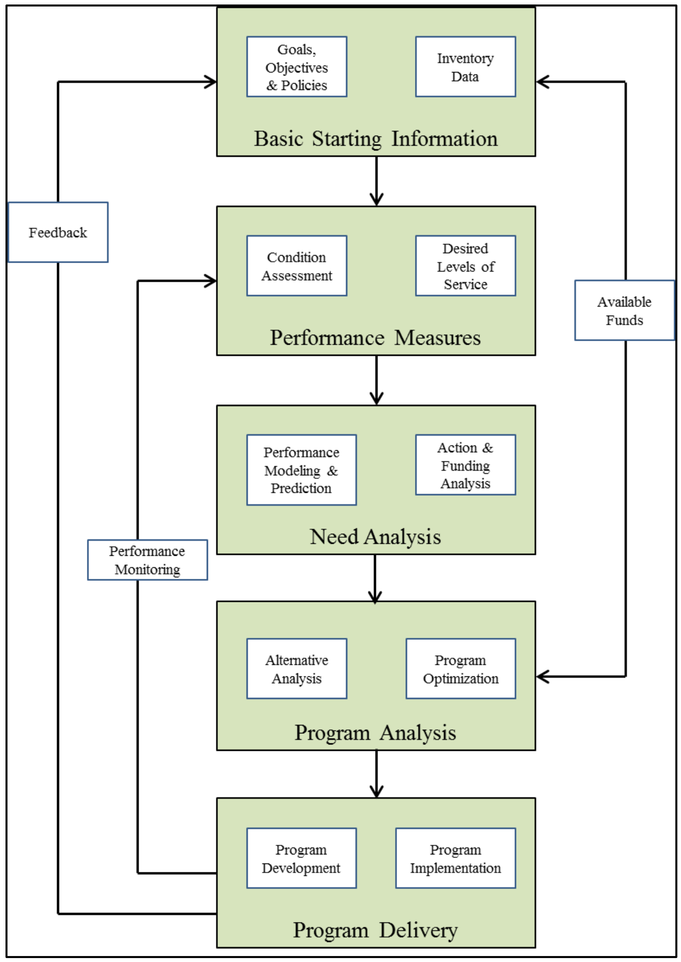


Figure 2.1 Components of an Asset Management System (Smith 2005).

In order to offer an effective process guide to transportation agencies for implementing AM, an AASHTO "Guide for Transportation Asset Management" was developed in 2002. In this guide, the principles of policy goals, objectives, and performance measures are presented in a generic framework as shown in Figure 2.1. Previously, the Transportation Association of Canada (Falls, et al., 2001) presented an overall framework of AM in 2000, as shown in Figure 2.2. These frameworks have been provided to DOTs and other transportation agencies to guide AM implementation.

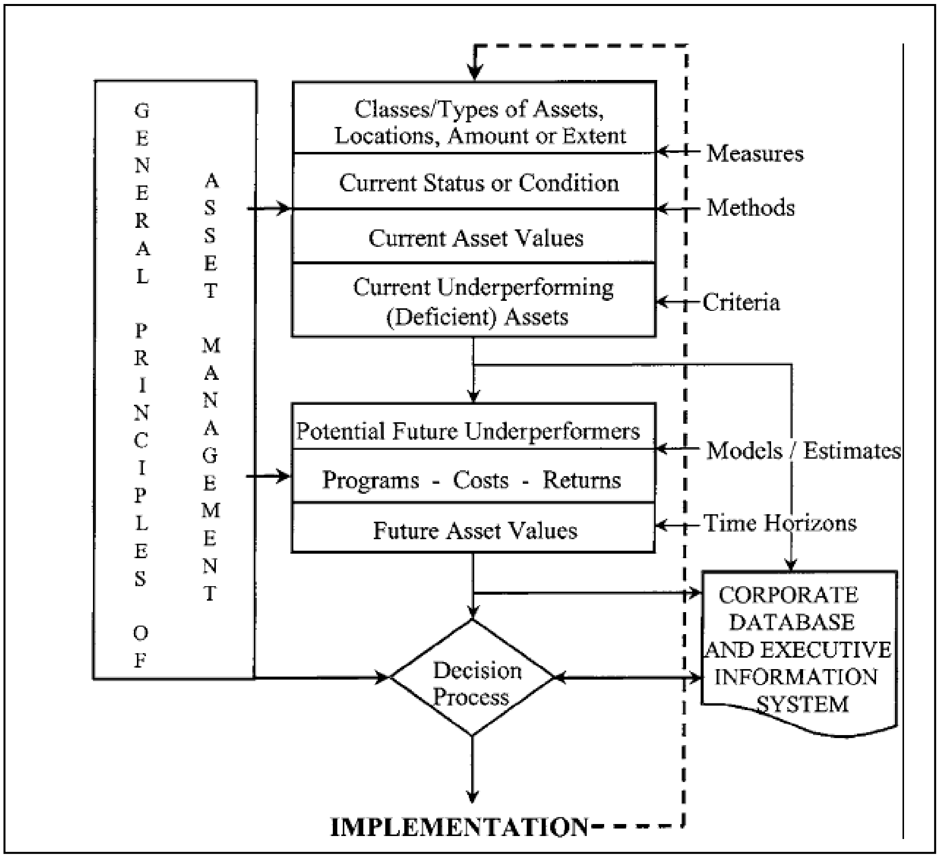


Figure 2.2 Overall framework for asset management (Falls et al. 2001)

While the concept of AM originated almost 20 years ago, it is still in its infancy (Winsor, et al. 2004). Agencies are still exploring both state-of-art and state-of-practice theories to improve their AM system by sharing and communicating best practices. Transportation Asset Management Today (TAMT) website was founded in 2000 as a national platform to contribute to the communication between agencies, practitioners and academia within the U.S. Together with the FHWA Asset Management website, they serve as communication networks for AM at the national level.

2.1.2 AM and Pavement Management

For many years, state DOTs have viewed AM as two separate systems: pavement management and bridge management (Krugler, et al. 2006). While the general AM framework is similar to the network level programming of a pavement management system (Haas and Chairman, 2001); individual AM systems in no way replace AM (Office of Asset Management 1999). AM applies to all infrastructure assets beyond pavements or bridges. Pavement management systems were the first implemented AM systems, which the agencies have most experience with. This experience can guide agencies in implementing AM principles to other infrastructure assets. Likewise, bridge management systems are common AM systems but with a relatively shorter history.

2.1.3 Potential Benefits of Integrating Safety Elements in AM

The main benefits of integrating safety elements into AM would be savings in human lives as well as resources, which are very important considerations for all road agencies. Some more specific benefits could be summarized as (FHWA, 2005):

- *Better resource allocation decisions.* AM techniques and tools help agencies to rationally optimize rationally the resource expenditure plans for asset maintenance, upgrading and operations. The rationale for expenditure decisions can be provided easily to upper management, other decision makers, the public, or the media.
- *Simplified economic processes and cost saving.* AM tracks costs. This cost tracking could support the preparation of more detailed and accurate cost estimates and budget plans. In addition, with better information, more accurate cost data, more timely

decisions, and other efficiency improvement plans, agencies could reduce the costs of maintenance, upgrade, and operating of assets.

- *Improving data access.* AM requires creating a complete, timely, and accurate database that can be accessed quickly. The inventory of assets, their location, condition, maintenance and repair history, and other relevant information can be shared in real time and updated continually. Easy access to information helps managers, executives, policymakers, and other relevant officers of an agency to make better decisions.
- *Improved data clarity and consistency.* The consistency of the shared standard definitions, measurements, and formats improve the accuracy and reliability of data.
- *Improved safety through faster response to customer service requests.* Consideration of the safety of signs, lightings, pavement markings, and other roadway safety elements account for a significant part of the interaction between transportation agencies and users. Quicker access to data about the safety elements facilitates faster customer service and makes roads safer.
- *Reduced duplication effort*. Because central and regional offices can share information, duplication of effort (for example, multiple data entry) is reduced or eliminated.

2.2 Review of Select Asset Performance and Safety Measures

The literature review revealed that very limited research has focused on utilizing AM for enhancing roadway safety, or the relationship between asset physical performance and safety performance. However, previous studies have been conducted for selected elements, such as pavement condition, pavement marking retroreflectivity, sign condition, and lighting, and their relationship to safety. Based on the previous finished reports and articles, each element has a different effect on safety.

2.2.1 Pavement Condition

Among studies, pavement condition was found to have significant effect on highway safety, and the magnitude of the effect could vary depending on the selected pavement condition measure and the confidence level of the analysis. There were few statewide studies on pavement distress and safety before 1990, because the data collection methodologies were not developed well enough at that time. Studies conducted in recent years can be basically divided into experimental studies and simulation studies. However, research studies about safety and pavement distress are still few, and most of them focus a single type of distress, such as rutting, roughness, as it relates to safety. (Chan, et al. 2008)

The severity of crashes related to pavement drop-off depends on several factors, such as speed, shoulder geometry, and lane width (Ivey, et al. 1990). Start et al. 1998 found that pavement rutting of 0.3 inches or deeper would significantly increase crash rate (Start, Kim and Berg 1998). Previous work has shown that the higher the International Roughness Index (IRI), the lower the brake force (Nakatsuji, et al. 1990), the higher the difference of friction on each tire (Chan, et al. 2008), and the higher the probability of crashes (Burns, Roughness and Roadway Safety 1981). In addition, the relationship between Present Serviceability Index (PSI) and crash rates on rural roads was found has significant effect on single- and multiple- vehicle accident rates, but no statistical influence on the total accident rate. In specific, it was revealed that the higher PSI, the lower accident single- and multiple- vehicle rate (Al-Masaeid 1997). PSI has been indicated as the second most important safety factor for rural two-lane highways and the fifth most important factor for rural multilane highways (Karlaftis and Golias 2002).

A study conducted by Cairney and Bennett (2008), examined the relationship between road surface characteristics, such as macrotexture, rutting, and roughness, and safety in Victoria, Australia (Cairney and Bennett 2008). It was found that the higher the macrotexture of the pavement, or the better condition, the lower the crash rate. Furthermore, it was shown that crash rate decreases, following an exponential distribution, when macrotexture increases. That study also found that the relationship between rutting and crash rate could be expressed by a power function, however, with a relatively low confidence factor, which could suggest that the depth of the rutting might not have significant or direct effect on crash rate. On the other hand, the relationship between roughness and crash rate was found to almost exactly follow a power function, and the authors concluded that roughness significantly affects crash rates.

Pavement roughness can also be measured by International Roughness Index (IRI) or Riding Number (RN) (Chan, et al. 2008). IRI has in recent years become the standard for assessing pavement surface roughness. It is based on a quarter-car model traveling the pavement surface at a constant speed. IRI has been proven to satisfactorily explain phenomena such as pavement performance and pavement deterioration (Surface Properties–Vehicle Interaction Committee 2009). The transportation department of New Zealand conducted a study on crashes from 1997 to 2002. The results indicated that crash rate does not have significant relationship with both IRI and rutting depth (Cenek & Davies, 2002).

In terms of classification, road segments with IRI lower than 1.5 m/km should be prior to overlay or rehabilitation (Perera & Kohn, 2002). In addition, a study conducted by the Washington State Transportation Center (TRAC) in 2002 provided supports to the federal IRI acceptability threshold of 2.7 m/km, recommended by the Federal Highway Administration (Shafizadeh, Mannering, & Pierce, 2002). For joint faulting, the Washington State DOT (WSDOT) set the limitation as 2.5 mm and 4 mm as acceptable and maintenance required thresholds, respectively(Pavement Interactive 2011), and the NCHRP Synthesis 334 suggests pavement faulting depth of 2.5 mm as acceptable and 5.0 mm or higher as poor level (McGhee 2004). For rutting depth, 6 mm and 15 mm are common criterion for good and poor condition thresholds among agencies, such as California DOT (Caltrans) and MaineDOT (Gallivan 2003) (Transportation Research Division 2006). In terms of friction, the NCHRP Guide for Pavement Friction indicated that road segments with friction number (FN) of 60 would be considered as good (Hall, et al. 2009), while the NCHRP Synthesis 291 Report suggested that FN lower than 35 should be considered as poor and maintenance could be performed(Henry 2000).

2.2.2 Pavement Marking Retroreflectivity

The review of the limited studies on the effect of pavement marking retroreflectivity on safety revealed mixed findings. A National Cooperative Highway Research Program (NCHRP) study conducted by iTRANS Consulting of Ontario Canada found no significant effect of pavement marking and marker retroreflectivity on crash rate (Harrigan E. T., 2006). More specifically, the presenting and visibility of markings are important to drivers, but it is less important with respect to safety that whether the markings have high retroreflectivity or relatively low retroreflectivity. One hypothesis is that drivers compensate by reducing their speed under lower visibility conditions, and maintain higher speeds under higher visibility. (Bahar, Masliah, et al. 2006) However, a study by Smadi et al. (2008), conducted a statistical analysis of three years of pavement marking retroreflectivity data and crash rate collected by Iowa Department of Transportation on all Iowa primary roads, indicated that the higher the retroreflectivity of the pavement markings, the lower the relative crash probability, regardless of traffic volume. This result applied to both yellow and white edge lines on either freeways or two-lane roads (Smadi, et al. 2008).

The minimum levels of marking retroreflectivity have been studied as well. The 3M Company conducted a study where subjects drove a test road marked similarly to one side of a four-lane freeway in 1986. A minimum value retroreflective of 100 mcd/m^2/lux was suggested as a conservative recommendation due to instrument variability (Ethen and Woltman 1986). The Minnesota Department of Transportation (MnDOT) sponsored a 1998 study that used a sample of drivers in the state. The study found that 90 percent of the participants rated yellow markings with a retroreflectivity of 100 mcd/m^2/lux as acceptable. Additionally, the researchers found that the acceptability ratings of the pavement markings increased dramatically as the retroreflectivity increased from 0 to 120 mcd/m^2/lux, much less as the retroreflectivity increased from 120 to 200 mcd/m^2/lux, and almost none as the retroreflectivity increased beyond 200 mcd/m^2/lux. The researchers recommended that MnDOT use 120 mcd/m^2/lux as the threshold between acceptable and unacceptable pavement marking retroreflectivity in its pavement marking maintenance program (Loetterle, et al. 2000). The NCHRP Synthesis 306 Report stated that minimum retroreflectivity of yellow marking is 100 mcd/m^2/lux and 150 mcd/m^2/lux for white marking. Also, any pavement marking retroreflectivity beyond 200 mcd/m^2/lux shoule be considered as in good level (Miglets and Graham 2002).

2.2.3 Sign Retroreflectivity and Safety

Literature on the relationship between sign retroreflectivity and highway safety is very limited. A study conducted in Virginia indicated that 4.3% for angle crashes can be reduced with stop signs with higher retroreflectivity (Cottrell and Dougald 2009). In addition, STOP signs with increased retroreflectivity had a significant reduction in crashes both urban and rural intersections, and also a significant reduction at low volume (1,200 AADT) intersections. However, the reduction in night-time and injury-related crashes due to higher sign retroreflectivity was not found significant (Persaud, et al. 2007).

2.2.4 Lighting and Safety

The relationship between lighting and safety has been examined in several past studies; however, the results vary among studies. Hasson & Lutkevic (2002) indicated that 20-30% crashes could be avoided when roadway lighting was installed (Hasson and Lutkevich 2002). Nighttime crashes at intersections were reduced by 45% of crashes after lighting (Green, et al. 2003). A study conducted by Iowa State University indicated that street lighting at isolated rural intersections would reduce 25-40% of crashes (Isebrands, et al. 2006). In 1980, Milwaukee’s freeway turned of all the lighting, with the exception of seven interchanges, to save money. Later analysis using from the previous 3 years of for comparison indicated that the total number of nighttime crashes increased 6%, injury crashes increased 5%, and number of injured motorists rose 50% (Hasson and Lutkevich 2002). Wanvik (2009) found that on Dutch motorways, roadway lighting reduces 28% injury crashes, 60% fatal trashes, 35% rural junction crashes and 50% motorway crashes. In addition, the same study determined that roadway lighting is more effective for older drivers than for younger drivers; under dry and sunny weather conditions than in rain; on high speed roads than on low speed roads; and on high traffic volume than low traffic volume roadways. (Wanvik 2009)

2.3 Summary

Asset management concepts, principles, and performance measures have recently received increased attention by transportation leaders, state agencies, and other transportation-related associations and institutes. Even though frameworks have been defined clearly, with several similar definitions having different points emphasized, AM is still in its infancy after 20 years of practice and investigation. Both the transportation academia and practice field are still, if not even more, interest in sharing experiment and study results via information sharing platform, such as the TAMT website. It can be concluded that AM framework is similar to the network level programming of a pavement management system, but with AM applied to all infrastructure (beyond each individual management system).

One of the potential benefits that have been expected by utilizing AM is the roadway safety improvement. Past research has revealed the relationship between pavement condition and safety; roadway lighting and safety; and pavement marking retroreflectivity and safety;

but the relationship between operational asset performance and safety performance has not been examined in a multivariate context. To date, the improvement of safety performance achieved by an operating asset management system has not been fully studied.

CHAPTER 3. DATA DESCRIPTION

The data sources that were used in this thesis include: Crash Data, Pavement Condition Data, and Pavement Marking Retroreflectivity Data. The data were provided by the Iowa Department of Transportation (Iowa DOT).

3.1 Crash Data

The Iowa DOT collects information on crashes that occur on all Iowa public roads. However, crashes that result in less than $1,500 in property damage only are not required to be reported in Iowa. This study used crash data for Iowa primary roads from 2004 through 2009. These data include crash location, date and time, coordinate information, and crash severity. Table 3.1 provides statistics and the crash distribution by year for these six years of crash data. The Iowa DOT also provided crash locations in each year in GIS format.

Table 3.1 Descriptive Statistics of Crash Data

Year	Mean	Std. Dev.	Number of Observations
2004	1.986	6.680	9,912
2005	2.282	6.892	9,833
2006	2.096	6.231	9,863
2007	2.331	6.765	9,838
2008	2.308	6.724	9,840
2009	2.208	6.314	9,828

3.2 Pavement Condition Data

The pavement condition data was available from the Pavement Management Information System (PMIS) of Iowa DOT, for state primary roads from 2004 through 2009. In each year's data file, information such as year and date when the pavement condition was measured, segment number, road classification, route, direction, segment beginning/ end mile post, length, construction year, pavement condition index (PCI), international roughness index (IRI), faulting depth, rut depth, friction number, average daily traffic (ADT), are available. An example plotted map is shown blow.

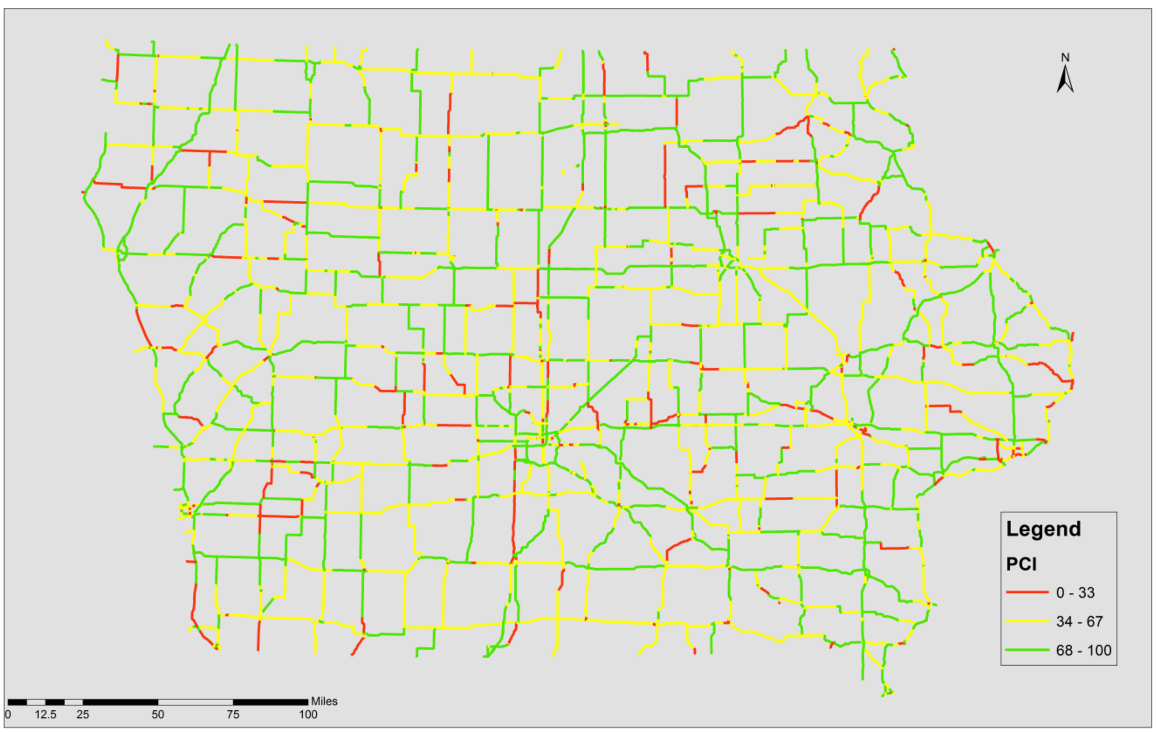


Figure 3.1 Pavement Condition Data Map, 2007, Iowa Primary Roads

3.3 Pavement Marking Retroreflectivity Data

Pavement marking retroreflectivity data were available from 2004 through 2009 using the IPMMS. The Iowa DOT collects pavement marking retroreflectivity on state primary roads twice each year, in the fall and spring. The data fields include route information, milepost, line type, direction, retroreflectivity value, data measured date, material type, marking length (5 mile segmentation), and coordinate information. In addition to the seasonal databases, the repainting database was also available and used. Every year, the Iowa DOT re-strips low retroreflectivity markings from April to September, so separated databases indicating repainted markings information were generated. The availability for this repainting database was 2004 through 2008, including painting dates, length, beginning/end mileposts, directions, retroreflectivity value, and some other related information. Pavement marking retroreflectivity maps by season of each year were generated using GIS. Figure 3.4 shows an example of one of these maps.

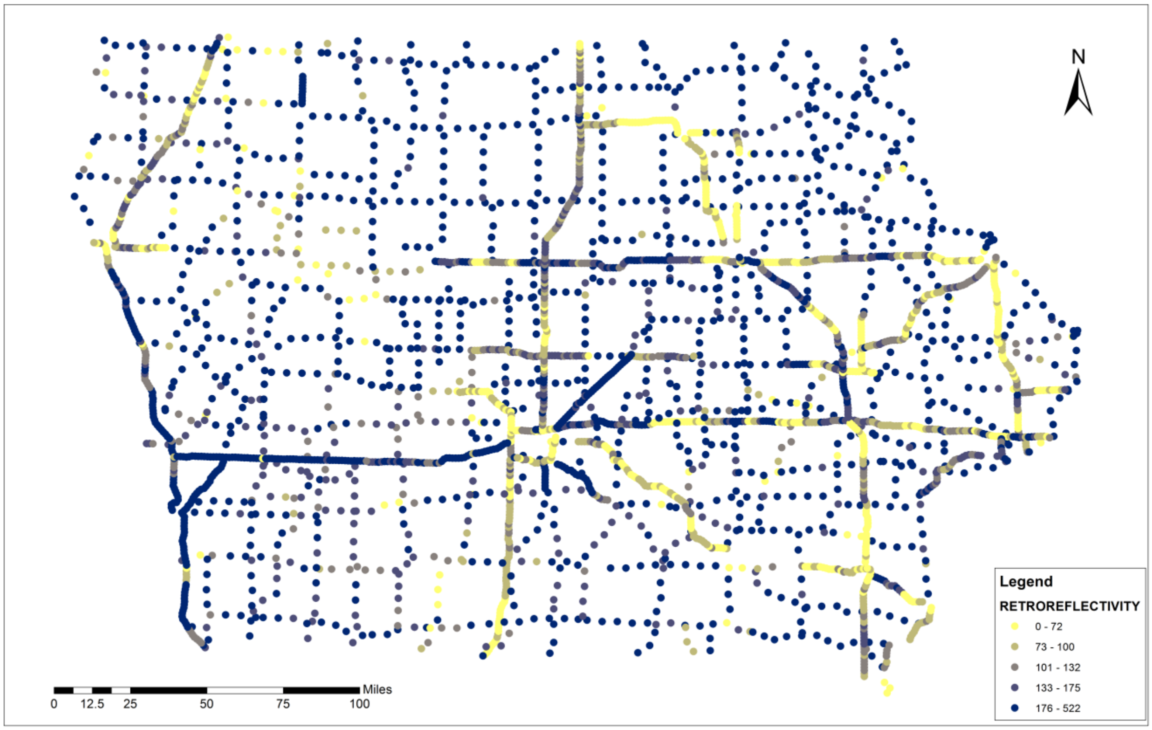


Figure 3.2 Pavement Marking Retroreflectivity Data Map, 2008, Iowa Primary Roads

3.4 Sign Inventory

Sign inventory data in Iowa was created back in 1990's, and updated throughout years. The earliest data was taken in April 1989, while the latest data was in September 2011. In order to keep the same analysis period across all datasets, sign inventory data collected after 2009 was eliminated. Signs are relatively fixed assets; once a sign is installed, it will not be removed until reconstruction or change of geometry design, so signs data was integrated by location only, regardless of years. Sign inventory data included sign locations, daytime condition, nighttime condition, and installation date.

3.5 Geographic Information Management System

The Iowa DOT Geographic Information Management System (GIMS) 2009 data was considered as a platform map file for data integration. GIMS data provides all Iowa road information such as segment ID, route, milepost, road class, lane number, speed limit, annual average daily traffic (AADT), median type and width, and so forth. Dynamic segmentation was utilized for data integration, and in dynamic segments, each of them was desired to have a constant condition and geometry within itself. In another word, as long as any roadway geometry or condition changes, a separated segment will start. Figure 3.5 is plotted map on GIS system.

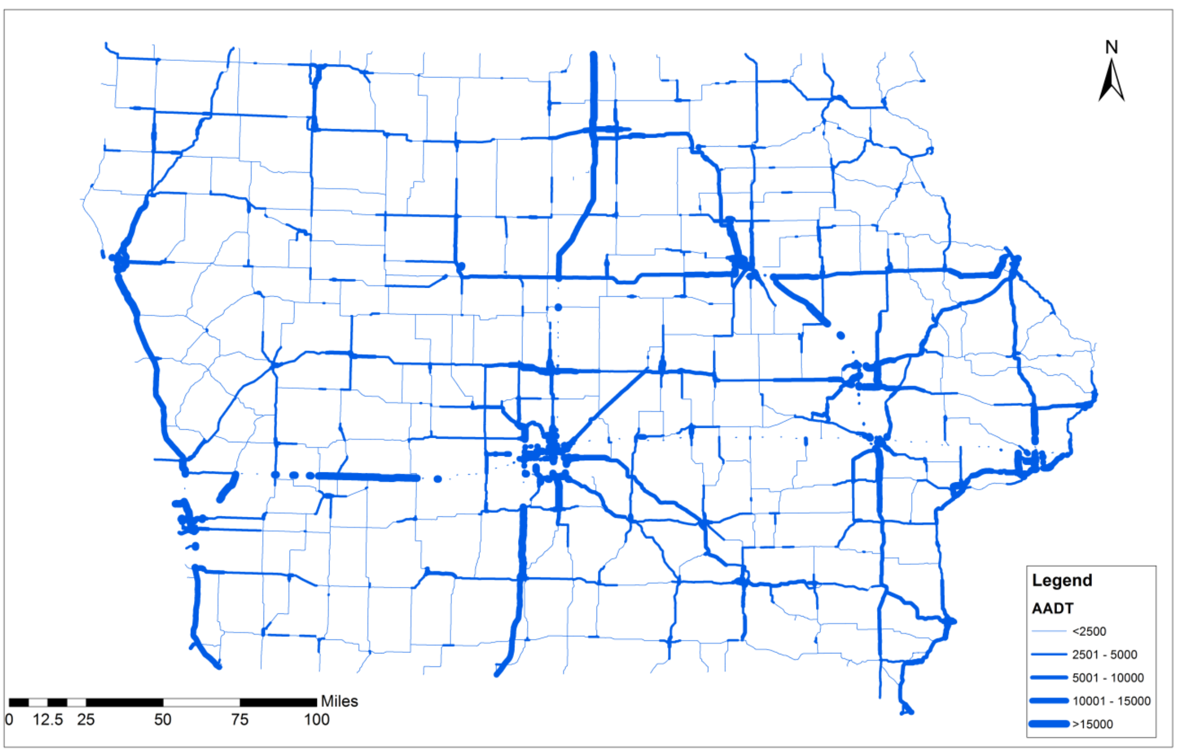


Figure 3.3 GMIS Map, 2009, Iowa Primary Roads

3.6 Linear Reference System (LRS)

A LRS data from Iowa DOT was collected that includes information on all Iowa primary roads by route and mileposts in 2010, such as latitude and longitude, route, milepost, direction, etc. The LRS integrates disparate roadway data using the data's linear locations as a common link. This LRS file was used for data integration by the location reference, instead of the GIS. Fixed segmentation was utilized by the location reference-based integration, and results were compared between the two methods.

CHAPTER 4. DATA INTEGRATION

As one of the most important processes under asset management, data integration provides spatial relationships between agency assets, enabling agencies to prioritize maintenance needs as well as evaluate returns on asset improvements. Two data integration methodologies were undertaken for this study: pure GIS-based integration and route milepost-based integration. The GIS-based method used the spatial integration and joining method, while the route milepost-based method applied the location-referencing method (LRM) to integrate assets by highway location and segments. In the second method of data integration, milepost based integration, the basic processes were conducted, and a Python GIS personalized tool was built to avoid duplicated efforts. A pilot study of a commonly used data storing and managing framework in GIS-geodatabase was also conducted to assess the feasibility of using this tool for data integration.

4.1 Data Integration Concepts in Asset Management

4.1.1 Data Integration and AM

Data integration is defined as the "process of combining or linking two or more data sets from different sources to facilitate data sharing, promote effective data gathering and analysis, and support overall information management activities in an organization" (FHWA, Data Integration Primer, 2010). The system level transportation decision-making, which is a primary goal of AM, requires different levels of asset data as inputs. With these inputs, data integration provides the spatial relationship between assets. Also, data integration supports comprehensive decision making processes, with quick and convenient access to data, as well as further economic analysis.

The data integration process includes 1) Requirement Analysis, 2) Data and Process Modeling, 3) Alternatives, Definition, Evaluation, and Selection, 4) Database Design and Specification, 5) Development, Testing, and Implementation (FHWA, Data Integration Primer, 2010). Requirement analysis consists of business processes, such as handling data problems; user requirements, such as, purpose and uses of data; character of agency and its skills and staff capabilities, data characteristics, such as data collection method and data type; and information system infrastructure, such as hardware or software requirements. After analyzing requirements of data, the process modeling will graphically represent the datasets and their relationships. Also, process modeling may estimate a flow diagram, helping to determine the design specification. With the design flow diagram or dataset relationships, alternatives of database type should be listed, evaluated, and selected. Common database types include fused database (single server), interoperable database (numerous databases with computer network links). Once the database type is determined, the next step is database design. This process is comprised of data model selection (structure and configuration of the database), data standards identification, data reference system selection, metadata and dictionary estimation, computer communication, etc. (FHWA, 2010). The design phase is followed by the development of prototype, testing or evaluation of the data models or interface and finally, the integrated data is ready to be implemented.

4.1.2 Common Methods of Integrating

Currently, the most commonly used data integration tools or techniques include dynamic segmentation, geo-coding /LRS, and SQL relationships.

Geo-coding and SQL are commonly used tools for data integration. Dynamic segmentation is the process of computing the spatial locations or segments of events for highway assets stored and managed in an attribute table using a linear referencing measurement system. Dynamic segmentation allows integration of multiple data events, data queries and event analysis among databases, and provides visualization of datasets linked to a common Linear Referencing System (LRS). Past work has argued that dynamic segmentation is the most powerful and suitable way for integration of AM databases (Ogle, Alluri, & Sarasua, 2010)

Applied to AM, GIS not only facilitates data collection, processing, and display but also integrates asset mapping with project management and budgeting tools so that construction, operational, and maintenance expenses can be centrally managed and accounted for. Once established, AM systems provide a framework to efficiently and equitably allocate scarce resources among competing objectives. Field personnel can take detailed GIS information with them on any number of mobile devices and quickly locate relevant facilities and perform detailed inspections. Deficiencies identified during inspection can generate new work orders for maintenance and repair (esri, GIS Solutions for Highway and Roadway, 2010)

Two applications of using GIS for data integration related to AM systems are as follows:

- "Heuristic" or "experience" based artificial intelligence (AI) methodologies to optimize snow removal for winter road and bridge maintenance in Iowa were investigated in University of Northern Iowa. (Salim, Strauss, & Emch, 2002) In this case study, a GIS database for all roads in the case study area (Black Hawk County, Iowa), obtained from the Iowa Department of Transportation (IDOT) and included traffic volume and roadway inventory information was integrated with the knowledge-based expert snow removal management system created by the researchers.

- GIS was used in Pierce County, Washington State, to integrate information and build an AM system on 190 traffic signals, over 1,000 street lights, 33,420 traffic signs, and about 1,500 miles of road in the county. (Butner, Rick; Lang, Greg, 2009)

4.2 GIS-based Integration

In this project, data was collected on various assets over a period of 2004-2009. All the datasets used are available in GIS formal can be transformed into GIS compatible form easily. Procedures for integrating are discussed in the following sections:

Step 1: Preparation of GIMS map.

The Iowa DOT Geographic Information Management System (GIMS) (2009) includes information for each road segment as well as bridge structures within the state.

Considering the scope of the project, primary roads including Interstate Highway, US Highway, and State Highways within rural area were selected.

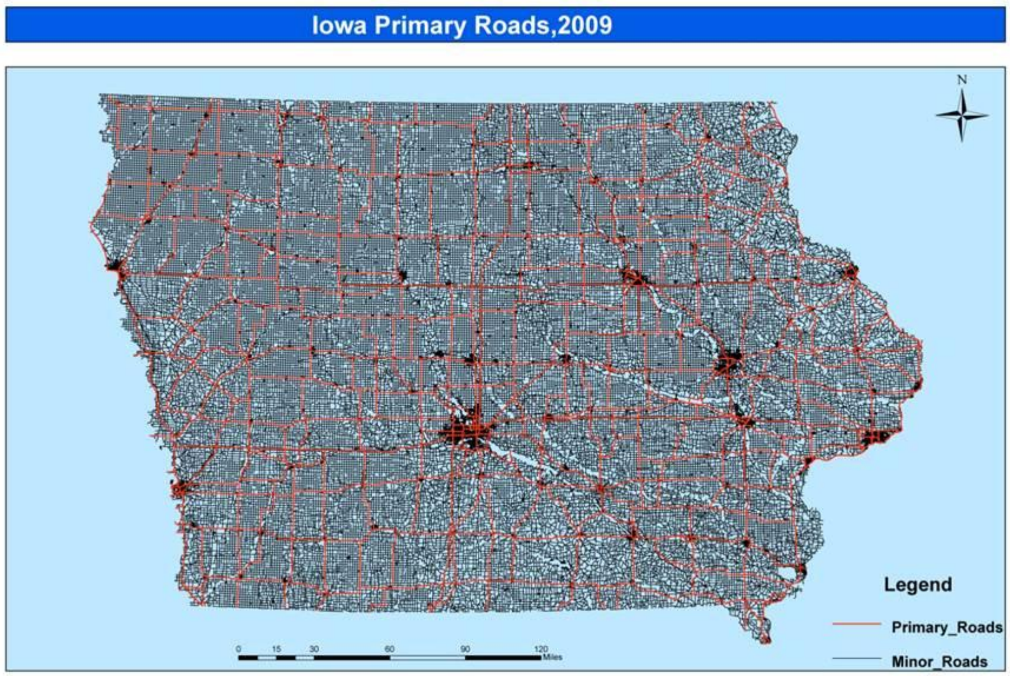


Figure 4.1 Iowa Primary Roads, 2009, Geographic Information Management System

Step 2: Crash Data Integration.

Crash data was integrated with the GIMS data to obtain roadway information for each single crash. This was done by spatially joining the crashes to GIMS. Each crash was assigned to the nearest roadway using the geographic coordinates of the crash. In other to ensure that each crash was assigned to the right roadway especially at intersections, quality control checks were conducted by comparing the route information in the crash data with that in GIMS. The spatial joined calculated a distance field that showed the offset distance from the crash location to the GIMS segment. This offset may be caused by several possible reasons: 1) Vehicle run off of road after crash; 2) GPS device accuracy; 3) Road systems changes; and 4) Cloud cover. With consideration of all these potential errors, the critical control point of the offset was set as 30 meters. In addition to the offset distance, route information is another concern as potential error. At interchange or intersection area, it is possible for a crash that actually happened on Highway A to be assigned to Highway B since it is spatially nearer to Highway B. In order to eliminate this type of error, a calibration was conducted by comparing route information of the crash point and the assign road segment.

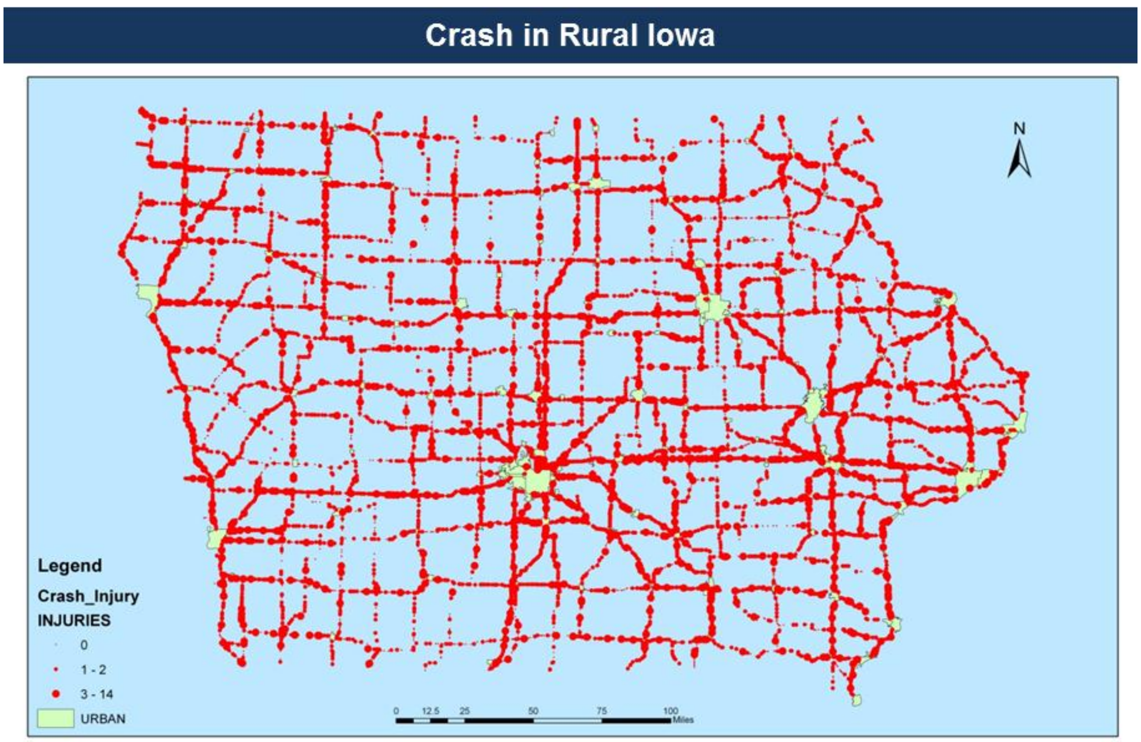


Figure 4.2 Crashes on Primary Roads, Rural Area, 2004-2009

Step 3: Pavement Marking Retroreflectivity Data Integration.

Before integrating, the two separated datasets of Spring-fall Marking Retroreflectivity and Repainting Data were mixed for each year. The procedure of integrating Pavement

Marking Retroreflectivity Data is the same as for the crash assignment. The only difference is that the offset distance was increased to 50 meters, since it was found that the accuracy of PMMS Data was slightly lower than Crash Data. After that, the similar process of quality control was conducted to ensure that the retroreflectivity data were properly located by comparing the route information with GIMS. So far, each row in the dataset represents an individual crash, with road information and pavement marking retroreflectivity value(s).

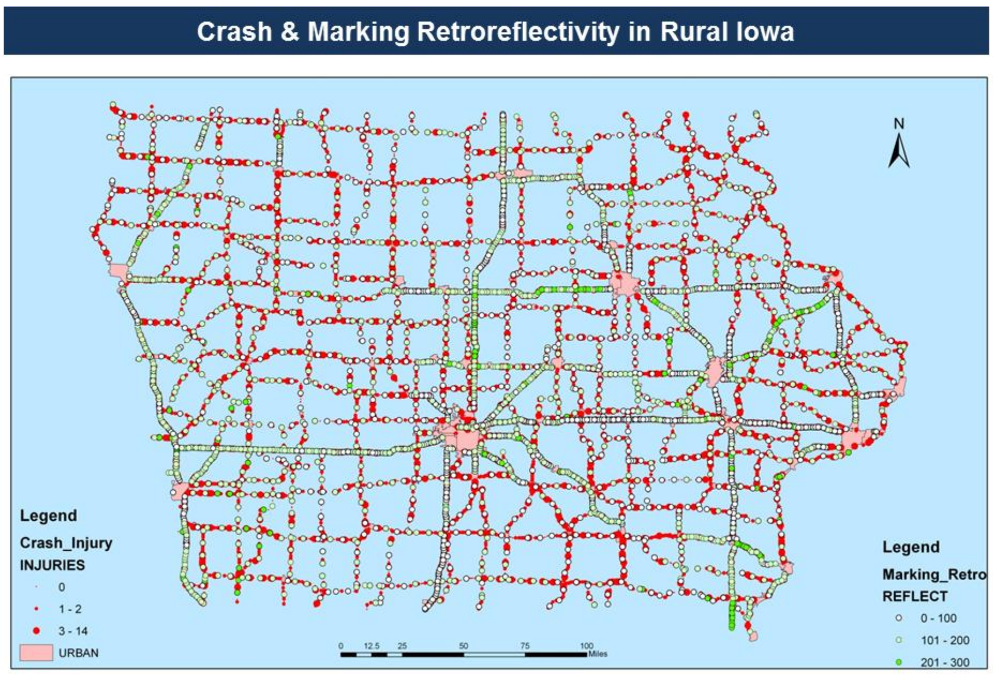


Figure 4.3 Crashes & Pavement Marking Data, Rural Iowa, 2004-2009

Step 4: Pavement Condition Data Integration.

The PCI data from Iowa DOT is available in GIS form. It provides PCI by direction of travel. In the dataset, road segments with medians were considered as two separated segments divided by direction codes (Dir. 1= North/ East; Dir. 2= South/ West). As a result, the integrated data was separated by direction of travel by using the direction of travel information in the crash data. At this point, a preliminary dataset of Asset Condition vs. Crashes was prepared:

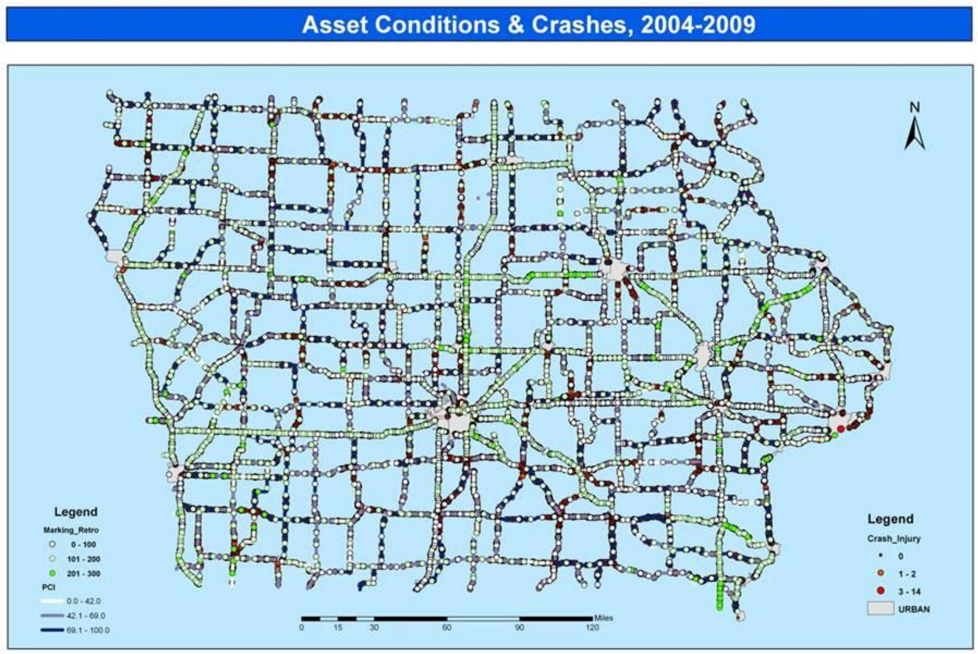
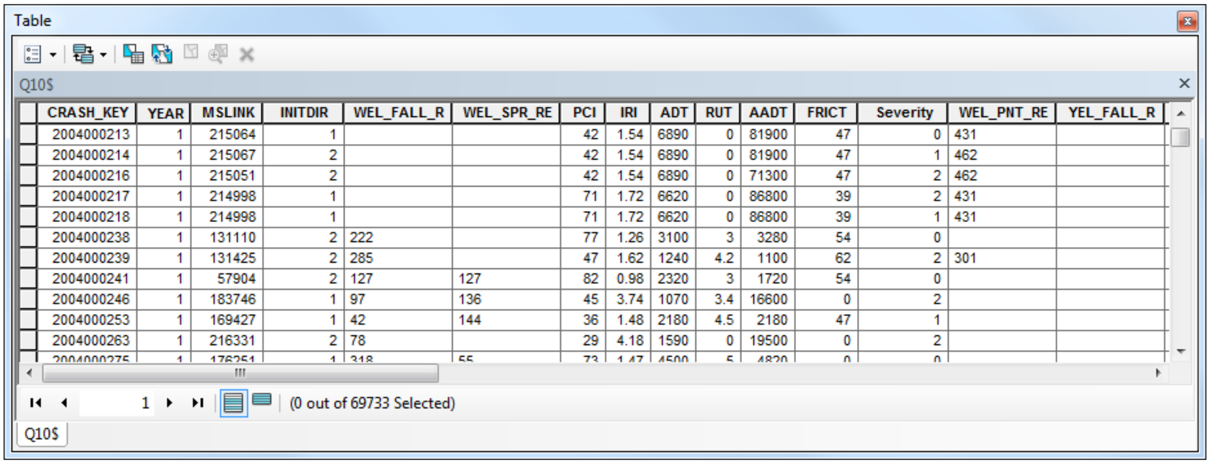


Figure 4.4 Asset Condition & Crashes, Rural Iowa, 2004-2009

Total observation for the dataset is 69,733, and each observation represents an individual crash with information such as crash time, direction, fall retroreflectivity value for white edge line or other line types in the crash year, pavement condition index (PCI) of the road segment that the crash located, international roughness index (IRI) of the road segment, AADT, and so forth.



Table

Q10$

CRASH_KEY	YEAR	MSLINK	INITDIR	WEL_FALL_R	WEL_SPR_RE	PCI	IRI	ADT	RUT	AADT	FRICT	Severity	WEL_PNT_RE	YEL_FALL_R
2004000213	1	215064	1			42	1.54	6890	0	81900	47	0	431	
2004000214	1	215067	2			42	1.54	6890	0	81900	47	1	462	
2004000216	1	215051	2			42	1.54	6890	0	71300	47	2	462	
2004000217	1	214998	1			71	1.72	6620	0	86800	39	2	431	
2004000218	1	214998	1			71	1.72	6620	0	86800	39	1	431	
2004000238	1	131110	2	222		77	1.26	3100	3	3280	54	0		
2004000239	1	131425	2	285		47	1.62	1240	4.2	1100	62	2	301	
2004000241	1	57904	2	127	127	82	0.98	2320	3	1720	54	0		
2004000246	1	183746	1	97	136	45	3.74	1070	3.4	16600	0	2		
2004000253	1	169427	1	42	144	36	1.48	2180	4.5	2180	47	1		
2004000263	1	216331	2	78		29	4.18	1590	0	19500	0	2		
2004000275	1	176251	1	318	55	73	1.47	4500	5	4820	0	0		

1 (0 out of 69733 Selected)

Q10$

Figure 4.5 Screenshot of Preliminary Integrated Data

As partially mentioned above, the possible error causes including: 1) Vehicle run off of road after crash; 2) GPS device accuracy; 3) Road systems changes; 4) Error record; 5) dynamic segmentation of the GIMS data; and 6) lack of milepost information of the GIMS data.

Considering the data type of each row representing a crash, trials were conducted for estimating linear regression models between crash severity versus asset condition values (PCI, IRI, friction, retroreflectivity value, etc.) and exposure (represented by AADT). Results turned out to be that none of the estimated models were significant. This may be because majority of crashes were at the property damage only (PDO) level or minor injury level of severity, and the statistical significances were hard for explore. With all of these reasons, a second method of data integration was started.

4.3 Route-milepost-based Integration

As a second method of data integration, a fixed segmentation road reference was used and integrated so each row of the final data would represent a one-mile road segment, instead of a crash, and models of crash number and asset condition could be estimated. The following procedures were applied for each year from 2004 through 2009 and consolidated for all years.

4.3.1 Processes

Step 1: Preparation of road reference.

The first step was to extract data needed from the LRS data. The route milepost reference that was prepared consisted by 11,955 rows and each row represents a milepost segment on different primary routes with a default direction of Dir.1 (North or East). If the segment is divided by median, two rows presenting the same route and milepost occurs, with Dir. 1=North/East and Dir. 2=South/West.

Step 2: Pavement Condition Data Integration.

Pavement condition data was integrated by dynamic segmentation with each observation indicating pavement condition values for various lengths of segments, with the lengths represented by beginning and ending milepost. Considering this situation, the pavement condition data was joined directly using Microsoft Access with the designed query as homogeneous route and direction in both datasets and referenced mileposts as smaller or greater than ending or beginning pavement condition data milepost, respectively.

Step 3: Pavement Marking Datasets Consolidation.

Both the seasonal detected data and the repainting retroreflectivity data are available in spreadsheet format, and both datasets are connected by the project so that a more comprehensive asset condition dataset could be compiled. While consolidating the data, the researchers noticed that the milepost information in the repainting dataset coincides with the pavement condition data, in that, beginning and ending milepost information are present for each repainted segment. On the other hand, the seasonal retroreflectivity data used a fixed segmentation of five miles. As a result, a similar procedure was undertaken to integrate marking retroreflectivity datasets, with an additional query of join by the same line type (with WEL for white edge line, YEL for yellow edge line, YCL for yellow centerline, and WDC for white dash line).

Step 4: Pavement Marking Retroreflectivity Data Integration.

Given the pavement marking data were collected with a five-mile segmentation, the dataset was enriched based on the assumption that each individual data value represents the retroreflectivity value within the nearest five miles (data located +2 mileposts forward and +2 mileposts backward). This modified dataset was then integrated with the extracted data in a manner consistent with the other Access queries for this project.

Step 5: Crash Data Preparation and Integration.

The original crash data from the Iowa DOT do not have milepost information available. As a result, it was required to prepare and modify the crash data before integrating them with other datasets. The crash data were spatially joined with the Geographic Information Management System (GIMS) map, again, and another GIMS file, GIMS_MP_2010, was used. In addition, the offset criterion of 30 meters for rural areas only and route number preparation was conducted as before so the error could be minimized. After integrating by the same manner as previous steps, around 140,000 rows were included in the final integrated data. However, the data includes a lot of duplicate rows with the same information, except for crash ID, and this is because each row is representing a comprehensive information row for a single crash. A pivot table summary indicating pavement condition, marking retroreflectivity, and crash number, was created and, at this point, the final integrated dataset was ready for further modification and study.

4.3.2 Data Modification

In the IPMMS dataset, pavement marking retroreflectivity was measured with five-mile segmentation. Compared to other datasets, such as the pavement condition dataset, which has a dynamic segmentation with the segment lengths within the rage of 0.5 to 1.5 miles, the pavement marking retroreflectivity dataset has a relatively long segmentation. In this case, with the data integration result produced by mileposts, every five miles or every five segments or further has a single retroreflectivity data row integrated. This situation could result in a potential inaccuracy or error for the study. Thus, an assumption was made that every retroreflectivity reading represents an average marking retroreflectivity within the nearest five miles, with 2.5 miles in front of the segment and 2.5 miles further from the segment for the same route index and direction.

With the assumption, a pavement retroreflectivity data gap sufficiency procedure was developed, and the result of the fulfilled dataset was expected to produce more accurate results and better developed relationship estimation between asset condition and safety performance.

4.4 Data Integration Validation by GIS Python Programming

Geographic Information System (GIS) is a well—known and commonly used tools in the field of transportation engineering. As a system designed to capture, store, manipulate, analyze, manage, and present all types of geographically reference data, GIS is expected to help agencies and workers save a lot of time by simplifying data integration processes, and this has been approved by many studies before. In addition to the basic GIS geoprocessing operations, such as joining, buffering, clipping, GIS automation is an easier, faster, and more accurate method. ArcGIS, as one of the most popular GIS software, provides three automated methods to accomplish tasks: model builder, code/ script, and ArcObject programming & interface customization. The first method was applied while the GIS-based integration and it worked smoothly and fast. In order to validate the integrated datasets under the different integration methods, a validation procedure is expected, and it can help choose a relatively better dataset for future steps. In this study, the code/ script method was chosen for integration validation, and the code used was Python programming.

4.4.1 GIS Python Programming

As one of the most commonly used computer languages, which has approximately one million users worldwide, Python has a wide range of usage, including gamming, robots, Andriod cellphone applications, YouTube, Intel, Cisco, JpMorgan, NASA, and also ESRI. ArcGIS accepts scripts written in Python, Visual Basic, Javascript, Perl, etc. The reasons that

Python was selected among computer language include that Python is relatively simpler and more readable that others; it needs typically fewer lines of code comparing to other computer languages; it is rapid development; and the most important, it is reusable and maintainable.

4.4.2 GIS Customized Toolbox

- Custom Toolbox is a script based tool under GIS. It is created by editing features and adding/ editing script. With this tool, users are able to create Python script with any build-in functions or mathematical processes in their customized manners. This tool and method of geoprocessing is expected to help users save a lot of time cost by the repeating manually steps.

- In this study, a customized toolbox was created, and its utilization considering five years of data are planned to be investigate, as the primary goal of the data validation. Main procedures within the personalized toolbox include:

a. Create a new shapefile and add columns needed for analyze;

b. Add reference post information in;

c. Calculate crash frequency;

d. Integrate crash frequency with milepost reference;

e. Compile AADT information with each milepost segment;

f. Calculate marking retroreflectivity value in each route milepost by directions and seasons;

g. Integrate Marking Retroreflectivity Data;

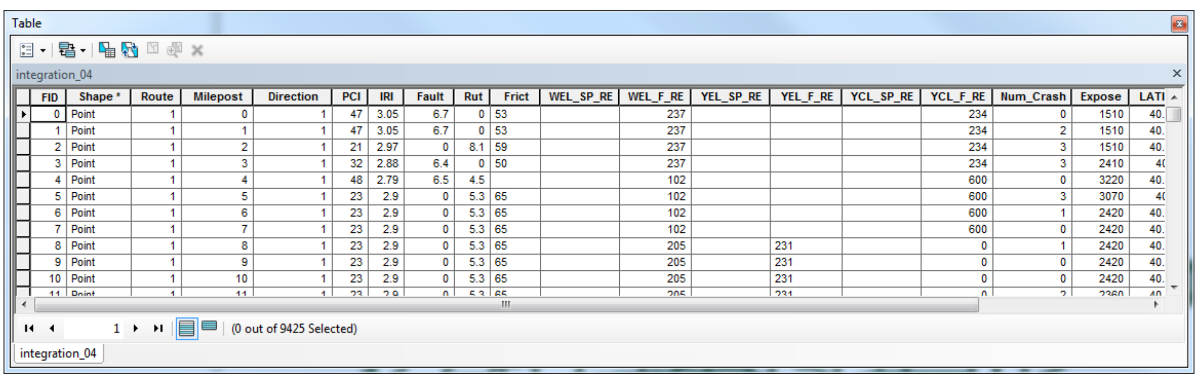
h. Integrate Sign Inventory Data;

i. Integrating PCI Data by route, mileposts, and directions

Note: Please see the script in Appendix A for detail codes.

The toolbox is supposed to be utilized for each year's datasets, and after that all five integrated shape files are going to be compiled.

In the validation dataset shown below, each row represents one milepost on Iowa primary roads. All the segments are identified by route, milepost, and direction index. As similar as the previous integrated datasets, each row includes asset conditions such as IRI, PCI, spring yellow edge line retroreflectivity, number of crashes, AADT, etc. One special information in this dataset is each segment are coming with latitude and longitude information, so that the map could be plotted, and in this way all relative asset condition data inputs are integrated into one single point, representing the asset and safety conditions for one segment.



Table

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FID	Shape *	Route	Milepost	Direction	PCI	IRI	Fault	Rut	Frict	WEL_SP_RE	WEL_F_RE	YEL_SP_RE	YEL_F_RE	YCL_SP_RE	YCL_F_RE	Num_Crash	Expose	LATI
0	Point	1	0	1	47	3.05	6.7	0	53		237				234	0	1510	40.
1	Point	1	1	1	47	3.05	6.7	0	53		237				234	2	1510	40.
2	Point	1	2	1	21	2.97	0	8.1	59		237				234	3	1510	40.
3	Point	1	3	1	32	2.88	6.4	0	50		237				234	3	2410	40
4	Point	1	4	1	48	2.79	6.5	4.5			102				600	0	3220	40.
5	Point	1	5	1	23	2.9	0	5.3	65		102				600	3	3070	40
6	Point	1	6	1	23	2.9	0	5.3	65		102				600	1	2420	40.
7	Point	1	7	1	23	2.9	0	5.3	65		102				600	0	2420	40.
8	Point	1	8	1	23	2.9	0	5.3	65		205		231		0	1	2420	40.
9	Point	1	9	1	23	2.9	0	5.3	65		205		231		0	0	2420	40.
10	Point	1	10	1	23	2.9	0	5.3	65		205		231		0	0	2420	40.

1 (0 out of 9425 Selected)

integration_04

Figure 4.6 Validation Dataset

4.5 Geodatabase Pilot Study

The geodatabase is a common data storage and management framework for ArcGIS. It offers users the ability to manage an affluent amount of spatial data in a unified location, to implement complicated rules and relationships to the data, to define advanced geospatial relational models, and to model the real world as simply or complexly as needed. (ESRI)

Considering the amount and complexity of the work, a geodatabase of 2004 Rural Primary Roads in Story County, Iowa was created as a pilot study for the feasibility of geodatabase in the whole Iowa roadway network.

4.5.1 Logical Data Model

Before creating geodatabase, a logical model, which would be used as the relationship between feature classes or items, was made. This pilot study was to management transportation asset conditions and crashes in rural Story County, Iowa. Relationships between conditions, crashes, and road network are shown as a United Modeling Language (UML) diagram in Figure 4.6. Feature classes that are included in the study are “Crash”, “Pavement”, “Road”, and “Marking”. “Crash” is a point feature that indicates crash locations and crash IDs. “Pavement” is a line feature which includes pavement condition data. “Road” is a Geographic Information Management System (GIMS) roadway segment location data in one mile fixed segmentation. It indicates road segment locations, traffic volume (expressed by Annual Daily Traffic or “ADT”), and some roadway physical information, such as median type. Detailed data decryptions can be found in the previous chapter.

a. The pilot study geodatabase was created based on the relational schema of:

b. Crash happens on one road segment, while a road segment holds zero or more crashes.

c. Pavement is located on one road segment, and a road segment carries on one or more pavements;

d. Pavement marking is painted on pavement, while a pavement segment contains zero or more markings.

Figure 4.7 gives an overview of the basic structure of the geodatabase, and the following sections will discuss each of the items, respectively.

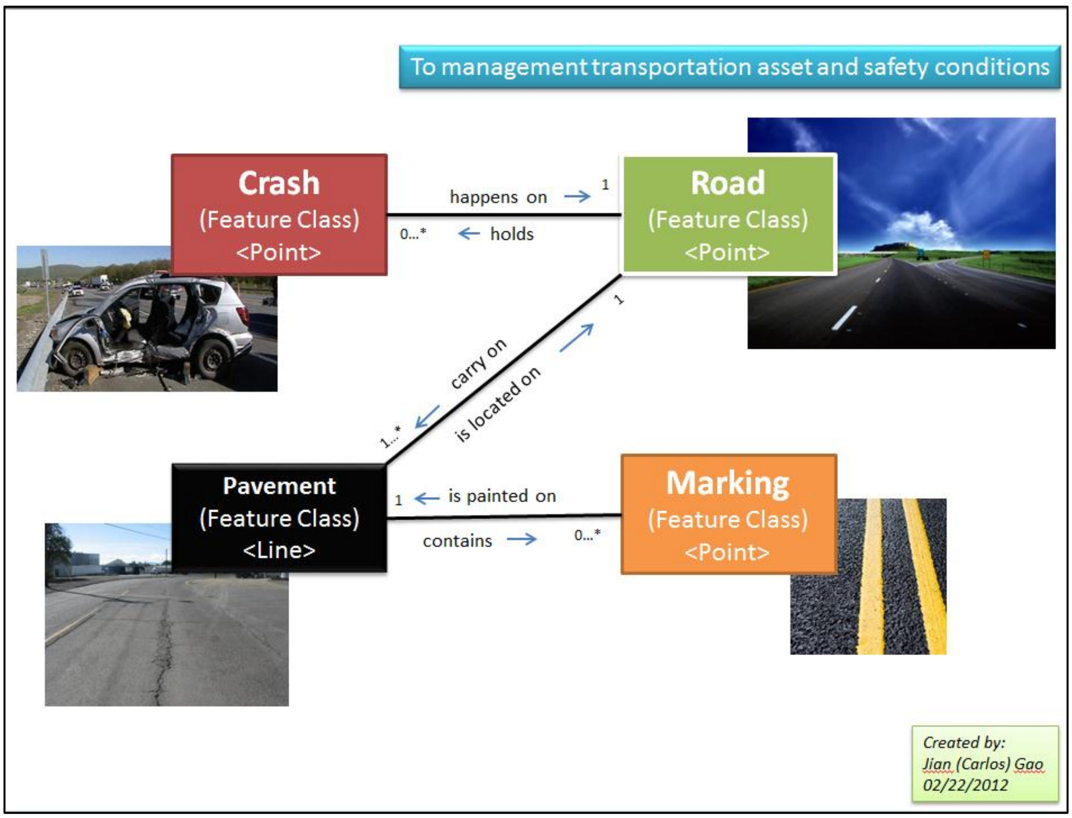


Figure 4.7 The UML Diagram of Geodatabase Relationships

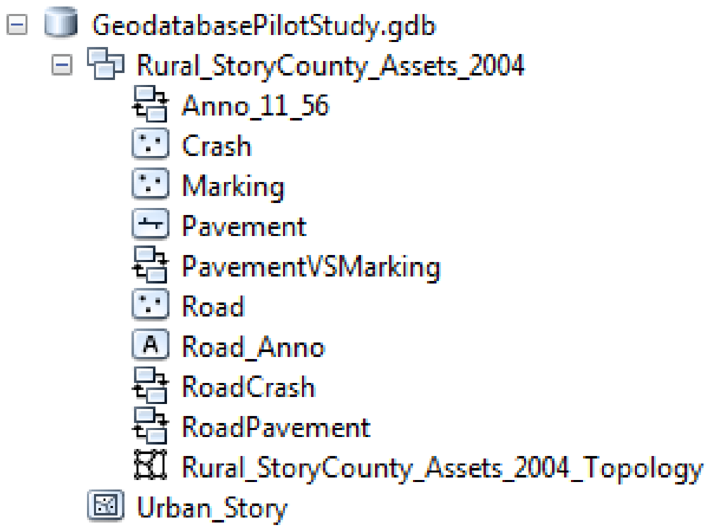


Figure 4.8 Structure of pilot study geodatabase

4.5.2 Basic Structure

Figure 4.7 shows the basic structure of the pilot study geodatabase. The geodatabase was named as "GeodatabasePilotStudy.gdb", and it contains one feature dataset (Rural_StoryCounty_Assets_2004), and within this feature dataset, there are four feature classes, which are Crash, Marking, Pavement, and Road. Data dictionary is shown in Table 4.1 through Table 4.4. The crash data is the locations where crashes happened in 2004, and its key feature is "CRASH_KEY".

Table 4.1 Field List of Feature Class Crash

	Feature Class			
	Crash			
Field name	Specification	Data Type	Length	Domain
OBJECTID		Object ID		
Shape		Geometry		
CRASH_KEY	The unique of a crash	Double		
MSLINK	The unique key of the located GIMS segm	Double		

Marking is the pavement marking data from the Iowa DOT Pavement Marking Management System (PMMS), which was collected in both fall and spring every other year. Four types of marking lines are included in this dataset, they are white edge (WEL), yellow center line (YCL), yellow edge line (YEL), and white dash line (WDL). The retroreflectivity value is a common measure of the reflection from vehicle illumination to driver at night time. (Bahar, et al. 2006) This value is used as the measure of pavement marking condition in this study.

Table 4.2 Field List of Feature Class Marking

	Feature Class **Marking**			
Field name	Specification	Data Type	Length	Domain
OBJECTID		Object ID		
Shape		Geometry		
LINE_TYPE	The marking line type	Text	8	LineType
TIME_YEAR	The season the retroreflectivity data taken	Text	9	Season
RTE	The route of the road segment	Double		
MP	The milepost of the road segment	Double		
DIR	The direction of the road segment	Double		
RETRO	The retroreflectivity of the pavement marki	Double		Retro
RMD	Specialized unique key	Text	50	

The Pavement feature class is from the Iowa DOT Pavement Management Information System (PMIS); year 2004. This data was collected every other year by Iowa DOT, and it linearly indicates roadway pavement condition by measures, such as pavement condition index (PCI), international roughness index (IRI), faulting depth, rut depth, and friction number. In the Literature Review Chapter, each of these terminologies was discussed.

The Road data feature class was obtained from the Iowa DOT Geographic Information Management System (GIMS), and integrated with the Linear Reference System (LRS). The reason of this integration is that the author chose fixed one mile segmentation, while GIMS data is dynamic segmentation and LRS data is with fixed segmentation. Since the LRS is a point feature, and integrated with a linear feature class of GIMS, the integrated Road feature is a point feature. Key attributes include segment location, route and milepost, speed limit, traffic volume, and so forth.

Table 4.3 Field List of Feature Class Pavement

Feature Class **Pavement**				
Field name	Specification	Data Type	Length	Domain
OBJECTID		Object ID		
Shape		Geometry		
ORIGKEY	The unique key of the road segment	Text	19	
ROUTE	The route of the road segment	Double		
PCI	The PCI of pavement in the road segment	Double		PCI
FRICT	The friction number of pavement in the roa	Double		
IRI	The IRI of pavement in the road segment	Double		
ADT	The ADT in the road segment	Double		AADT
FAULT	The faulting depth of pavement in the road	Double		
RUT	The rutting depth of pavement in the road s	Double		
Direction	The direction of the road segment	Double		
MP	The milepost of the segment	Short Integer		
RMD	Specialized unique key	Text	50	
Shape_Length	The length of the segment	Double		

Table 4.4 Field List of Feature Class Road

	Feature Class			
	Road			
Field name	Specification	Data Type	Length	Domain
OBJECTID		Object ID		
Shape		Geometry		
LATITUDE	The latitude of the data	Double		
LONGITUDE	The longitude of the data	Double		
Route	The route of the road segment	Double		
Milepost	The milepost of the shape file	Double		
MSLINK	The unique key of the original data	Double		
MedianType	The median type of the road segment	Short Integer		MedianType
LIMITEMPH	The speed limit of the road segment	Short Integer		
AADT	The AADT on the road segment	Double		AADT
RMD	Specialized unique key	Text	50	
Dir	The direction of the road segment	Double		

4.5.3 Topology

Topology is a set of governing rules applied to feature classes that define the spatial relationships that must exist between items. Table 4.5 shows the topology rules that applied to this study.

Table 4.5 Topology Rules

Feature Class	**Topology rule**	**Feature Class**
Marking	Point Must Be Covered By Line	Pavement
Crash	Point Must Be Covered By Line	Pavement
Road	Point Must Be Covered By Line	Pavement

The cluster tolerance, which is a distance range in which all vertices and boundaries will be considered as identical, or coincident, was set as 5 meters, based on literature. (Ogle, Alluri, & Sarasua, 2010) While creating topology, each feature class must be assigned with a rank to control how much the features will move when the topology is validated. The higher the rank (highest rank is 1), the less the features will move. According to the real-world relation between transportation assets and crashes, a topology rank, shown in Table 4.6, was built for this study.

Table 4.6 Topology Rank

Feature Class	**Rank**
Marking	3
Crash	3
Road	1
Pavement	2

This defined accuracy ranks indicates that ”Road” is the most accurate feature class, “Pavement” is the second, and “Marking” and “Crash” are the least accurate features. This ranking was built based on data source accuracy by contacting with data managers.

After creating the topology, a validation was conducted immediately. During validation, the participating feature classes are evaluated against the topology rules to discover any features violating them, in order to find errors. It was found that no error was detected.

4.5.4 Attribute Domain

Attribute domains are a property of geodatabase that could provide a way to minimize the potential for errors, to specify valid values for attributes, to allow users to check validation of attribute data. There are two types of attribute domains, range domains and coded values domains. In this study, six attribute domains were built, based on the real-world condition and data, three of them are coded value domain and three are range domains. Reasons of defining these domains were made based on data source or literature. Table 4.5 - Table 4.10 show the detail domain lists.

Table 4.7 Median Type Domain Code List

Name:	MedianType
Description:	Type of road median
Field Type	Short Integer
Domain Type:	Coded values
Code	*Description*
0	No barrier (< .152 meter curb)
1	Hard surface without barrier (Raised Median) (PV)
2	Grass surface without barrier (SL)

In the original GIMS data, the median type attribute was expressed by codes with descriptions, so this domain was built to illustrate median types by codes.

Table 4.8 Line Type Domain Code List

Name:	**LINE_TYPE**
Description:	Type of marking lane
Field Type	Text
Domain Type:	Coded values
Code	*Description*
1	yellow center line (ycl)
2	yellow edge line (yel)
3	white edge line (wel)
4	white dash line (wdl)

The pavement marking retroreflectivity data includes four types of marking lines, and here a code domain was defined to express line type by number so that further analysis could be contacted easier.

Table 4.9 Season Domain Code List

Name:	Season
Description:	Season of marking painted
Field Type	Text
Domain Type:	Coded values
Code	*Description*
1	spring
2	fall

As mentioned before, marking retroreflectivity data was collected in both spring and fall every year, so this code domain was made.

Table 4.10 PCI Domain Range

Name:	PCI
Description:	Pavement Condition Index (PCI) of segment
Field Type	Double
Domain Type:	Range
Range	
Minimum value	0
Maximum value	100

Since PCI is as index ranges from 0 to 100 (Haas, 1997), this range domain was made for controlling the unproductive data.

Table 4.11 Retroreflectivity Domain Range

Name:	Retro
Description:	The retroreflectivity of the pavement marking
Field Type	Double
Domain Type:	Range
Range	
Minimum value	0
Maximum value	600

Usually, the pavement marking retroreflectivity value is as high as 100 mcd/m^2/lux and as low as zero (Bahar, Masliah, Erwin, Tan, & Hauer, 2006), so this range domain was made.

Table 4.12 AADT Domain Range

Name:	AADT
Description:	Average Annual Daily Traffic
Field Type	Double
Domain Type:	Range
Range	
Minimum value	0
Maximum value	200000

Considering literature review and the descriptive analysis of attributes, the maximum of ADT was set as 200,000 vehicles by a range domain. (Karlaftis & Golias, 2002)

4.5.5 Relationship Classes

Relationship class is a geodatabase property that provides a way to model relationships that exist between real-world objectives, and it could help users reflect the real world accurately. In this study, three relationship classes were created, according to the UML diagram shown in Figure 4.6. The details of each relationship class are shown by Figure 4.9 through Figure 4.11

Name:	PavementVSMarking
Type:	Simple
Cardinality:	1 - M
Notification:	Both

Origin Table/Feature Class

Name:	Pavement
Primary Key:	ORIGKEY
Foreign Key:	OriginalKey

Destination Table/Feature Class

Name:	Marking
Primary Key:	RMD
Foreign Key:	Route_Milepost_Direction

Labels

Forward:	contains
Backward:	is painted on

Figure 4.9 Relationship Class Property of “PavementVSMarking”

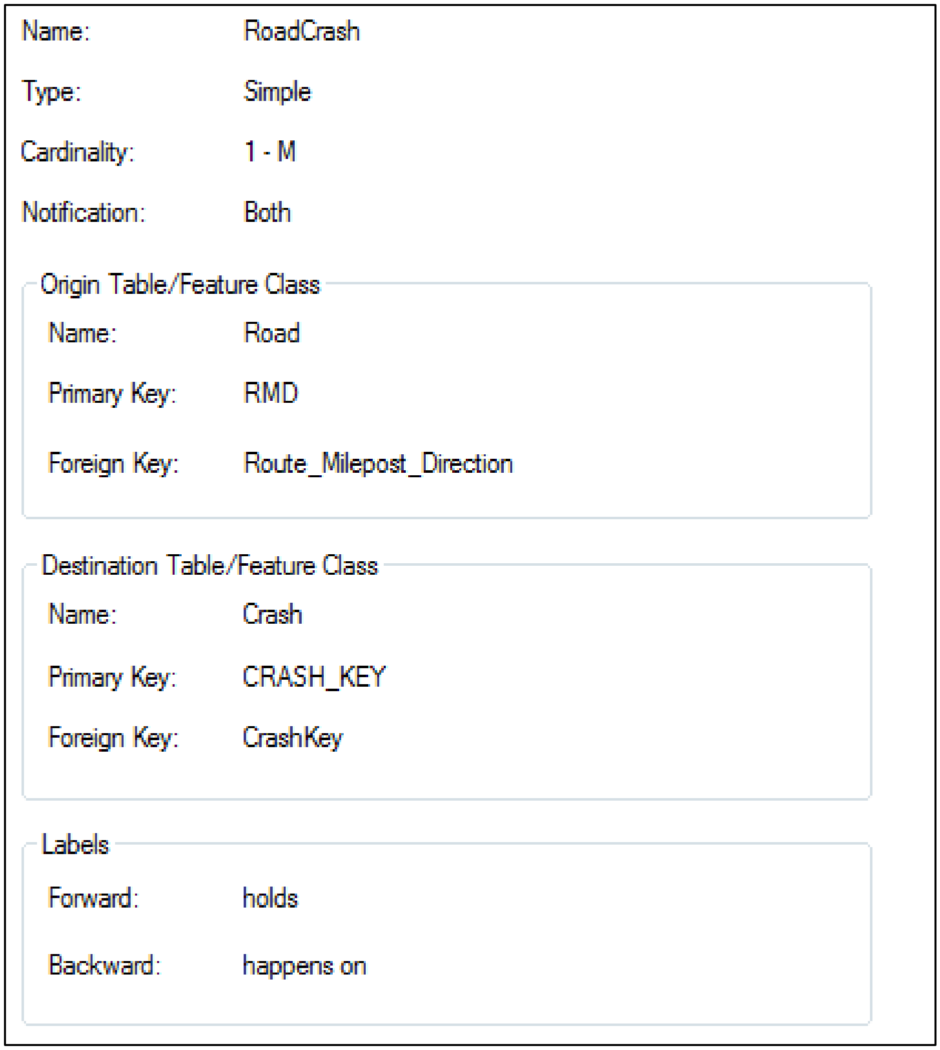


Figure 4.10 Relationship Class Property of “RoadCrash”

Name:	RoadPavement
Type:	Simple
Cardinality:	1 - M
Notification:	Both

Origin Table/Feature Class

Name:	Road
Primary Key:	RMD
Foreign Key:	route_milepost_direction

Destination Table/Feature Class

Name:	Pavement
Primary Key:	ORIGKEY
Foreign Key:	OriginalKey

Labels

Forward:	carry on
Backward:	is located on

Figure 4.11 Relationship Class Property of “RoadPavement”

4.5.6 Hypothetical Scenarios

In this section, three hypothetical scenarios will be addressed. By these scenarios, the geodatabase, especially the relationship classes and domains will be tested if work or not; the structure will be clarified clearly; and the applicability would be approved.

Scenario 1: A crash happened on I-35, and its unique ID is 2004033840. The pavement condition measures are needed for investigating the relationship between crash and pavement condition.

The crash with "CRASH_KEY" equals to 2004033840 is selected in the crash attributes table, as shown in Figure 4.12.

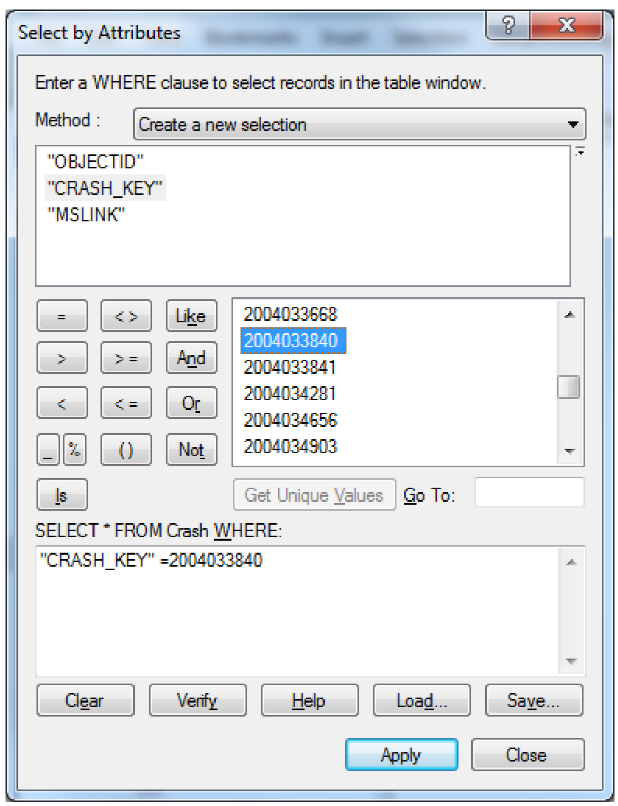


Figure 4.12 Selecting of Specific Crash

Then in the related tables list, the "RoadCrash_happens on" was the only one found. This is reasonable because in the relationship diagram, "road" is the only feature class that is related with "crash". Also according to the relationship class, "pavement" is related with "road", so after selecting the related table of "road", the corresponding pavement condition measure could be found in "pavement", shown in Figure 4.13.

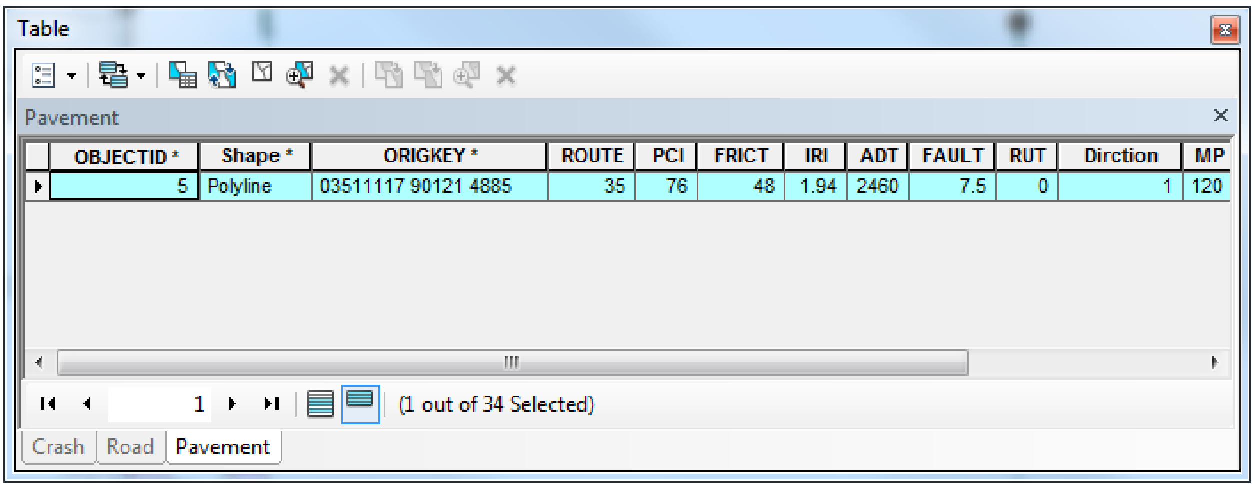


Figure 4.13 Selected Specific Crash

Scenario 2: A research is investigating the low speed roads safety, and it needs the useful data from this county as well. Low speed road is defined as roadways with posted speed limit lower or equal to 35 mph.

In a similar manner, the road segments with low speed selected by the "Select by Attributes" window, and the selecting and result tables are shown in Figure 4.14 and 4.15. Two roadway segments were selected.

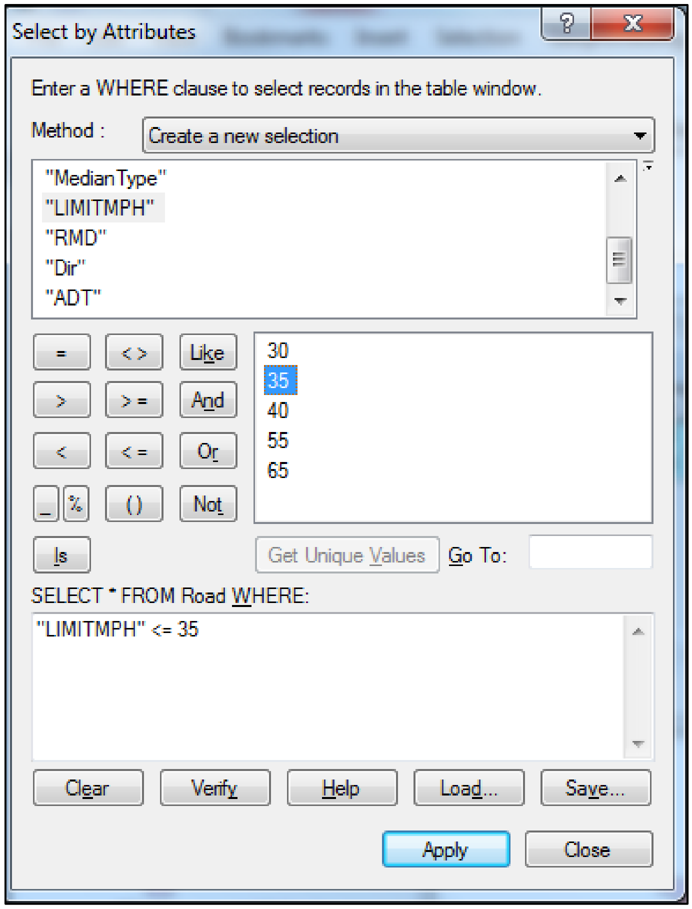


Figure 4.14 Selecting Low Speed Roads

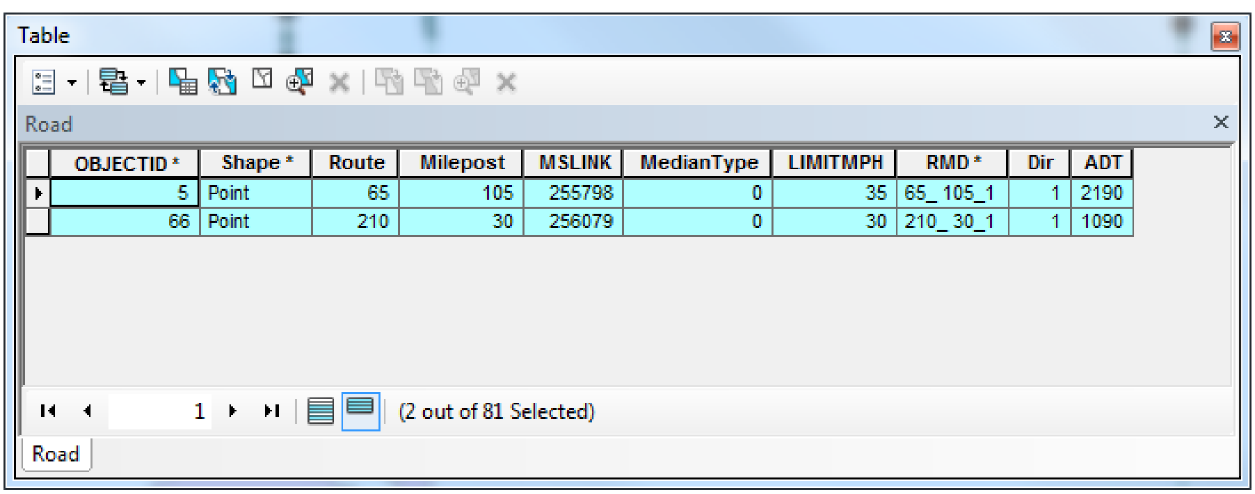


Figure 4.15 Selected Low Speed Road Segments

The corresponding crashes on these selected roadway segments are found by clicking on “RoadCrash: holds” in the “Related Tables” list, shown in Figure 4.16.

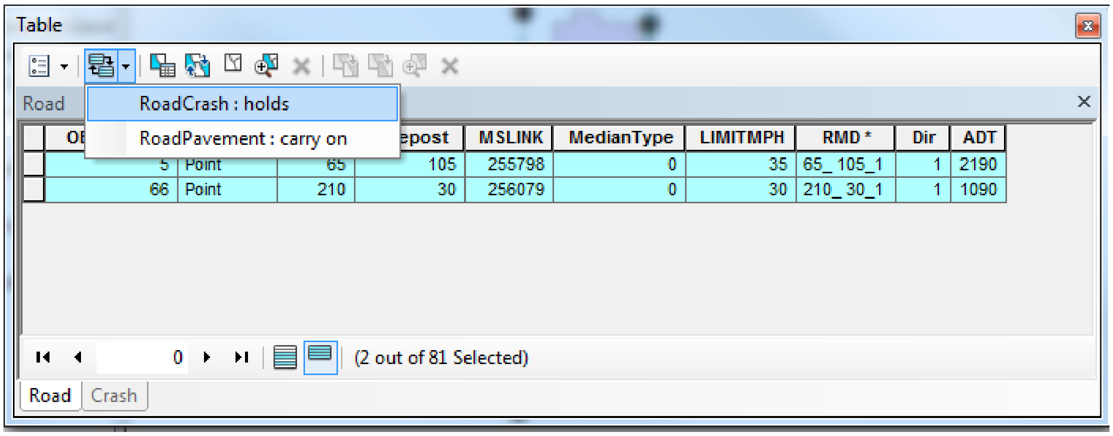


Figure 4.16 Selecting Related Table

After selecting results map is shown in Figure 4.17. As shown, two crashes on Route 210 were selected, with low speed.

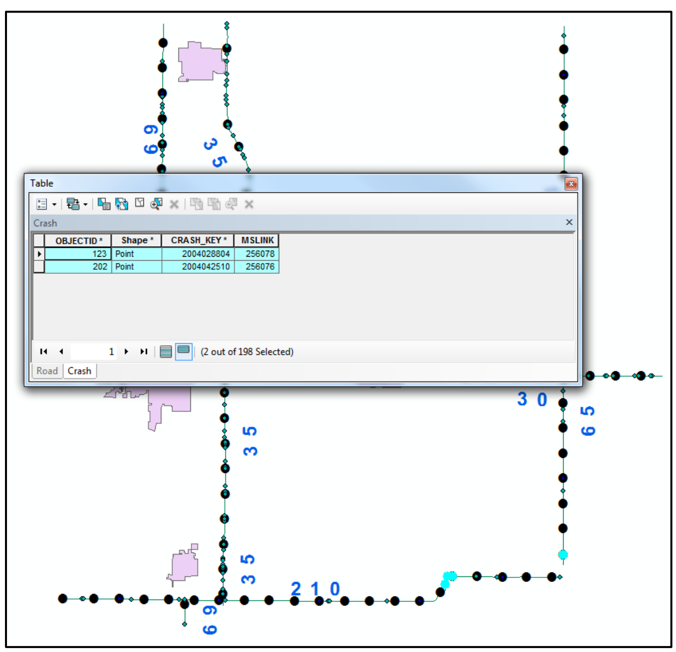


Figure 4.17 Result of Scenario 2

Scenarios 3: A research task force is investigating the relationship between safety and white dash line pavement marking. They need the corresponded white dash line pavement marking and the crashes happened in the relative roadway segments.

The first step is to select all white dash line markings in the area. According to Table 4.7, white dash line is coded as "4", so in the selecting by attributes window, the setting and selecting options would be like shown in Figure 4.18.

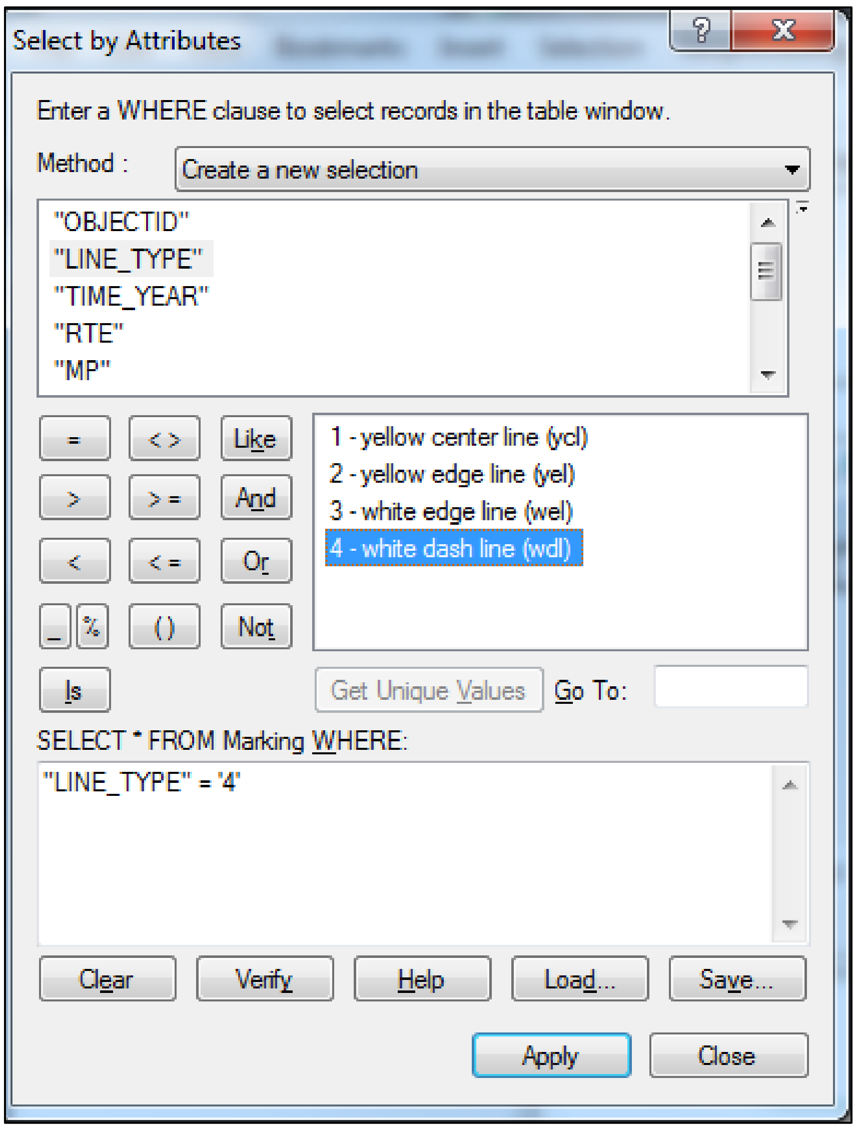
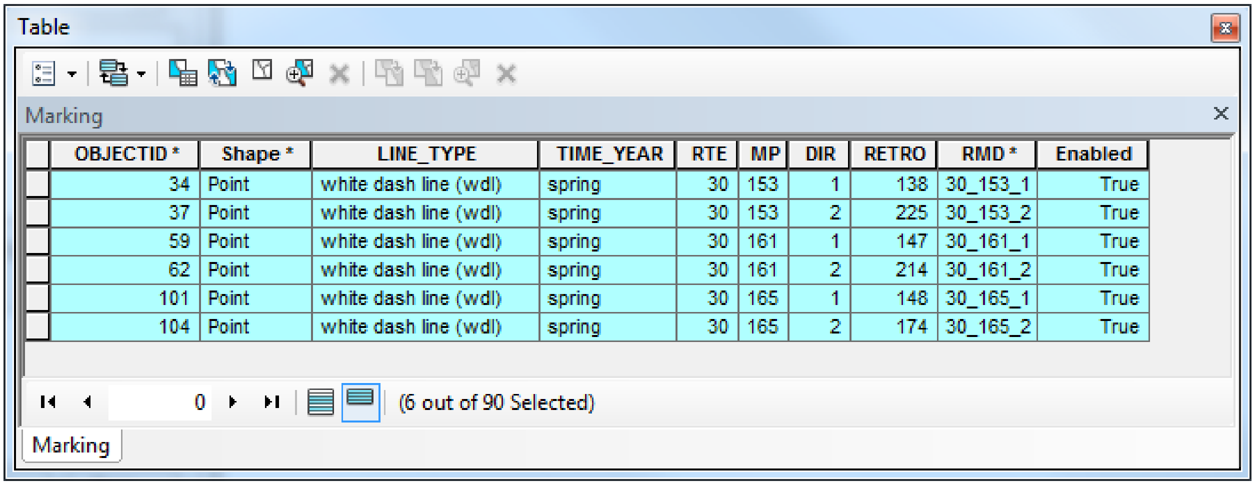


Figure 4.18 Selecting of White Dash Line Markings

Six out of ninety marking recoded were selected, as shown in Figure 4.19.



Table

Marking

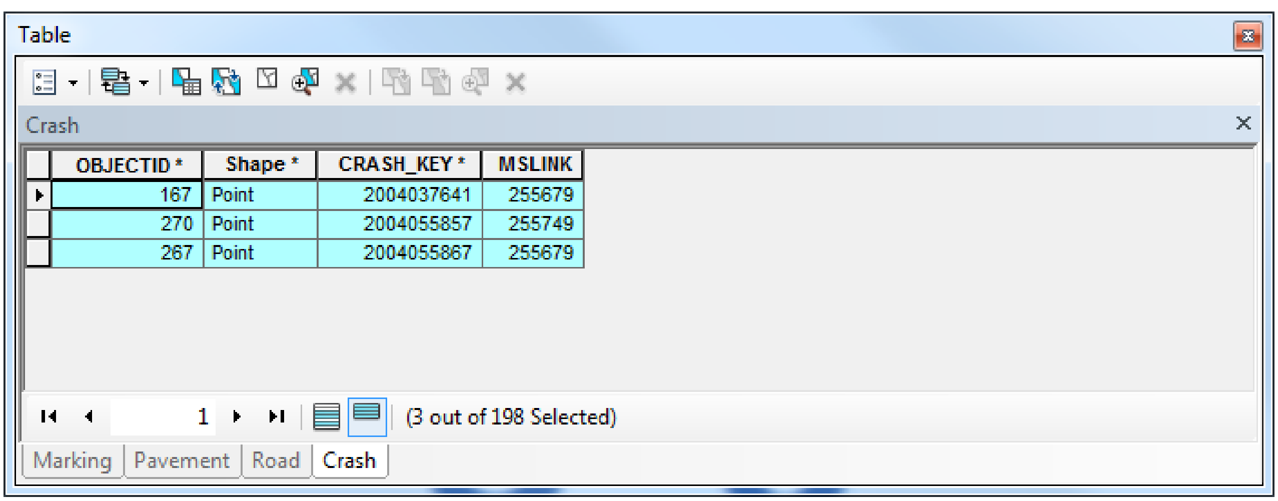
OBJECTID *	Shape *	LINE_TYPE	TIME_YEAR	RTE	MP	DIR	RETRO	RMD *	Enabled
34	Point	white dash line (wdl)	spring	30	153	1	138	30_153_1	True
37	Point	white dash line (wdl)	spring	30	153	2	225	30_153_2	True
59	Point	white dash line (wdl)	spring	30	161	1	147	30_161_1	True
62	Point	white dash line (wdl)	spring	30	161	2	214	30_161_2	True
101	Point	white dash line (wdl)	spring	30	165	1	148	30_165_1	True
104	Point	white dash line (wdl)	spring	30	165	2	174	30_165_2	True

0 (6 out of 90 Selected)

Marking

Figure 4.19 Selected of All White Dash Line Markings

Then, by selecting the related tables, the corresponding crashed could be selected. According to Figure 4.7, the pattern from pavement marking to crash would be “making”—“pavement”—“road”—“crash”. The result of related crashes table is show in Figure 4.20.



Table

Crash

OBJECTID *	Shape *	CRASH_KEY *	MSLINK
167	Point	2004037641	255679
270	Point	2004055857	255749
267	Point	2004055867	255679

1 (3 out of 198 Selected)

Marking | Pavement | Road | Crash

Figure 4.20 Selected of Crashes Related to White Dash Line Markings

4.5.7 Annotation and Labeling

Labeling features on a map can facilitate manage and analysis geographic data. Annotation is the process of automating text placement and labeling on a map. In this study, an annotation feature class was created for road routes. The reference scale was set as 1:100,000 in feet, the label engine was selected to be ESRI Maplex Label Engine, and the each route was annotated at a reasonable space, instead of every single section. Figure 4.21 shows the final map of the pilot study.

4.6 Summary

In the field of transportation engineering, large amounts of data are generated from management systems, such as asset management system. Datasets come in different formats, resulting in the need for innovative techniques in terms of managing, editing, plotting, integrating, and analyzing these data. A GIS system is a valuable tool for evaluating roadway safety performance. In GIS, it is relatively easy and efficient to manage crash, roadway, and numerous other types of spatial data. Based upon GIS spatial proximity, crashes can be subjectively assigned roadway characteristics and conditions. Or vice versa, roadway segments and asset conditions can be assigned crashes.

Figure 4.21 shows all data feature classes in the pilot study geodatabase of Story County, in year of 2004. The small black points are crash locations, the small red stars are road segment locations, the green points are marking recorded locations, and the green line feature indicates pavement condition, with symbolized by traffic volume. It should be noticed that Route 35 (I-35) is the busiest road in the county, since it has the thickest label in traffic (ADT) and it has the highest number of crashes. Because this pilot study only focuses on rural area, it could be found that no data is considered in the urban areas, such as Ames, Nevada, and so forth.

Even though geodatabase is found to be a powerful data storing and managing framework in GIS, one of the tasks of this research is to physically integrate all datasets as one, so that each data row could represent the entire physical asset condition of a segment and the number of crashes that occurred on a given segment. A geodatabase framework enablesthe data feature classes to be logically related to each other. However, identifying the related feature classes requires a manual process, so for the purpose of this study, the milepost-based integration was deemed most applicable.

In this study, datasets were integrated focusing on both crashes and roadway segments, and results indicated that the route-milepost-based integration is a more applicable method, considering the integrated data characteristics. In addition, a GIS system, by both spatial proximity tool and advanced personalized Python tool box, was proved to be an innovative, efficient, and accurate data integration tool for transportation asset management systems. Furthermore, a Story County Geodatabase was created as a pilot study of the application of geodatabase for asset data management.

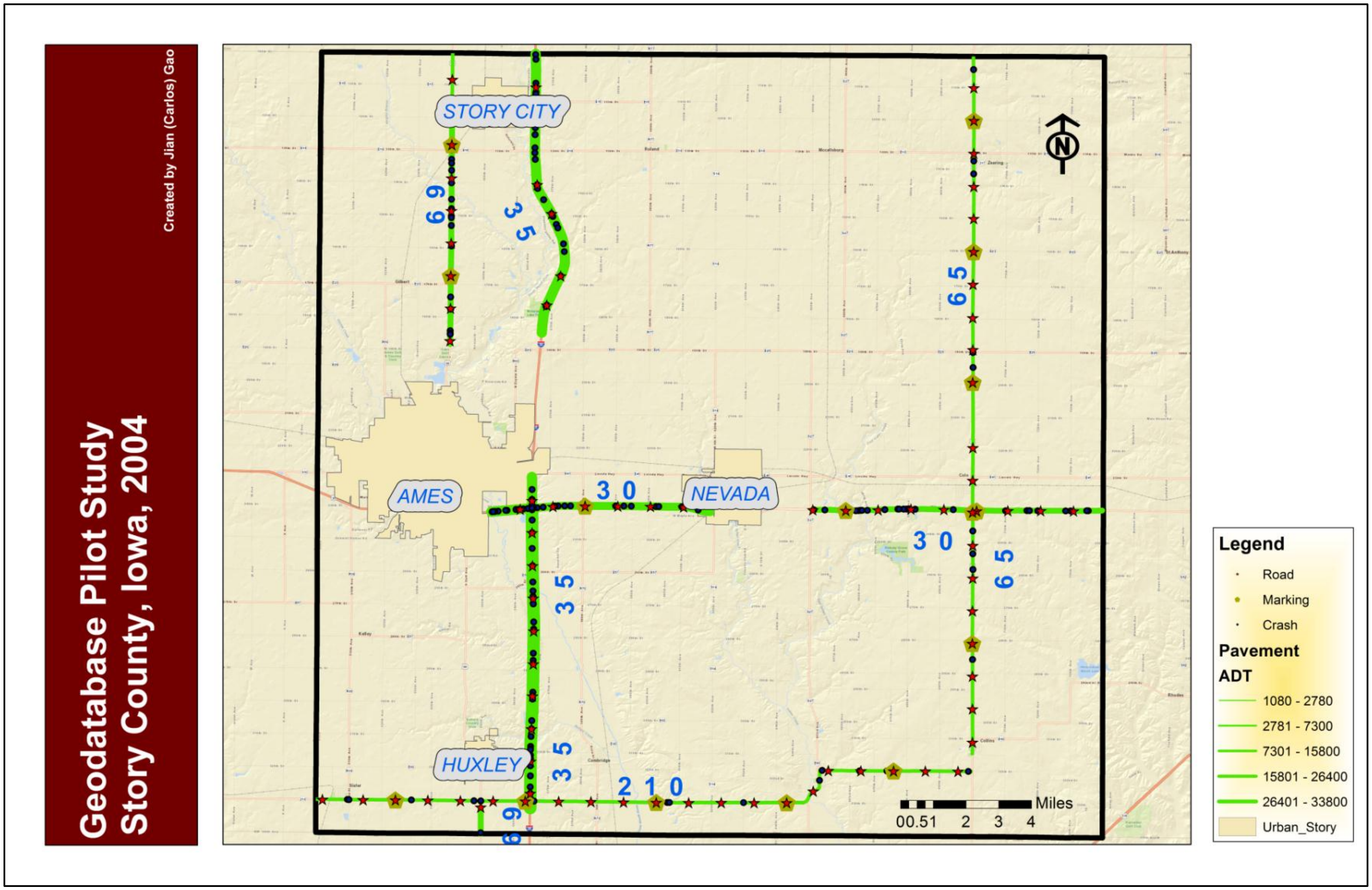


Figure 4.21 Final Map of Geodatabase Pilot Study, Story County, Iowa, 2004

CHAPTER 5. ESTIMATION OF ASSET CONDITION

This chapter discusses the estimation the overall asset condition of a roadway segment using a unique index, the ACI. The ACI combines performance measurement data on pavement condition and pavement marking retroreflectivity, such as IRI, faulting depth, friction, rutting depth, white marking line retroreflectivity, and yellow marking line retroreflectivity. The ACI provides a numerical rating for the condition of road segments, where 1 is the worst possible condition and 3 is the best.

5.1 Literature Review

Constructing an index to indicate condition, given measures or performance, is a widely used method in the field of transportation engineering and, in general, civil engineering. For instance, the U.S. Army Corps of Engineers (USACE) developed the PCI to represent the condition of a pavement surface as a numerical index between 0 and 100. Another study conducted by Oswald et al. (2011) provided a step-by-step methodology to construct a U.S. transportation infrastructure index, for understanding economic trends and promoting prosperity throughout the business sector (Oswald, Li, McNeil, & Trimbath, 2011). The Transportation Index provides a rich source of historical information related to the performance of the complex and extensive transportation infrastructure system.

5.1.1 Weighting Methods

In multi-criteria decision-making, one of the key procedures is the explicit or implicit assignment of relative weights to each performance measure to reflect its importance among different criteria. Weighting was an important step in developing the ACI. To determine the most suitable methodology for weighting of the data, some typical weighting methods were reviewed, as summarized in Table 5.1.

Table 5.1 Summary of Weighting Methods

Method	**Description**
Equal Weighting—same weight assigned to all performance criteria (Sinha & Labi, 2006)	Pros: simple and easy Cons: may yield flawed results since it does not incorporate with the relative references that may exist among criteria Main procedure: assuming a weight of 1 for every performance measure
*Direct Weighting—decision makers directly assign numerical weight values (Li & Sinha, 2009) (Sinha & Labi, 2006)	Two approaches: (easy but may not represent importance effectively) a. Point allocation- assign weights by a number of points in proportion to their importance. Could be either global (directly assign specific weights to data ranges), or local (assign weight to one range first, and weight the rest relative to the assigned range) *Pros: cardinal rather than ordinal scale of importance (better meaning to relative importance of criteria/ measures)* b. Ranking-decision maker manually weights performance criteria/ measures orderly by decreasing importance as perceived *Pros: useful for large number of criteria/ measures*
Observer-based Weighting Method (Sinha & Labi, 2006) (Li & Sinha, 2009)	Observer assigns scores to performance criteria or measures and their overall impact score, then establishes a functional relationship between total scores (response variable) and individual scores assigned (explanatory variable) through regression analysis

Table 5.1 (continued)

Method	**Description**
Gambling Method (Sinha & Labi, 2006) (Li & Sinha, 2009)	1. Initial ranking of performance 2. Compare between two performance measures a. sure thing: the measure is at its most desirable level (best performance) and the other is at the worst performance b. gamble: in an outcome, set p% possibility that all criteria are at best level, and 1-p at the worst level 3. Repeat step 2 to derive the weights for remaining performance measures Pros: useful for determining the relative weights of performance criteria in the outcome risk scenario Cons: may be difficult to comprehend or administer
Swing Method (Sinha & Labi, 2006) (Li & Sinha, 2009)	1. Hypothetically assign all criteria/ measures at worst level; 2. Determine the more preferred measure to swing from worst up to best; 3. Determine the second preferred, and so on; 4. The most preferred measure is assigned as a weight of 100, and second as a lower value, etc.
Indifference Trade-off Weighting Method. (Li & Sinha, 2009)	Used for survey respondents.
Pairwise Comparison of the performance criteria (Analytic Hierarchy Process [AHP])) (Sinha & Labi, 2006) (Li & Sinha, 2009)	1. Decomposition—construct a hierarchy of levels 2. Comparative judgments—decision maker determine relative weights 3. Syntheses-relative weights are combined to establish the overall optimal weights 4. Check for consistency
Delphi Technique (Li & Sinha, 2009)	Used for surveys to aggregate the perspectives from individual experts for consensus building and ultimately for a holistic final assessment

Table 5.1 (continued)

Method	Description
Factor Analysis (Hermans, Van den Bossche, & Geert, 2008)	1. Following guidelines, assess the optimal factor number (Sharma, 1996) 2. Enhance the interpretability, results in each indicator having a large factor score on one of the factors only. 3. Deduce indicator weights. Pros: reduce number of dimensions Cons: weights are based on correlations which do not necessarily correspond to the real-world links between the phenomena being measured
Data Environment Analysis (DEA) (Hermans, Van den Bossche, & Geert, 2008)	• Used for evaluating the relative efficiency of decision-making units (DMU's). The efficiency is defined as the ratio of the weighted sum of outputs to the weighted sum of inputs. • A general DEA model for indexes has been proposed in Cherchye et al. (2006). • Most valuable when only one expert opinions are available • Constraints: smaller than 1; non-negative • Pros: Can handle raw values; weights are endogenously determined and derived directly from the data • Cons: this implies that the weights do not sum up to one, which makes the comparison of indicator weights with other weighting methods impractical.
Simple Multi-attribute Rating Technique (SMART) (Poyhonen & Hamalainen, 2001)	1. Rank the importance of the changes in the attributes from the worst to the best level; 2. Make ratio estimates of the relative importance of each attribute relative to the one ranked lowest in importance

5.2 ACI Estimation

Pavement condition (PC) and pavement marking (PM) retroreflectivity are the two main sectors of ACI. The sub-indices under pavement condition are IRI, faulting depth, friction number, and rutting depth; and the sub-indices under pavement marking retroreflectivity are white marking line retroreflectivity and yellow marking line retroreflectivity. The white marking line retroreflectivity is the average of retroreflectivity of white edge line (WEL) and white dash line (WDL) in road segment. Both of these line types are applied for dividing traffic in the same direction. On the other hand, the yellow marking line retroreflectivity sub-index includes yellow edge line (YEL) and yellow center lines (YCL), on undivided roadway and divided roadway, respectively. Both of them are utilized for dividing traffic in different directions.

5.2.1 Principal Component Analysis (PCA) for Asset Condition

In order to discover the possibility to reduce the dimensionality of the data (in other words, examine whether all the sub-indices need to be included in the ACI) and to develop a statistical rational weighting matrix, a Principal Component Analysis (PCA) was conducted. Principal Component Analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. (Adbi & Williams, 2010) It involves computing the eigenvectors and eigenvalues of the variance-covariance matrix or correlation matrix, as the first step. The eigenvectors are used to project the data from a number of dimensions down to a lower dimensional representation. The eigenvalues give the variance of the data in the direction of the eigenvector (Esbensen & Geladi, 1987).

The results indicated that PC analysis was not able to reduce dimensionality for the data. The correlations, shown in the correlation matrix in Table 5.2, are all relatively low. (Krzanowski & Marriott, 1994) In addition, the eigenvalues associated with the estimated principal components all have a similar size, as shown in Table 5.3 (Gorsuch, 1974). Therefore the result form PC analysis, shown in Table 5.4, indicated that all seven estimated principal components have similar importance, and close proportions of variance (Harman, 1976). Even though the values range from 0.12 to 0.23, but none of them were significantly greater than other. As such, the ACI will be estimated using all the sub-indices (shown in Table 5.2).

Table 5.2 Correlation Matrix

	IRI	FAULTING	FRIC-TION	Rut	AVE. WHITE.	AVE. YELLOW.
IRI	1	0.156	-0.075	0.233	-0.077	-0.021
FAULTING	0.156	1	-0.039	0.005	0.040	-0.025
FRICTION	-0.075	-0.039	1	-0.050	-0.016	0.046
Rut	0.233	0.005	-0.050	1	-0.071	-0.003
AVE.WHITE.	-0.077	0.040	-0.016	-0.071	1	0.176
AVE.YELLOW.	-0.021	-0.025	0.046	-0.003	0.176	1

Table 5.3 Eigenvalues

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalues	1.351	1.149	1.019	0.972	0.793	0.716

Table 5.4 Importance of Components

	PC1	PC2	PC3	PC4	PC5	PC6
Standard deviation	1.162	1.0720	1.010	0.986	0.891	0.846
Proportion of Variance	0.225	0.192	0.170	0.162	0.132	0.119
Cumulative Proportion	0.225	0.417	0.587	0.749	0.881	1.000

5.2.2 Scoring

Before developing the ACI, sub-indices were scored considering the data value. The detail scoring thresholds are shown in Table 5.5. All of the scores and thresholds were assigned based on the literature review in Chapter 2, with the researcher team's judgment.

As shown in Table 5.2, if a data value of a measure is in the range of the thresholds for good condition, it is scored as 3 points. In the same manner, a data value that indicates poor condition is assigned as 1 point.

Table 5.5 Score Matrix of ACI Sub-Indices

Asset Condition Catalogs (Sectors)	Asset Condition (Sub-Indices)	Scores		
		3 (Good)	2 (Moderate)	1 (Poor)
Pavement Condition	IRI (m/km)	<1.5	1.5-2.7	>2.7
	Faulting (mm)	<2.5	2.5-5	>5
	Friction	>60	60-35	<35
	Rutting (mm)	<6	15-6	>15
Pavement Marking	White Marking [WEL+WDL] (mcd/m^2/lux)	>200	200-150	<150
	Yellow Marking [YEL+YCL] (mcd/m^2/lux)	>200	200-100	<100

As discussed before, the WEL and WDL are grouped in White Marking, while YEL and YCL are incorporated in the Yellow marking group. To elaborate, the groupings are for the following reasons:

- Marking types in each color have the similar function, that is, both white edge line and white dash line are used for separating traffic in same direction, while both yellow edge line and yellow center line are for dividing traffic in different directions;

- Different color markings have different retroreflectivity evaluating thresholds, that is, white marking is treated as in poor condition if the retroreflectivity is 150 mcd/m^2/lux or lower, while for yellow marking it is 100 mcd/m^2/lux.

5.2.3 Weighting

By comparing the simplicity among methods listed in Table 5.1, Equal Weighting and Direct Weighting were selected for this study. All relative weights were assigned directly to sectors and sub-indices, considering their relative significance on highway safety. Figure 5.1 provides an overview of the ACI sector and sub-index calculation layout.

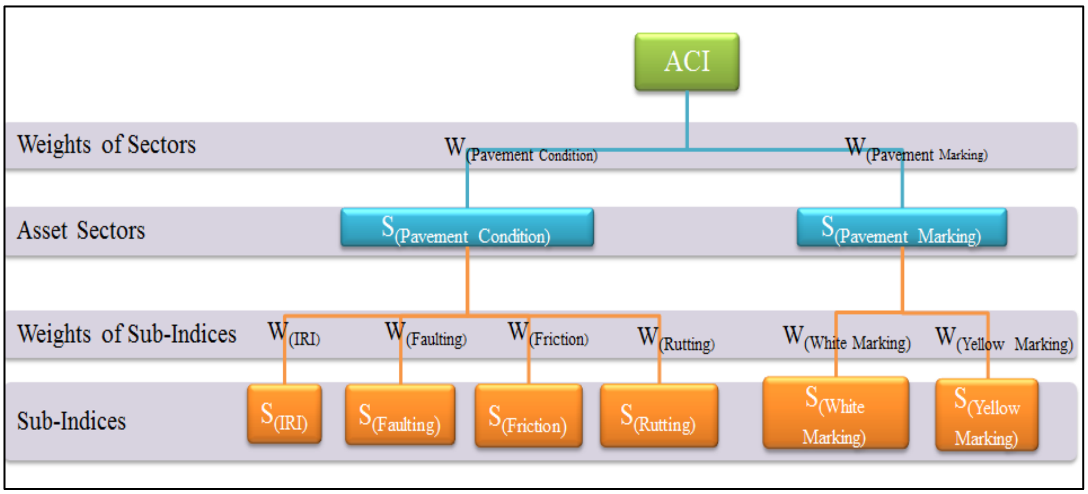


Figure 5.1 ACI sector and sub-index weighting layout

As shown in Figure 5.1, the ACI is estimated by adding the weighted scores of PC and PM. Their weights are assigned as 0.6 for PC and 0.4 for PM. A sensitivity study of the weights was conducted and, based on the literature review, pavement condition is considered to have slightly more effect on roadway safety than pavement marking retroreflectivity, indicating that a higher weight should be assigned to it. Each asset condition sub-index is scored and weighted first, as shown at the bottom of Figure 5.1. In a similar manner to sectors, asset condition scores (sub-indices) were weighted according to their significance on safety, and the sector score was calculated by summing all the weighted scores. The following functions (5.1 through 5.3) present the ACI calculations.

$$ACI = \sum_{i=Sectors} S_i \times W_i = S_{PC} \times W_{PC} + S_{PM} \times W_{PM} \tag{5.1}$$

$$S_{PC} = \sum_{i=Sub-indices} S_i \times W_i = S_{IRI} \times W_{IRI} + S_{Faulting} \times W_{Faulting} + S_{Friction} \times W_{Friction} + S_{RD} \times W_{RD} \tag{5.2}$$

$$S_{PM} = \sum_{i=Sub-indices} S_i \times W_i = S_{WM} \times W_{WM} + S_{YM} \times W_{YM} \tag{5.3}$$

where:

$S_{(PC)}$=Score of pavement condition sector

$S_{(PM)}$=Score of pavement marking retroreflectivity sector

$S_{(IRI)}$=Score of IRI

$S_{(Faulting)}$=Score of faulting depth

$S_{(Friction)}$=Score of friction number

$S_{(RD)}$=Score of rutting depth

$S_{(WM)}$=Score of white marking retroreflectivity

$S_{(YM)}$=Score of yellow marking retroreflectivity

$W_{(PC)}$=Weight of pavement condition sector

$W_{(PM)}$=Weight of pavement marking retroreflectivity sector

$W_{(IRI)}$=Weight of IRI

$W_{(Faulting)}$=Weight of faulting depth

$W_{(Friction)}$=Weight of friction number

$W_{(RD)}$=Weight of rutting depth

$W_{(WM)}$=Weight of white marking retroreflectivity

$W_{(YM)}$=Weight of yellow marking retroreflectivity

It should be noted that under each sector, the sum of weights equals to 1, for instance, under sector “pavement condition”,$W_{IRI} + W_{Faulting} + W_{Friction} + W_{Rd} = 1$.

5.3 Summary

An Asset Condition Index (ACI) was developed as a simple, convenient and understandable indicator for representing the overall physical asset condition of a roadway segment and assisting agencies in the decision-making for pavement preservation and maintenance activities. This chapter presented a step-by-step methodology for calculating a unique condition index of multiple asset conditions and assists agency to monitor asset condition using a convenient indicator.

The ACI contains two general sectors and six sub-indices. Sectors and sub-indices were scored based on available performance and measurement data, and the score thresholds were based on the findings of the literature review.

The Equal Weighting and Direct Weighting methods were chosen among the reviewed weighting methods.

The next chapter examines the relationship between the calculated ACI, exposure information (ADT), and number of crashes using statistical models.

CHAPTER 6. STATISTICAL ANALYSIS OF CRASH FREQUENCY

This chapter covers the statistical models that were estimated to reveal the relationship between the ACI and safety. The number of crashes, which occurred on each one-mile segment on Iowa primary roads from 2004 through 2009, was estimated by developing a negative binomial regression model. The researchers controlled for exposure by including annual average daily traffic (ADT) of the roadway segments as an independent variable in the regression models.

6.1 Descriptive Statistics

6.1.1 ACI

Table 6.1 shows the descriptive statistics for the ACI. Note that the ACI is between 1 and 3, where 1 indicates poor asset condition and 3 indicates excellent condition.

Table 6.1 Descriptive statistics of the ACI

Moments	
Mean	2.271
Standard Deviation	0.340
Number of Observations	24,052
Skewness	-0.419

In Figure 6.1, the average ACI for different years of the study period is presented. The ACI for all six study years were above 2.0, which represent an overall good condition.

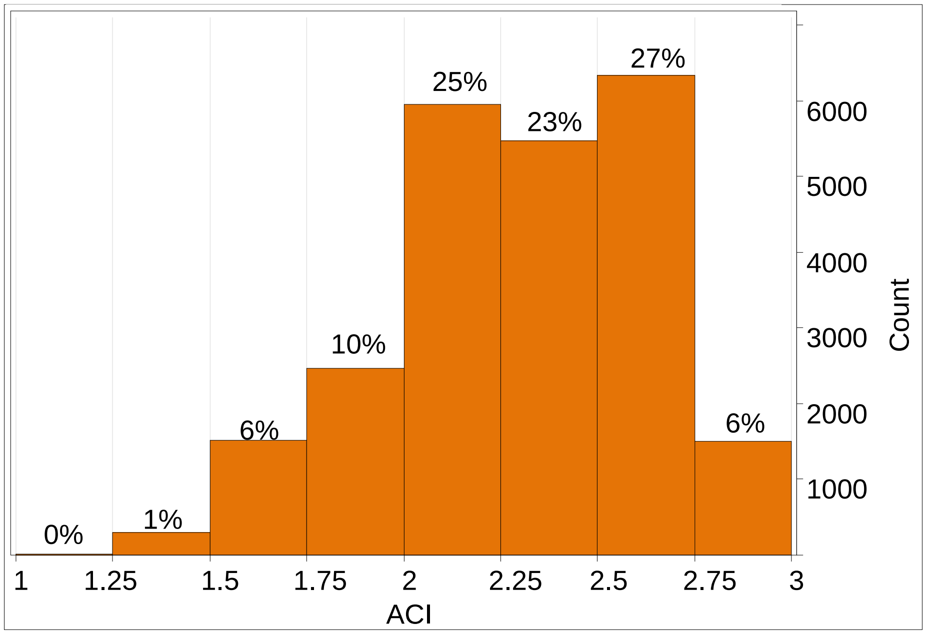


Figure 6.1 Histogram of ACI

Figure 6.2 shows the mean ACI for 2004 through 2009. The mean ACI for all six study years was above 2.0, which represents an overall good condition.

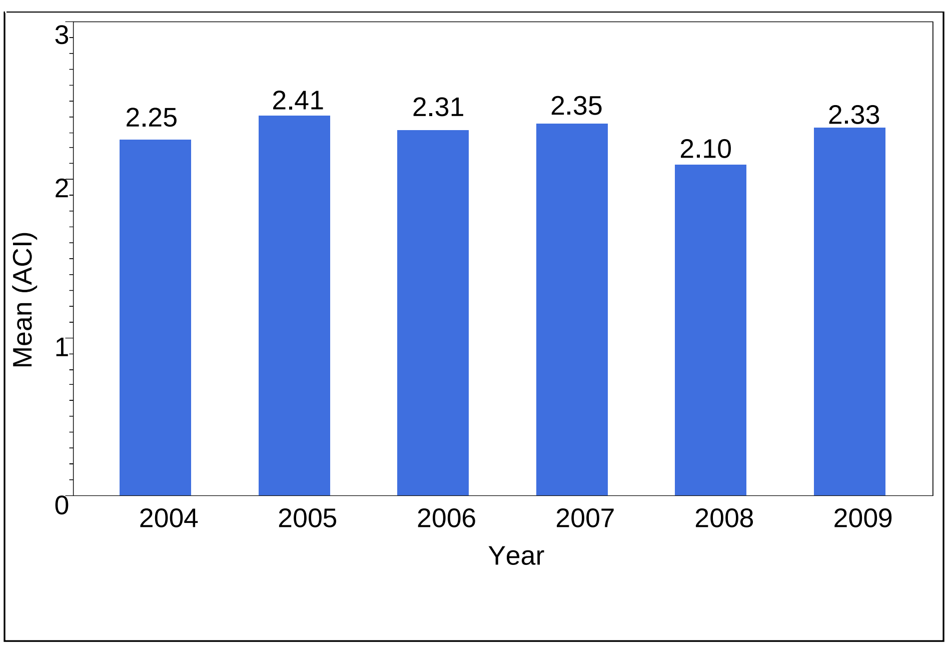


Figure 6.2 Distribution of ACI by year

6.1.2 ADT

This section presents the descriptive statistics of the ADT. The ADT data follows a right-skewed normal distribution (Figure 6.3), and the descriptive statistics are listed below in Table 6.2.

Table 6.2 Descriptive Statistics of ADT

Moments	
Mean	5758.471
Standard Deviation	8656.995
Number of Observations	24,052
Skewness	4.288

As it can be observed in Table 6.2, ADT has a large variance. As such, the natural logarithm of the ADT [Log(ADT)] was calculated and used in the models . The descriptive analysis for Log(ADT) is presented next.

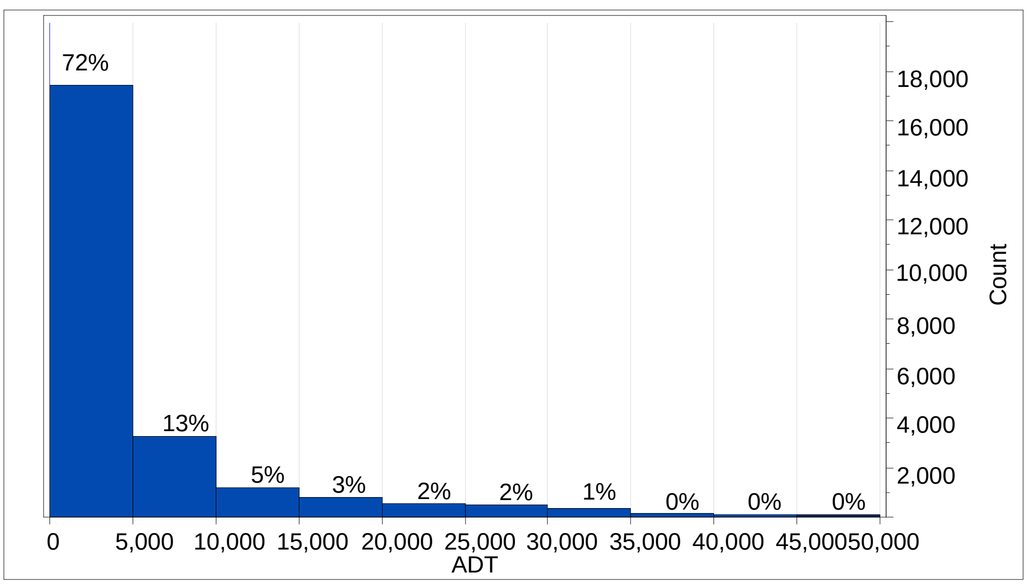


Figure 6.3 Histogram of ADT

6.1.3 Log(ADT)

As mentioned in the previous section, the purpose of converting ADT into Log(ADT)is to change the order of magnitude of ADT so that the orders of magnitude of all factors are close enough for estimating a statistic model rationally. The mean of Log(ADT) is around 8.1, which is in the same order of magnitude of the other factors (Table 6.1, Table 6.4). The standard deviation (1.003) is also much smaller than the standard deviation of ADT (8656.9), which indicates that the Log(ADT) is much more concentrated around the mean.

Table 6.3 Descriptive Statistics of Log(ADT)

Moments	
Mean	8.069
Standard Deviation	1.003
Number of Observation	24,052
Skewness	0.608

The Log(ADT) follows a right-skewed normal distribution, as shown in Figure 6.4, and the skewness is 0.608.

As shown in Figure 6.5, the mean of Log(ADT) for each study year were all around 8.0, except for 2007 and 2009, which were approximate 9.3 and 9.5, respectively. The reason of these changes in Log (ADT) in 2007 and 2009 could be attributed to socio-economic factors at that time or some other factors. However, for the purpose of estimating statistical models, these changes are treated as natural variance.

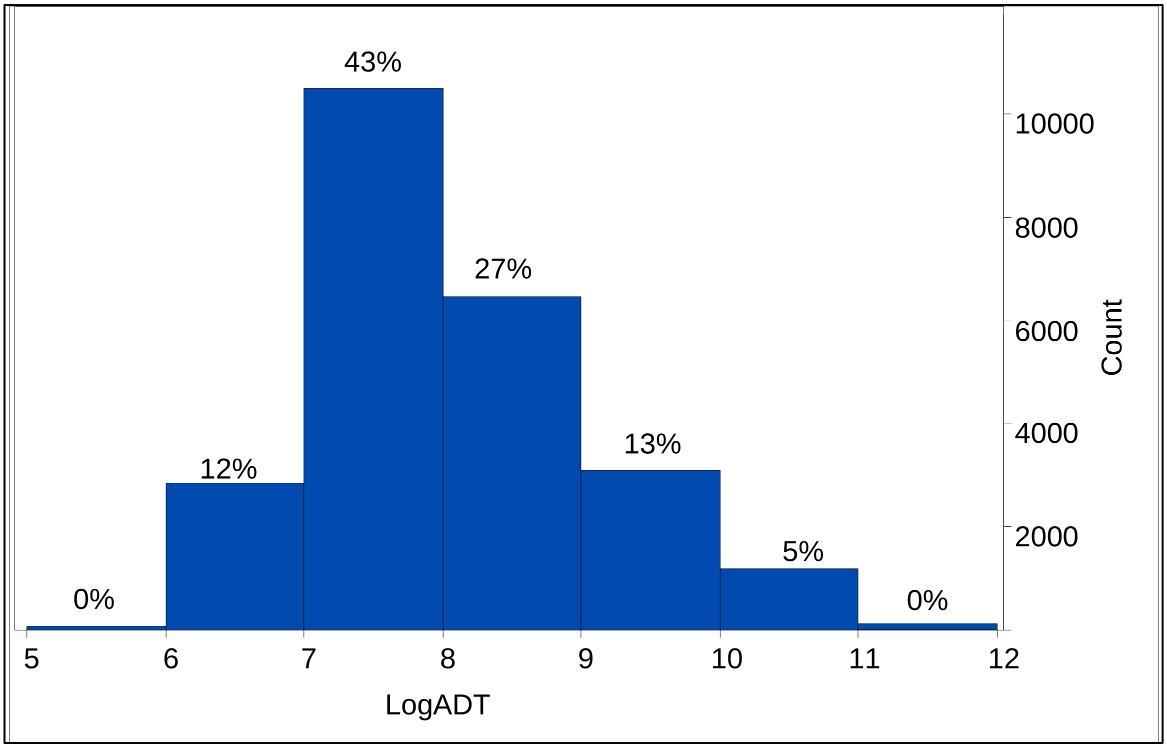


Figure 6.4 Histogram of Log(ADT)

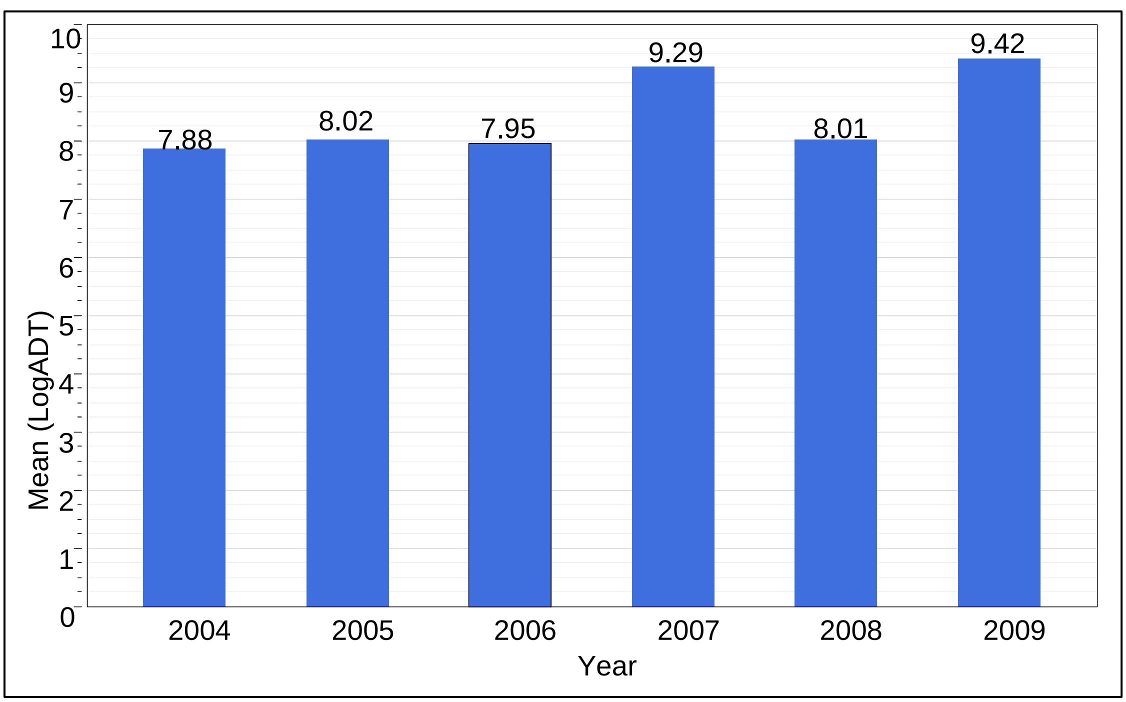


Figure 6.5 Distribution of Log(ADT) by year

6.1.4 Number of Crashes

Table 6.4 displays the descriptive statistics of the number of crashes. Throughout the six study years, the average number of crashes per mile on Iowa primary roads was around 1.6 per year and the standard deviation shows it could vary ± 3.9 crashes per mile. In addition, the total number of crashes from 2004 through 2009 on Iowa primary rural roads was over 38,000; on average 6,386 reported crashes occurred per year, which including fatalities, major injury, minor injury, and property damage only (PDO). Figure 6.6 shows that the distribution of crashes follows a negative exponential distribution, as expected.

Table 6.4 Descriptive Statistics of Number of Crashes

Moments	
Mean	1.593
Standard Deviation	3.891
Number of Observation	24,052
Sum	38,318
Skewness	8.951

Figure 6.6 shows that almost half of the study roadway year segments have no crash and 88% of the segments had fewer than four crashes.

Figure 6.7 displays the distribution of crashes by year. The mean number of crashes in 2004 was the lowest. More crashes occurred in 2007 and 2009. Recall that the mean ADT was higher in 2007 and 2009 as well.

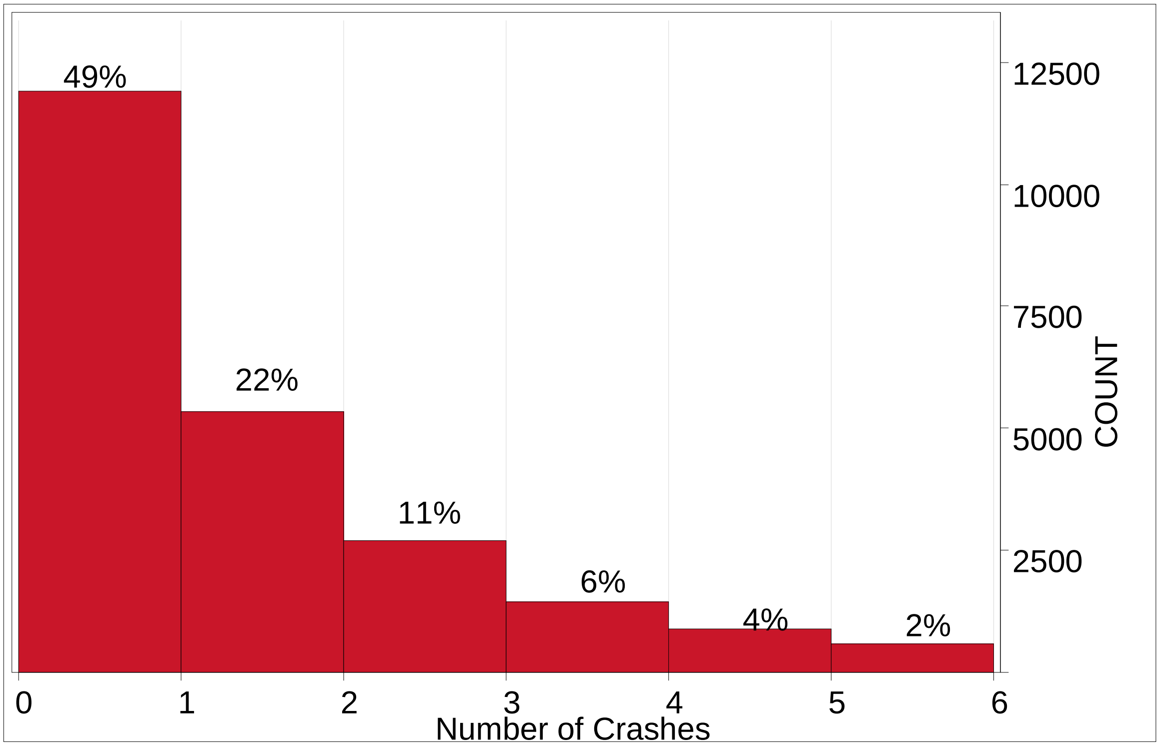


Figure 6.6 Histogram of Number of Crashes

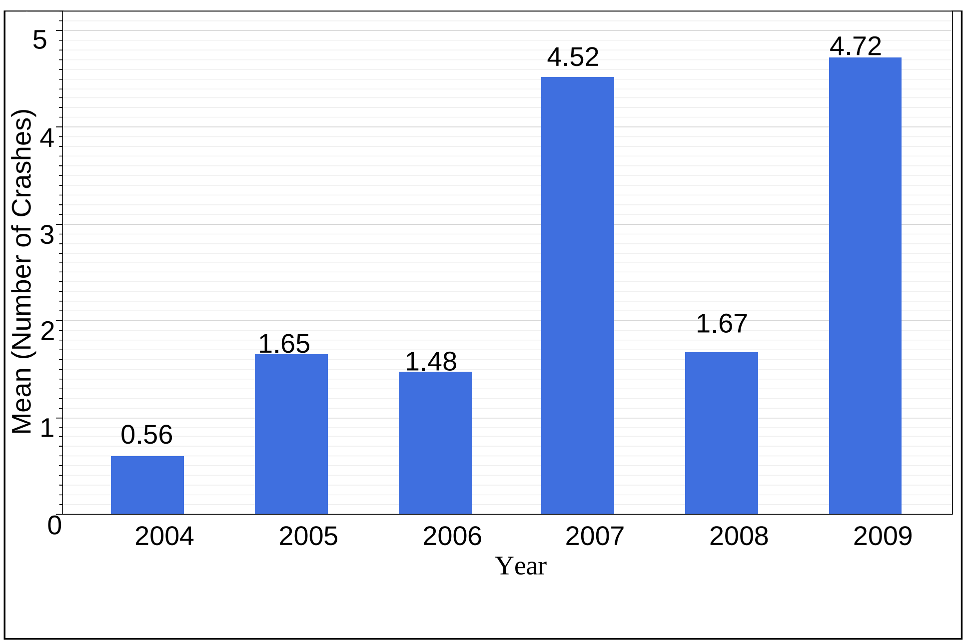


Figure 6.7 Distribution of Number of Crashes by year

6.1.5 Correlation Matrix

Before estimating a statistical model of crash frequency as a function of ACI and log(ADT), it was necessary to examine the correlation among the variables. Table 6.5 shows that ACI and log(ADT) are not correlated, so multicollinearity should not be an issue in the model.

Table 6.5 Correlation Matrix

	Log(ADT)	**ACI**	**Number of Crashes**
Log(ADT)	1	0.048	0.394
ACI	0.048	1	-0.017
Number of Crashes	0.394	-0.017	1

6.2 Statistical Analysis

6.2.1 Model Selection

One of the research goals is to estimate the relationship between ACI, Log(ADT), and crash frequency. Crash frequency was selected as the dependent variable. Since the numbers of crashes represent count data, Negative Binomial and Poisson were considered as regression model candidates. 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. To choose the more suitable model, the variance and the mean were compared as shown in Equation 6.1.

$$(\text{Variance}_{\text{number of crashes}} = 15.14) > (\text{Mean}_{\text{number of crashes}} = 5.19) \qquad (6.1)$$

Since the crash data are overdispersed, a Negative Binomial model was chosen.

6.2.2 Spatial Correlation

Before estimating the negative binomial model, the spatial correlation between adjacent roadway segments was checked, using ACI as the indicator. The reason of checking spatial correlation is that ACIs, as a continuous feature for roadway segments, in adjacent segments are considered to be close to each other. In addition, the potential of the correlation between segments could result in errors or increasing residuals in the model (Haining, 2003).

The methodology used for checking the spatial correlation was estimating variogram (also called "semivariogram") and developing geostatistical variogram fit models (Bailey & Gatrell, 1995). In this study, it was assumed that the process which generated the samples is a random function Z(s) composed of a mean and residual

$$Z_{(s)} = m + e(s), \tag{6.2}$$

with a constant mean

$$E\left(Z_{(s)}\right) = m, \tag{6.3}$$

and a variogram defined as

$$\gamma(h) = \tfrac{1}{2}E\big(Z(s) - Z(s+h)\big)^2 \tag{6.4}$$

where Z is variance, s is location, h is distance, m is mean, and γ is variogram.

Sample data on Route 30 in 2008 was extracted; 113 observations in total. A histogram of ACI in the sample is shown in Figure 6.8. Based on this figure, it could be concluded that the sample data has a right skewed normal distribution. After plotting the data points by longitude and latitude degrees, distances between segments were calculated. Then the semivariogram was developed using statistical software R (Bivand, Pebesma, & Gomez-Rubio, 2008).

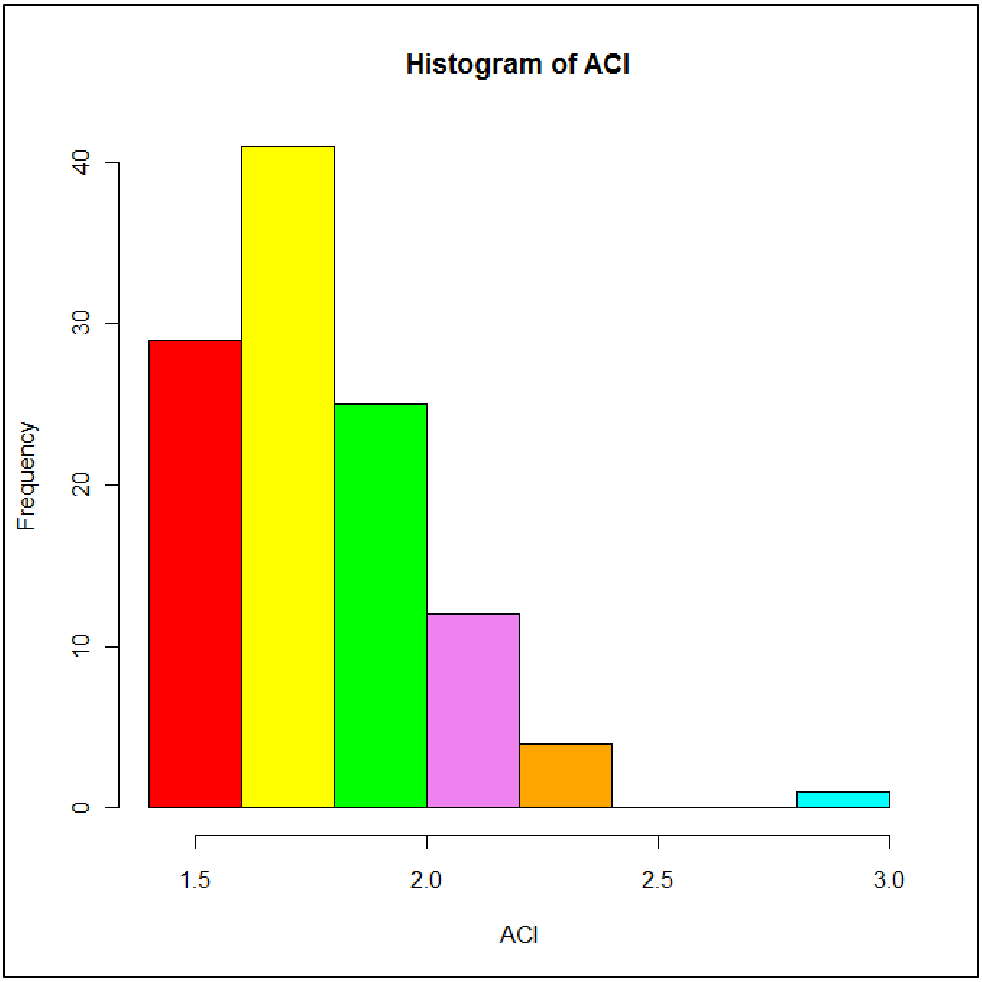


Figure 6.8 Histogram of ACI in sample

In order to investigate the spatial correlation between ACIs on adjacent segments, some variogram fit models were developed. The first step of estimating variogram model is to create an estimator. In this study, both Empirical and Cressie-Hawkins estimators were created (Cressis, 1993), and the plots are shown in Appendix B. After this, some models were fitted for the semivariogram based on the estimators. The Hole model was selected based on the semivariogram plot trends, while all the rests were commonly used models (Chiles & Delfiner, 1999). Results of model SSEs summary, shown in Table 6.6, indicated that the Spherical model has the lowest Sum of Squared Errors, thus it explains the semivariogram the best (Schabenberger & Gotway, 2009). Detailed fit model results are shown in Appendix C.

Table 6.6 Model SSE Summary

	Model SSEs			
Estimators	Hole	Exponential	Spherical	Gaussian
Empirical	3.492	3.162	2.822	3.018
Cressie-Hawkins	2.698	2.838	1.978	2.496

The spherical variogram model is expressed by

$$\gamma(h) = (s-n)\left(\left(\frac{3h}{2r} - \frac{h^3}{2r^3}\right) 1_{(0,r)}(h) + 1_{[r,\infty)}(h)\right) + n1_{(0,\infty)}(h) \quad (6.5)$$

where s is sill, n is nugget, r is range, h is lag, and γ is variogram (Cressis, 1993). The plot of the spherical variogram model with Cressie-Hawkins estimator is in Figure 6.9, and the attributes can be found in Appendix B.

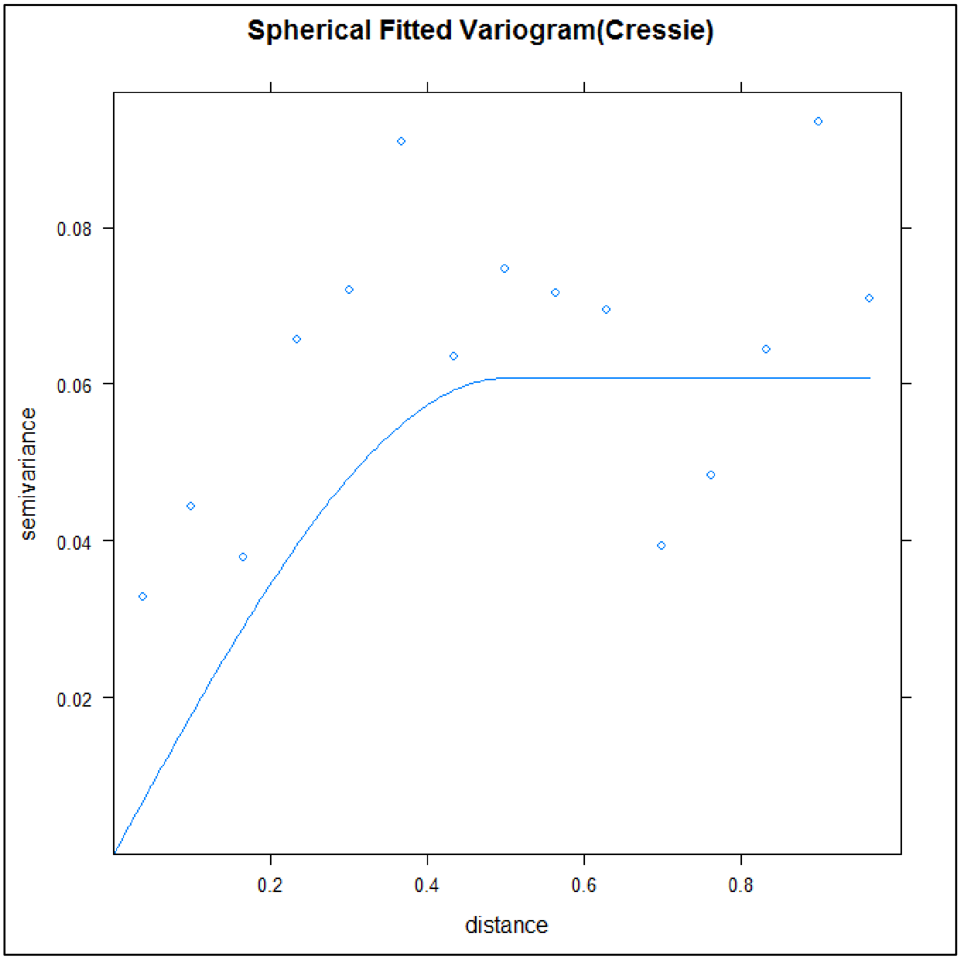


Figure 6.9 Spherical Fitted Variogram Model with Cressie Estimator

According to the figure above and the model attributes, it is found that the maximum correlation between ACIs on any adjacent roadway segment s is about 0.06, which is very low. Based on literature (Wackernagel, 2003) (Haining, 2003), this small value can hardly affect the statistic model, in terms of errors and residuals. Thus the spatial correlation is not going to affect the negative binomial model estimation discussed in the next section.

The author also examined the correlation between the number of crashes on adjacent roadway segments. Figure 6.10 shows a plot of the number of crashes versus mileposts. It can be observed that there is no steady pattern that could indicate strong spatial correlation.

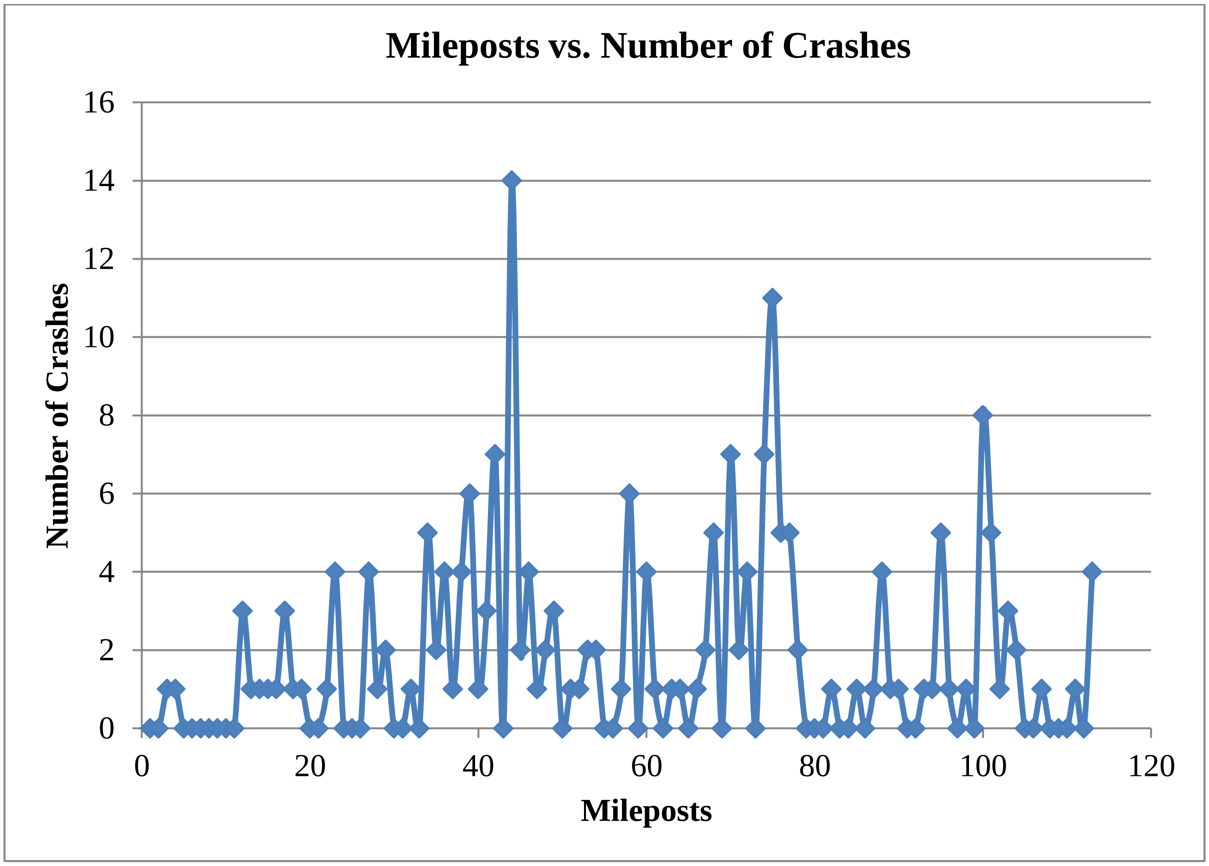


Figure 6.10 Number of Crashes vs. Mileposts, US30, 2008

The following figure shows a plot of ACIs versus numbers of crashes, and it can be observed that there were higher number of crashes occurring on segments with ACI between 1.5 and 1.9. Therefore, it is necessary to estimate some statistical models to investigate the relationship between ACI and crash frequency.

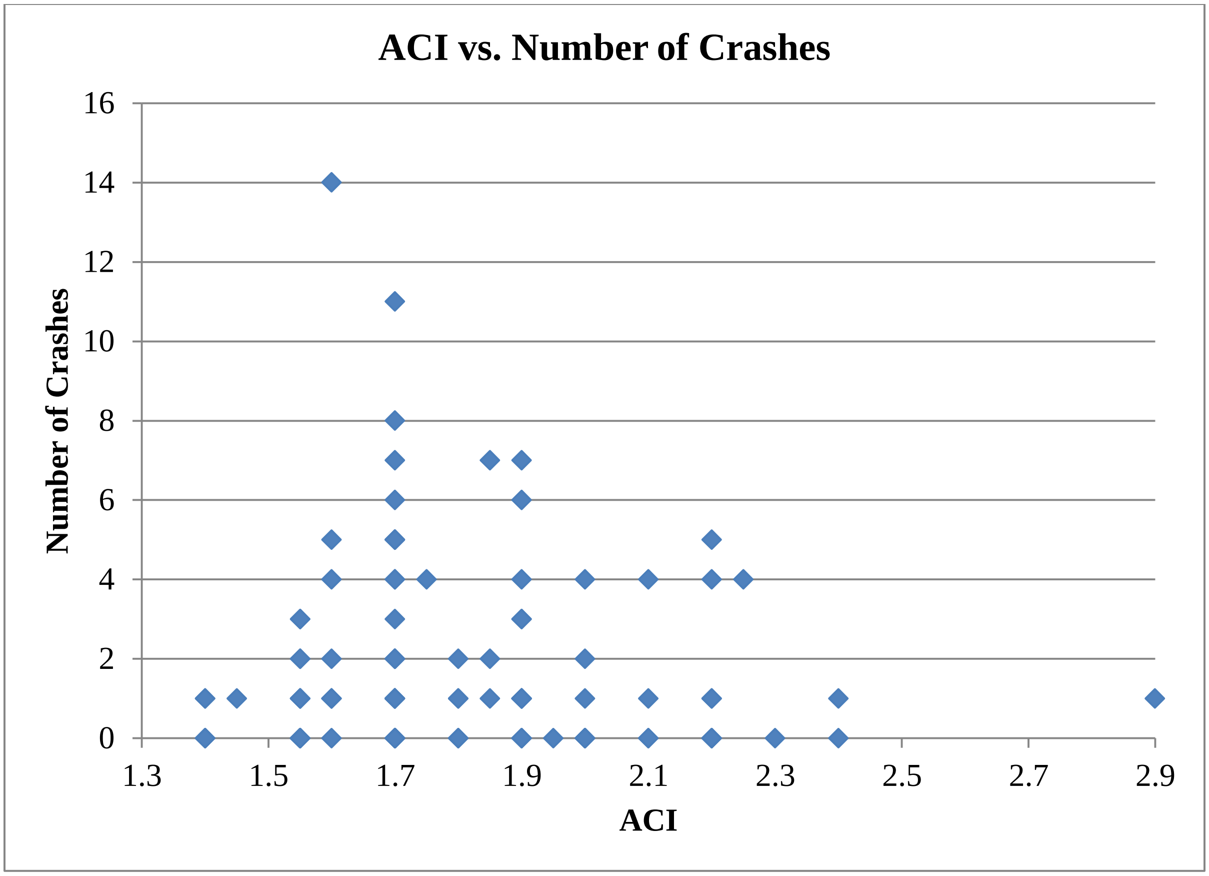


Figure 6.11 ACI vs. Number of Crashes, US30, 2008

6.2.3 Negative Binomial Model

The negative binomial model is derived by the rewriting the equation below such that for each observation i

$$\lambda_i = e^{\sum \beta \chi_i + \varepsilon_i}, \tag{6.6}$$

where $e^{\varepsilon_i}$is a Gamma-distributed disturbance term with mean =1 and variance = α . This model has an additional parameter, α, which is often referred to as the overdispersion parameter, such that

$$VAR[y_i] = E[y_i]\big[1 + \alpha E[y_i]\big] = E[y_i] + \alpha E[y_i]^2, \tag{6.7}$$

This α is a criteria of selecting between Poisson and Negative Binomial regression. The α perimeter indicates the overdispersion parameter. The negative binomial distribution has the form

$$P(y_i) = \frac{\Gamma\big((1/\alpha)+y_i\big)}{\Gamma(1/\alpha)y_i!}\left(\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right)^{1/\alpha}\left(\frac{\lambda_i}{(1/\alpha)+\lambda_i}\right)^{y_i} \tag{6.8}$$

where $\Gamma(.)$ is a gamma function. (Washington et al., 2011)

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., 2011)

The zero-inflated negative binomial (ZINB) was developed to account for this dual-state system. The ZINB model assumes that events $Y = (y_1, y_2, \ldots, y_n)$are independent and

$$y_i = 0 \text{ with probability } p_i + (1 - p_i)\left[\frac{1/\alpha}{(1/\alpha)+\lambda_i}\right]^{1/\alpha} \tag{6.9}$$

$$y_i = y \text{ with probability} (1 - p_i)\left[\frac{\Gamma\big((1/\alpha)+y_i\big)u_i{}^{1/\alpha}(1-u_i)^y}{\Gamma(1/\alpha)y_i!}\right], \text{ y=1,2,3,}\ldots \tag{6.10}$$

where $u_i = (1/\alpha)[(1/\alpha) + \lambda_i]$. In order to test the appropriateness of using ZINB model versus a classic NB model, Vuongs' statistic was calculated. It is calculated as, for each observation I

$$m_i = LN\left(\frac{f_1(y_i|X_I)}{f_2(y_i|X_I)}\right) \tag{6.11}$$

where $f_1(y_i|X_I)$ is the probability density function of model 1 and $f_2(y_i|X_I)$ is the probability density function of model 2. Using this equation, the Vuongs' statistic for testing the two models is

$$V = \frac{\sqrt{n}\left[(1/n)\sum_{i=1}^{n} m_i\right]}{\sqrt{(1/n)\sum_{i=1}^{n}(m_i - \bar{m})^2}} = \frac{\sqrt{n}(\bar{m})}{S_m} \tag{6.12}$$

where $\bar{m}$ is the mean $\left((1/n)\sum_{i=1}^{n} m_i\right)$, S_m is standard deviation, and *n* is simple size. The Vuongs' statistic is asymptotically normally distributed, and if $|V|$ is less than $V_{critical}$ (7.96 for 85% 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., 2011).

The models were estimated using the statistical program Limdep (Greene, 2007). The model outputs are provided in Appendix C. The Vuongs' value was found to be -1.3151. 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 6.7 shows the Negative Binomial model estimation results. It was found that crash frequency increases with exposure, and the higher the ACI the fewer crashes are expected. These results are in line with the author's a priori expectations.

Table 6.7 Negative Binomial Model Estimation Results

Variable Description	Estimated Parameter	t-Statistic
Constant	-5.381	-135.919
Log(ADT)	0.771	226.502
ACI	-1.291	-16.713
Number of Observations, *N*	28.835	
Restricted Log-likelihood, *LL(0)*	-61,707.76	
Log-likelihood at convergence, *LL(β)*	-45,714.20	
Chi-square, χ^2	31,987.11	
Rho-square, ρ^2	0.259	

After checking by both ρ^2 –value and χ^2 –value, it could be determined that the model is statistical significant (Washington, Karlaftis, & Mannering, 2011). The chi-square value for α=0.001 and three parameters is $\chi^2_{3,0.0001} = 21.1075$, which is much smaller than 31,987.12, thus the model is statistically significant.

6.2.4 Sensitivity Analysis of the Weights

A sensitivity analysis was conducted to assess how the variation (uncertainty) in the output of the statistical model can be attributed to different variations in the weights. In total, eight weight combinations/ groups were generated (including default group) for sensitivity analysis, shown in Table 6.6. Group A in Table 6.6 is the default group, and all weights in this group were obtained from the literature review. The rest of the groups are all created based on Group A by increasing or decreasing the weights. By comparing models among groups, the sensitivity and variation of weights can be assessed. For example, Group B and

C have all the same weights as Group A, except for the weights for White Marking and Yellow Marking.

In addition, after estimating statistical (negative binomial regression) models relating crash frequency and ACI for each of the groups of weights and comparing the resulting coefficients, the author could assess the combination of weights which is the most suitable. Table 6.7 shows the results of the statistical analysis. The coefficients of determination of all statistical models are around 0.26, and the coefficient of the variable ACI is relatively similar across all models. As such, it can be concluded that the models are not sensitive to the weights of the sectors and sub-indices, and the default weight combination in Group A is rational and powerful enough to represent the relative significances both between sectors and among sub-indices.

Table 6.8 Sensitivity Analysis of Weights

Group	Weights							
	Marking		Pavement Condition				Asset Condition	
	White	Yellow	IRI	Faulting	Friction	Rutting	Marking	Pavement Condition
A (Default)	**0.4**	**0.6**	**0.2**	**0.2**	**0.3**	**0.3**	**0.5**	**0.5**
B	0.5	0.5	0.2	0.2	0.3	0.3	0.5	0.5
C	0.3	0.7	0.2	0.2	0.3	0.3	0.5	0.5
D	0.6	0.4	0.2	0.2	0.3	0.3	0.5	0.5
E	0.7	0.3	0.2	0.2	0.3	0.3	0.5	0.5
F	0.4	0.6	0.25	0.25	0.25	0.25	0.5	0.5
G	0.4	0.6	0.2	0.2	0.3	0.3	0.4	0.6
H	0.4	0.6	0.2	0.2	0.3	0.3	0.6	0.4

Table 6.9 Statistical Model Estimation Results for Sensitivity Study

Group	Descriptive Analysis			Models (Dependent variable: Number of crashes per mile)				
	Mean	Std. Dev.	Number of Observations	R^2	Number of Observations	NB* estimation results		
						constant	β_{ACI}	t-statistic
A	**2.27**	**0.34**	**24,584**	***0.259***	**24,425**	**0.799**	**-0.134**	**-6.233**
B	2.27	0.35	24,584	*0.259*	24,425	0.941	-0.197	-8.668
C	2.26	0.34	24,584	*0.259*	24,425	1.120	-0.177	-8.149
D	2.28	0.35	24,584	*0.260*	24,425	0.844	-0.153	-6.904
E	2.28	0.36	24,584	*0.260*	24,425	0.75	-0.111	-5.17
F	2.25	0.34	24,584	*0.251*	24,425	0.741	-0.123	-5.161
G	2.28	0.39	24,584	*0.260*	24,425	0.761	-0.116	-5.827
H	2.25	0.31	24,584	*0.258*	24,425	1.409	-0.108	-9.809

**NB =Negative Binomial Model*

Figure 6.12 shows the predicted crash frequency with respect to ACI. It can be observed that crash frequency is higher for ACI values between 1 and 1.5. As such, the author examined whether it is statistically significant to estimate separate models for different ACI ranges. The results of this test are presented next.

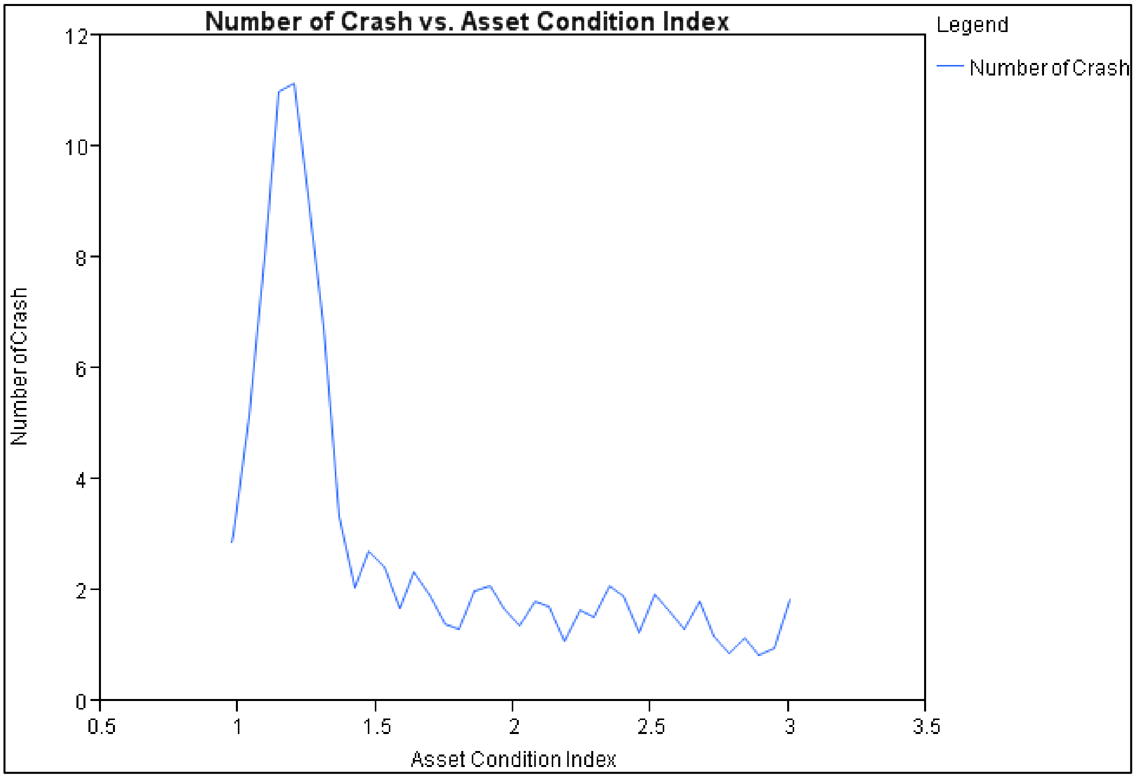


Figure 6.12 Predicted Crash Frequency versus ACI

6.2.5 Transferability Test

The likelihood ratio test (Washington et al. 2011), which is also called the transferability test, was conducted to determine whether separate models for different ACI ranges were statistically significant. This test was conducted using the same variables in all three models (all data, ACI lower than or equal to 1.5, and ACI higher than 1.5) as shown in Equation 6.13 (Bahar, et al. 2006):

$$\chi^2 = -2\left(LL_{\beta} - LL_{\beta_a} - LL_{\beta_b}\right) \tag{6.13}$$

Where LL_{β} is the likelihood at convergence of the model estimated with the data from both regions, $LL_{\beta a}$ is the log-likelihood at convergene of the model using region *a* data, and $LL_{\beta b}$ is the log-likelihood at convergene of the model using region *b* data. (Bahar, Masliah, Erwin, Tan, & Hauer, Pavement Marking Materials and Markers: Real-World Relationship Between Retroreflectivity and Safety Over Time, 2006)

Table 6.10 shows the estimation results of this test. The resulting χ^2 statistic showed that it was statistically significant to estimate two separate models.

Table 6.10 Transferability test estimation for ACI ranges

	All data (LL_β)	ACI<1.5 (LL_{β_a})	ACI>1.5 (LL_{β_b})	χ^2	$\chi^2_{0.0001,4}$
Log-likelihood at Convergence $LL_{(\beta)}$	-45,714.20	-1,999.84	-43,570.57	287.59	23.5127
Number of parameters	4	4	4		

6.2.6 Final Models

Table 6.11 shows the final negative binomial model estimation results for crash frequency as a function of log(ADT) and ACI lower or equal to 1.5; or ACI higher than 1.5. The model outputs are provided in Appendix C.

Table 6.11 Summary of separate Negative Binomial Models

Variables	ACI<1.5		ACI>1.5	
	Coefficient	t-test	Coefficient	t-test
Constant	-0.780	-11.776	-5.761	-79.495
ACI	-1.668	-20.708	-0.179	-7.905
Log(ADT)	0.316	42.050	0.784	137.986
ρ^2	0.499		0.242	
Number of observations	906		27929	

The final model for ACI≤1.5 is

$$Number\ of\ Crashes_{ACI\leq 1.5} = e^{-0.7799-1.6679\times ACI+0.3162\times LogADT}, \tag{6.14}$$

and the final model for ACI>1.5 is

$$Number\ of\ Crashes_{ACI>1.5} = e^{-5.761-0.179\times ACI+0.784\times LogADT} \tag{6.15}$$

The overall ρ^2-values for these models are 0.500 and 0.242, respectively. The model for segments with ACI lower than or equal to 1.5 shows a relatively higher fit, most likely because of the smaller number of observations. In addition, comparing to the previous model, on all the data (Table 6.7) the suitability of fit is superior.

All parameter coefficients in both separate models have the expected signs. Comparing the two models, the absolute value of the coefficient of ACI is higher in the model for segments with ACI⩽1.5, while the coefficient of Log(ADT) is relatively lower. This means for those road segments with ACI lower than or equal to 1.5, the ACI has a larger effect on safety.

6.3 Summary

The researchers used negative binomial models to predict the relationship between crash frequency and the ACI. The estimation results indicated that the higher the ACI of a roadway segment, the lower the number of crashes expected. Also, the higher traffic exposure Log(ADT) on a roadway segment, the higher the number of crashes expected.

The sensitivity analysis of weights revealed that the statistical model estimation results relating crash frequency to ACI were not sensitive to the assumed weights of ACI sectors and sub-indices. These results suggested that the default assumptions (based on the literature review) could be adopted.

In addition, the transferability test showed that separate negative binomial models for different ACI ranges better explain the relationship between crash frequency, ACI and Log(ADT). The researchers found that the effect of ACI on crash frequency on roadway segments with ACI lower than or equal to 1.5 was higher and, as such, these segments should have priority for preservation or maintenance.

CHAPTER 7. EVALUATION OF ASSET TREATMENT STRATEGIES

This chapter describes the methodology used to evaluate six different pavement condition or pavement marking improvement strategies in terms of economic efficiency and safety and the corresponding results. The estimated results using the models presented in the last chapter were used to assess the economic feasibility of these treatment strategies, so that agencies can utilize the information to select projects and make better decisions. Economic efficiency was evaluated using two methods: single-year benefit-cost ratio (BCR) analysis and five-year net present value (NPV) analysis, one year and five years after implementing alternative treatment strategies, respectively. Benefits represent safety improvements.

7.1 Goal of the Evaluation

The goal of this evaluation is to develop a method for selecting asset treatment strategies that have an impact on both asset condition and safety. The Benefit-Cost Ratio (BCR) analysis and five-year Net Present Value (NPV) analysis were adopted for different study periods in a bid to prioritize the treatment strategies in the short and long run.

7.2 Treatment Alternatives

The researchers selected and grouped six improvement treatments into the three that would improve pavement condition and the three that would improve pavement marking. PC treatment improvement alternatives included pavement reconstruction, major rehabilitation, and minor rehabilitation. The three PM material replacement types selected were regular paint, durable material marking, and tape markings.

7.2.1 Pavement Condition Alternatives

The selection of a treatment strategy among reconstruction, major rehabilitation, and minor rehabilitation is based on the current pavement condition, the target level of service, and budget constraints.

Pavement reconstruction involves the complete removal of an existing pavement to the sub-grade and construction of a new pavement structure. This most expensive treatment is usually needed when the existing pavement has deteriorated to a condition that cannot be salvaged with corrective action (MassDOT, 2006). The estimated unit cost of this type of pavement treatment is approximately $1,000,000/mile. Service life of a pavement after reconstruction is expected to be 20 years.

Pavement rehabilitation, a major activity for all highway agencies, can be defined as "a structural or functional enhancement of a pavement which produces a substantial extension in service life, by substantially improving pavement condition and ride quality" (Hall et al., 2001). When selecting a rehabilitation strategy, agencies select the most cost-effective rehabilitation strategy given a set of criteria, which may include reduced service life, life-cycle cost, and budgetary constraints. According to the current pavement condition, different rehabilitation strategies can be selected for different types of pavement, distress types, levels of rehabilitation, and target service life extension. Major rehabilitation can be selected when maintenance is needed on the pavement structure, relatively more serious distresses are observed, or longer service life extension is expected. The cost of this type of work is estimated as $500,000/mile, and life cycle is assumed to be 10 years. On the other hand, minor rehabilitation involves surface overlaying, repairing joints, and some other relatively smaller maintenance operations. The cost of this type of work is approximately $150,000/mile, and its life cycle is assumed to be 3 years.

7.2.2 Pavement Marking Alternatives

Three types of pavement marking materials were selected as pavement marking replacement alternatives: regular paint, durable marking, and tapes marking. These alternatives are currently used by the Iowa DOT on different types of marking lines.

Regular paint is the most commonly used treatment among agencies. Over 95 percent of roadways in Iowa are marked using fast-drying waterborne paints. It costs relatively less than other types of markings; however, life cycle is also usually shorter. As mentioned in the Chapter 4, the Iowa DOT repaints pavement markings twice per year, in Spring and Fall, so the service life of this type of marking is assumed to be half a year. The cost of regular paint marking is assumed to be $1,188/mile.

Durable markings are expected to have relatively longer service lives, and as a result, a higher cost-effectiveness or lower life-cycle cost than regular paint. Iowa DOT started to evaluate and utilize durable waterborne paints with glass beads in 2005. Given the need in Iowa for snow plowing (due to winter weather), pavement markings can deteriorate significantly. The estimated unit cost of durable marking is $11,880/mile and the service life is assumed to be two years. (The cost of winter maintenance is not taken into account in this unit cost.).

Tape marking is typically used as a transverse marking material (e.g., crosswalks, stop bars). It performs well on both portland cement concrete (PCC) and asphalt cement concrete (ACC) pavements (Thomas & Schloz, 2001). In general, tape marking has a high initial cost; however, tape marking is relatively easy to install and has a long durability. In addition, when tape is installed on new ACC pavement sections, the road can be open to traffic as soon as the pavement is ready. Tape marking provides the additional advantage of avoiding the need for temporary marking materials. The estimated unit cost of tape marking is $47.520/mile, and the service life is assumed to be 5 years.

7.3 Relative ACI Improvement and Depreciation Rate

Before conducting the economic analysis, each treatment alternative was assigned a relative improvement value on the ACI scale of 0 to 3. The relative improvement values were estimated considering the alternative's impact on safety in terms of reducing crash frequency, as documented in the literature. Given that ACI is an index between 1 and 3, the improved ACI cannot be higher than 3 regardless of initial condition. AC depreciation is an important consideration for monitoring, performance measuring, and pavement life-cycle cost analysis. This study considers AC depreciation and straight-line depreciation in the five-year NPV analysis. In the previous chapter, it was shown that roadway segments with ACI lower than or equal to 1.5 have relatively higher crash frequency. Thus, 1.5 is considered as a critical value of ACI. Based on straight-line depreciation, the depreciation rate is calculated as shown in Equation 7.1.

$$Depreciation\ Rate = \frac{ACI_{optimal} - ACI_{critical}}{Service\ Life} = \frac{3.0-1.5}{Service\ Life} = \frac{1.5}{Service\ Life} \qquad (7.1)$$

The relative improvement values for treatment alternatives, respective costs, service lives and depreciation rates are shown in Table 7.1.

Table 7.1 Attributes of Treatment Alternatives

Treatment Alternatives	Price (per mile)	Relative Improvement of ACI	Service Life (yrs)	Depreciation Rate
Maintenance				
Reconstruction	$1,000,000.00	2	20	0.075
Major Rehab	$500,000.00	1	10	0.15
Minor Rehab	$150,000.00	0.5	3	0.5
Replacement				
Regular Paint	$1,188.00	0.01	0.5	3
Durable Materials	$11,880.00	0.05	2	0.75
Tapes	$47,520.00	0.2	5	0.3

7.4 Identifying Costs and Benefits

The unit costs (price per mile) of treatment alternatives were identified and presented in Table 7.1. Since the costs are expressed in dollars per mile, and each data row represents a one-mile road segment, costs for each alternative on each segment is the same as the unit cost. However, all these costs are the capital costs that were invested in the first year of the project, while the study periods in this research are one year and five years, so these capital costs need be converted into Equivalent Uniform Annual Cost (EUAC).

Benefits in this analysis are measured as the improvement in safety from each alternative treatment. The statistical models (presented in Chapter 6) showed that the number of crashes would decrease when the ACI is higher. Therefore, it is expected that after implementing the six ACI improvement alternatives, number of crashes on each treated road segment should decrease.

The economic cost of crashes, which is borne by individuals, insurance companies, and government, consists of property damage, loss of household productivity, loss of market productivity, and workplace costs. Intangible costs include pain and suffering, and loss of life. In addition to the nation-wide crash cost estimates, each state government has their own crash cost estimate table. In this thesis, the crash costs in Iowa, shown in Table 7.2, were used to monetize the safety benefits of the treatment strategies.

Table 7.2 Iowa Crash Costs in 2007

Iowa Crash Costs (2007)	
Collision Type	**Crash Cost**
Fatal (K)	$3,500,000
Disabling Injury (A)	$240,000
Evident Injury (B)	$48,000
Possible Injury (C)	$25,000
PDO (O)	$2,700

It should be noted that the crash cost values are provided by crash severity, so the reduction in the number of crashes need to be distributed by severity, as well. Table 7.3 shows the distribution of crashes by crash severity for each study year, and on average, over the study period. It was assumed that the reduction in the number of crashes would follow a similar distribution to that shown on the second to last row of Table 7.3.

Table 7.3 Distribution of Crashes by Severity

		Severity				
		Fatal(K)	Disabling Injury (A)	Evident Injury (B)	Possible Injury (C)	PDO(O)
2004	Percentage	1.1%	4.1%	11.8%	18.8%	64.2%
	Counts	125	473	1354	2159	7367
2005	Percentage	1.4%	4.5%	11.4%	20.1%	62.6%
	Counts	167	541	1369	2406	7496
2006	Percentage	1.4%	4.2%	11.9%	19.7%	62.7%
	Counts	151	443	1266	2089	6652
2007	Percentage	1.3%	3.7%	11.3%	18.7%	65.1%
	Counts	161	470	1439	2389	8330
2008	Percentage	1.0%	2.9%	3.1%	35.8%	57.1%
	Counts	157	437	469	5366	8571
2009	Percentage	1.2%	3.5%	10.9%	18.6%	65.9%
	Counts	115	348	1071	1829	6493
Total	***Percentage***	***1.2%***	***3.8%***	***9.7%***	***22.6%***	***62.6%***
	Counts	***876***	***2712***	***6968***	***16238***	***44909***

7.5 Single-year Benefit-Cost Ratio (BCR) analysis

The single-year BCR analysis investigated which improvement alternative would achieve the highest benefit-cost ratio, one year after implementation of the treatment strategy. The procedure is as follows:

a. Calculate improved ACI, using the relative improvement for each alternative treatment (Table 7.1);
b. Predict the number of crashes expected on the segment given the new ACI (Table 6.8);
c. Calculate the reduction in the annual number of crashes because of the improvement in ACI terms (scale of 0 to 3);
d. Calculate the reduction in the annual number of crashes by severity (Table 7.3);
e. Monetize safety benefits by multiplying crash costs (Table 7.2) and reduction in the annual number of crashes by severity;
f. Calculate the total annual benefits of the alternative in 2007 dollars;
g. Covert to 2011 dollars (a discount rate of 4% was used), by

$$Benefit_{2011} = Benefit_{2007} \times (1+i)^4, \text{ where i=discount rate,} \tag{7.2}$$

h. Convert cost into Equivalent Uniform Annual Cost (EUAC), by

$$EUAC_{Alt.i} = Cost_{Alt.i} \times \left[\frac{i(i+1)^{Service\ Life}}{(1+i)^{Service\ Life_{-1}}}\right], \text{ where i=discount rate;} \tag{7.3}$$

i. Calculate NPV and BCR as

$$NPV_{Alt.i} = Benefit_{Alt.i} - EUAC_{Alt.i} \tag{7.4}$$

$$B/C_{Alt.i} = \frac{Benefit_{Alt.i}}{EUAC_{Alt.i}} \tag{7.5}$$

As shown in Table 7.4, minor rehabilitation has the highest Benefit/Cost Ratio among all alternatives, and durable material marking holds the highest Benefit/Cost Ratio among the pavement marking treatments. As a result, if considering only one year after implementation, minor rehabilitation seems to be the most economic efficient alternative for improving asset condition and safety.

Table 7.4 NPV and BCR of Treatment Alternatives, one year after implementation

Alternatives	Economics	
	NPV	**BCR**
Reconstruction	$38,650.53	1.525
Major	$50,217.62	1.815
Minor	$55,743.38	**2.031**
Paint	$482.44	1.195
Durable	$4,850.66	**1.770**
Tape	$4240.80	1.400

7.6 Five-year Net Present Value (NPV) analysis

This analysis evaluated the alternatives over a longer study period (5 years), considering both asset condition depreciation and time value of money.

Before calculating ACIs and predicting numbers of crashes, the dataset was divided into six ranges based on ACI:

a) $ACI \leq 1.5$;

b) $1.5 < ACI \leq 2.00$;

c) $2.0 < ACI \leq 2.25$;

d) $2.25 < ACI \leq 2.50$;

e) $2.5 < ACI \leq 2.75$;

f) $2.75 < ACI \leq 3.00$.

By breaking the dataset into ranges, the results would provide recommendations among alternatives based on the current ACI, and make the project selection process more practical and feasible.

A similar procedure to that outlined in the last section was adopted. In addition, utilizing the depreciation rate, the change in ACI over five years was estimated. Meanwhile, the alternatives with service life shorter than five years would be implemented again in the following year after the service life. This procedure was applied to each of the six ACI ranges.

Table 7.5 and Figure 7.1 show the analysis results for major rehabilitation on segments with ACI ranging from 1.5 to 2.0. All the results are shown in Appendix B.

Figure 7.2 and 7.2 shows the summary of the NPV analysis for all alternatives, by ACI ranges. The researchers observed that for different ACI ranges, the recommended alternative, which is the one with the highest NPV, may change, especially for the two lowest ACI ranges

Table 7.5 Example Analysis Result Table for Major Rehabilitation in Range b

Major Rehabilitation						
year	Number of Crashes			Benefit	Cost (EUAC)	PV
	non-treated	treated	reduced			
0	0	0	0	-	$61,645.47	$-61,645.47
1	0.2409	0.0741	0.1668	$12,316.02	$61,645.47	$-47,432.17
2	0.4629	0.0884	0.3745	$27,651.97	$61,645.47	$-31,428.91
3	0.988	0.1055	0.8825	$65,161.18	$61,645.47	$3,125.45
4	2.011	0.1259	1.8851	$139,190.18	$61,645.47	$66,285.54
5	3.5365	0.1503	3.3862	$250,026.94	$61,645.47	$154,835.84
					NPV	***$83,740.28***

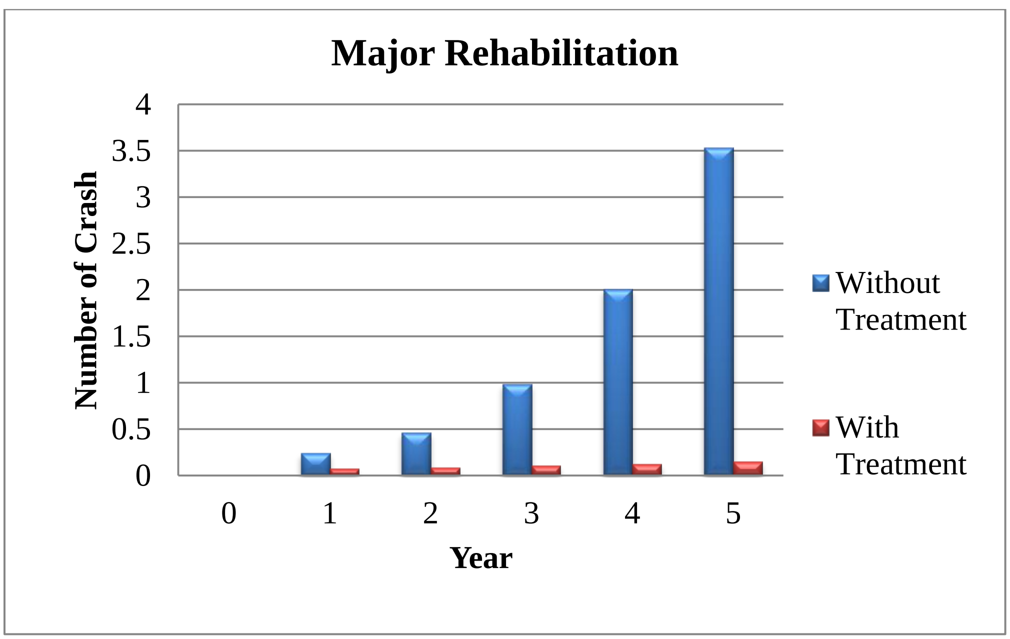
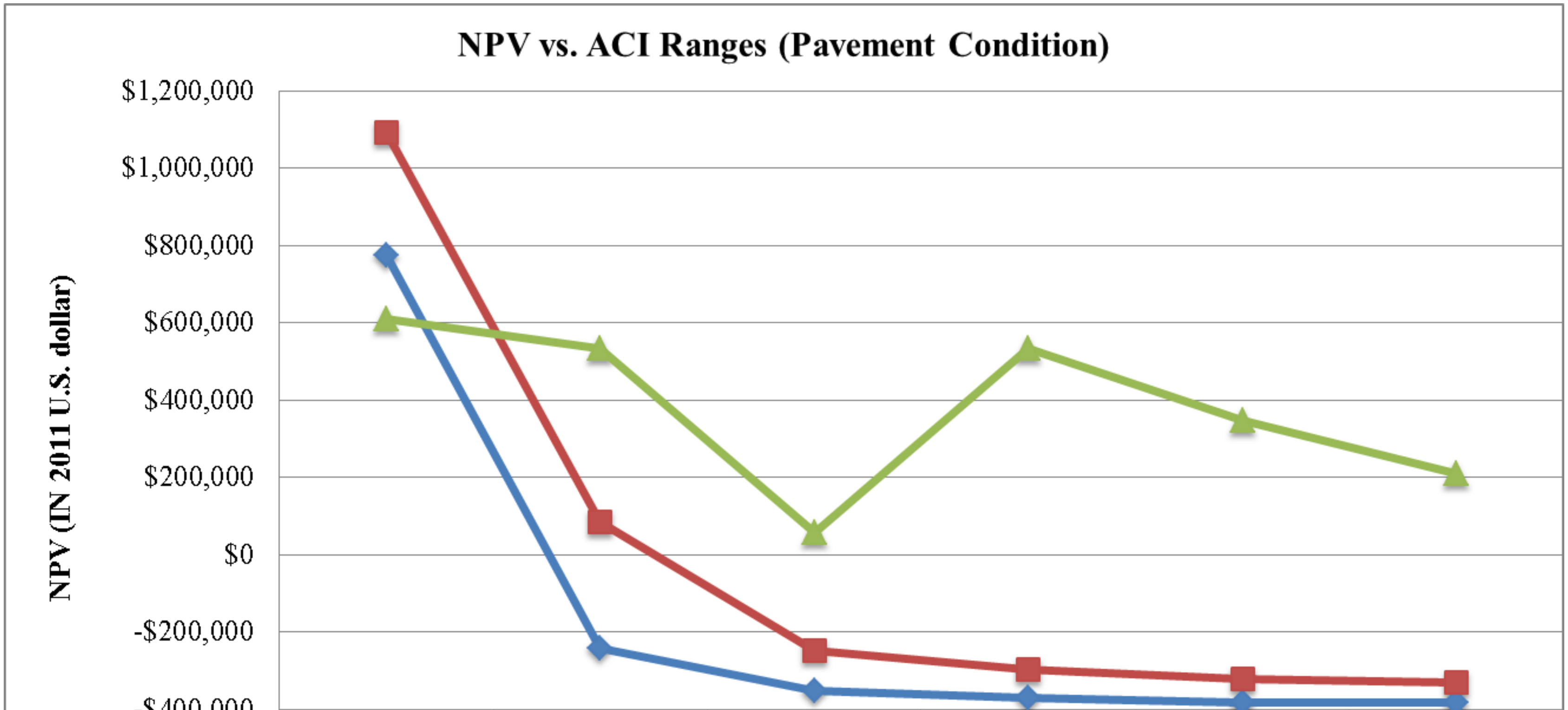
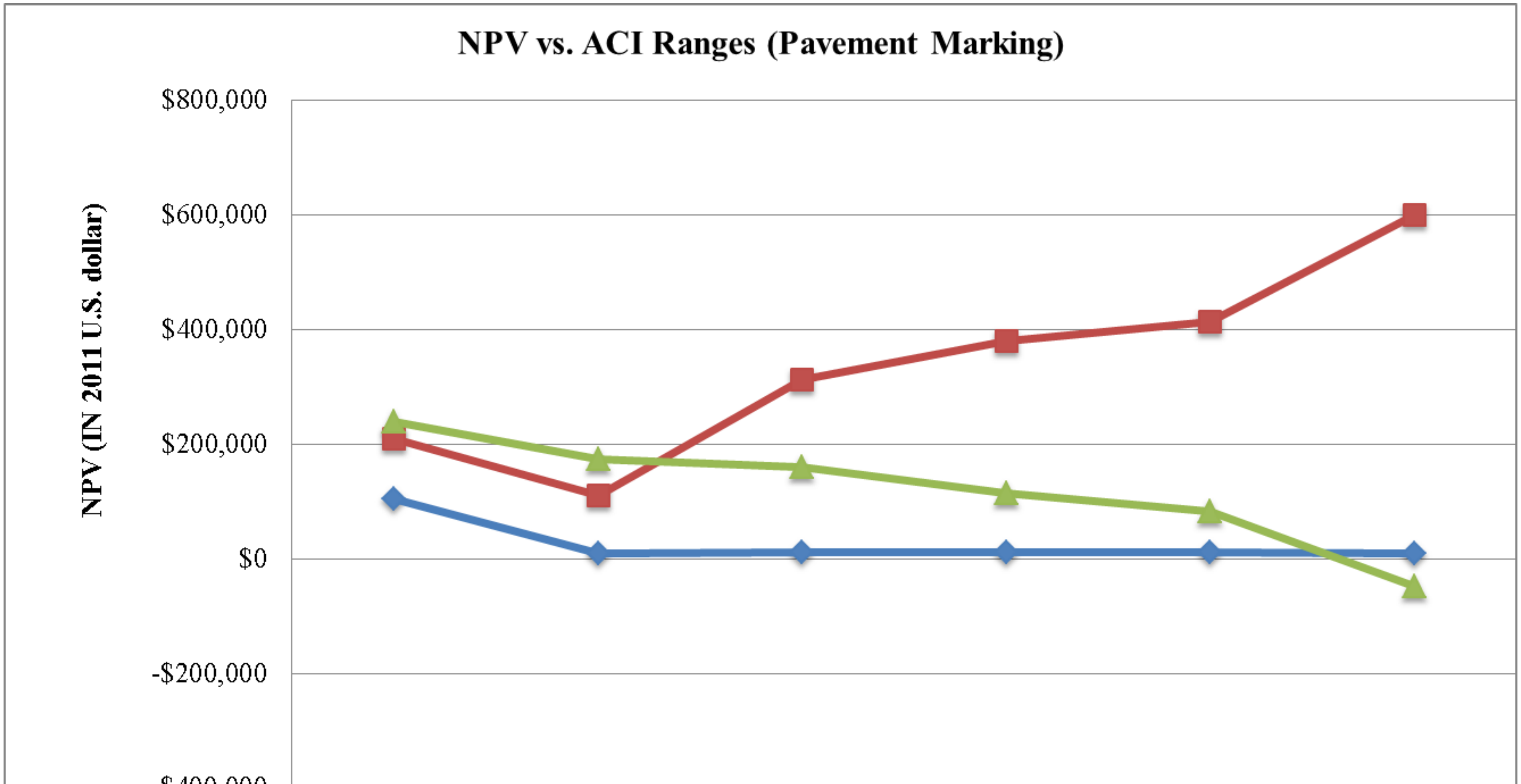


Figure 7.1 Crash Trends before and after Treatment



	ACI≤1.50	1.50<ACI≤2.00	2.00<ACI≤2.25	2.25<ACI≤2.50	2.50<ACI≤2.75	2.75<ACI≤3.00
Reconstruction	776,676.51	-241,381.06	-353,625.25	-370,103.21	-383,279.32	-383,279.32
Major	1,092,326.69	83,740.28	-247,205.25	-298,399.11	-320,636.58	-329,375.24
Minor	610,903.09	534,122.00	58,034.25	532,496.94	347,850.45	209,691.47

Figure 7.2 NPV for Pavement Condition Group Alternatives, by ACI Ranges



	ACI≤1.50	1.50<ACI≤2.00	2.00<ACI≤2.25	2.25<ACI≤2.50	2.50<ACI≤2.75	2.75<ACI≤3.00
Paint	104,929.66	10,241.30	10,706.02	11,347.67	11,738.71	10,234.25
Durable Material	210,563.54	110,273.72	313,610.75	379,476.41	413,977.49	600,445.70
Tape	240,378.69	174,719.46	161,123.49	114,873.28	82,830.31	-47,855.48

Figure 7.3 NPV for Pavement Marking Group Alternatives, by ACI Ranges

For segments with an ACI higher than 2.0, minor rehabilitation is more cost-effective than the other treatments to improve pavement condition, while durable markings are more cost-effective than the other treatments to improve pavement marking condition. For segments with an ACI between 1.5 and 2.0, minor rehabilitation and tape marking are recommended, while for segments with an ACI lower or equal to 1.5, major rehabilitation and tape markings are the preferred alternatives.

7.7 Summary

In this chapter, the single-year Benefit-Cost Ratio (BCR) analysis and five-year Net Present Value (NPV) analysis were presented. Both short-term and long-term safety benefits and treatment costs were estimated for six alternative treatment strategies.

Minor rehabilitation and durable marking are recommended as more cost-effective treatment alternatives in the short-run. In the long-run, the same recommendation holds for segments with ACI is higher than 2.0. For segments with ACI lower than 1.5, major rehabilitation and tape marking are highly recommended.

CHAPTER 8. CONCLUSIONS AND RECOMMENDATIONS

8.1 Research Summary

This thesis studied the relationship between asset performance and safety performance, on rural Iowa primary roads. To achieve this, the author examined the applicability of GIS spatial proximity, personalized Python toolbox, and geodatabase for data integration; developed a methodology for estimating a composite index of asset condition (ACI); estimated statistical models of crash frequency as a function of ACI while controlling for traffic exposure; and examined the economic feasibility of six asset condition improving strategies, using two economic analysis approaches. The methodology presented in this thesis can be useful to the Iowa DOT as well as other transportation agencies for prioritizing asset condition improvement strategies based on safety considerations.

8.2 Key Findings

8.2.1 GIS Analysis

Asset condition datasets were integrated with crash data and roadway segments, and the route-milepost-based integration was found to be a more applicable method based on the data characteristics. In addition, GIS was found to be an efficient and accurate data integration tool for transportation asset management systems, by using both spatial proximity and advanced personalized Python toolbox. A geodatabase for Story County was created as a pilot study for feasibility assessment, and a geodatabase for the whole state network is recommended based on the results.

8.2.2 Estimation of Asset Condition Index

An Asset Condition Index (ACI) was developed as a simple, convenient and easy to understand indicator for representing the overall physical asset condition of a roadway segment and assisting agencies in the decision-making for pavement preservation and maintenance activities. A step-by-step methodology for calculating a unique condition index of multiple asset condition measures was developed. The methodology involved scaling and weighting asset condition components such as pavement condition and pavement retroreflectivity as well as their sub-components. The resulting ACI provides values from 1 (indicating poor condition) to 3 (indicating good condition).

8.2.3 Statistical Analysis

Negative binomial models were estimated to predict the relationship between crash frequency and ACI, while controlling for exposure. The estimation results indicated that the higher the ACI of a roadway segment, the lower the expected number of crashes. In addition, it was found that separate negative binomial models for different ACI ranges explain the relationship among crash frequency, ACI and exposure (ADT) better than a single model. The impact of ACI on crash frequency for roadway segments with ACI lower or equal to 1.5 was higher compared to that for roadway segments with ACI higher than 1.5.

8.2.4 Economic Analysis

Both short-term and long-term safety benefits and treatment costs were estimated for six alternative treatment strategies, via a single-year Benefit-Cost Ratio (BCR) analysis and a five-year Net Present Value (NPV) analysis. Minor rehabilitation and use of durable pavement marking materials are recommended as more cost-effective treatment alternatives in the short-run. In the long-run, the same recommendation holds for segments with ACI higher than 2.0. For segments with ACI lower than 1.5, major rehabilitation and tape marking are recommended.

8.3 Study Limitations

There are some limitations pertaining to this study, as discussed next.

8.3.1 Data Integration

In the GIS-based integration procedure, the tolerance of spatial joining was set as ten meters, which means that potentially a crash location could be marked as far as ten meters away from the pavement and the roadway. This assumption affects the assignment of crashes to roadway segments and potentially, the level of accuracy.

8.3.2 Data

The pavement marking retroreflectivity data was collected every five miles, while all the other datasets were recorded per mile. As a result, only one out of five segments was assigned a pavement marking, and this caused a lot of missing data in the final dataset. To resolve this, it was assumed that the pavement marking condition of road segments within a 5-mile segment would be the same. As such, the same values were recorded for segments 2.5 miles forward and 2.5 backward of the available data point.

8.3.3 Selection of Crashes

All crashes, regardless of reasons, seasons, and so forth, happened between 2004 and 2009 were included in this research. This decision was based on the assumption of that all crashes are related either directly or indirectly to asset condition. Even though the ACI was estimated only on pavement condition and pavement parking, it is considered as a general index that indicates the overall asset condition of a roadway segment, including all individual measures. As a result, these assumptions may overestimate the effect of asset condition on safety. A further process of selecting the related crashes according to asset performance measures, based on crash reasons, is expected to improve the accuracy of the research.

8.3.4 Estimation of ACI

The thresholds that were used for the operational performance subcomponents (such as IRI, faulting, paint, etc.) in order to classify segments into ACI categories of 1 to 3 were based on the literature. It is recommended that an expert panel reviews these thresholds and scores as well.

8.3.5 Statistical Analysis

In this study, all crashes were considered as related only with asset condition. The characteristics of the driver, vehicle and the roadway environment (besides roadway condition) were not taken into account in the statistical analysis.

8.3.6 Economic Analysis

The discount rate throughout the economic analysis was assumed to be 4%. This rate is commonly used by benefit-cost analysis, however, during the analysis period, banking discount/ interest rate was lower (approximately 1%). Secondly, straight-line depreciation was applied for calculating asset condition depreciation. In fact, the depreciation rate could follow normal, exponential, logarithm, and other distributions, depending on the assets characteristics. Lastly, the study period for the second approach was set as five years. Usually when alternatives have different service lives, the study period of economic analysis should be the lowest common multiple of the service lives. In this study, an equivalent annual return analysis was used that may not have taken into account all the costs and benefits throughout the service life of the asset. Therefore, a more comprehensive economic analysis is recommended.

8.4 Recommendations for Future Research

In order to better understand the relationship between asset performance and safety performance the following recommendations are offered for future studies.

1. **Analysis of future data**

A longer study period for the database developed in this study would help to define the relationship between asset performance and safety performance more accurately. A further process of relating crashes to asset performance measures, based on crash reasons, is expected to improve the accuracy of the research.

2. **Replication of this study in other states**

The methodology of this research could be implemented by other state or regional agencies. A replication of this study in other states would help verify the results and/or identify differences among states. Similar data resources would be necessary. Otherwise, procedure for estimating ACI needs to be improved, in terms of the weighting and score board.

3. **Consideration of additional asset performance measures**

Only pavement condition and pavement marking performance were included in this study; additional asset conditions that could be considered in future work include sign inventory, lighting inventory, rumble strips inventory, or guardrail condition.

4. **Creating a comprehensive geodatabase for all public roads in Iowa**

This study has created a geodatabase for rural primary roads in Story County, as a pilot study. Since this methodology is widely considered as an innovative and efficient method for managing data, a comprehensive geodatabase for the whole state or just larger areas is recommended.

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Appendix A GIS Customized Toolbox Python Script

```
# Author: Jian Gao (jiangao@iastate.edu)
# Data: December 5th, 2011
# Version: Python 2.6
# Purpose:  This script was written for the project of Asset Management & Safety.

# Import modules
import arcpy, os

# Input and output paths and setup environment variables
fp = r'Z:\students\jiangao\project\reference_post\Reference_post.shp'
retro = arcpy.GetParameterAsText(0)
#retro = r'Z:\students\jiangao\project\shapefiles\04\retro.shp'
crash = arcpy.GetParameterAsText(1)
#crash = r'Z:\students\jiangao\project\shapefiles\04\crash.shp'
pci = arcpy.GetParameterAsText(2)
#pci = r'Z:\students\jiangao\project\shapefiles\04\PCI_MP.xls'
output_path = arcpy.GetParameterAsText(3)
#output_path = r'Z:\students\jiangao\project\shapefiles\04'
newshape = arcpy.GetParameterAsText(4)
#newshape = 'inter_04.shp'
outTableC = arcpy.GetParameterAsText(5)
outTableR = arcpy.GetParameterAsText(6)
outTableP = arcpy.GetParameterAsText(7)


arcpy.env.workspace = output_path
arcpy.env.overwriteOutput = True

# Define Projection
sr = arcpy.SpatialReference('C:\Program Files (x86)\ArcGIS\Desktop10.0\Coordinate
Systems\Projected Coordinate Systems\UTM\South America\Corrego Alegre UTM
Zone 24S.prj')

# Create a new shapfile
print('Creating new shapefile...')
new_shapefile = arcpy.CreateFeatureclass_management(output_path, newshape,
'POINT', '', '', '', sr)

# Add new columns
Route = arcpy.AddField_management(new_shapefile,'Route','DOUBLE',15,6)
```

```
Milepost = arcpy.AddField_management(new_shapefile,'Milepost','DOUBLE',15,6)
Direction = arcpy.AddField_management(new_shapefile,'Direction','DOUBLE',15,6)
PCI = arcpy.AddField_management(new_shapefile,'PCI','DOUBLE',15,6)
IRI = arcpy.AddField_management(new_shapefile,'IRI','DOUBLE',15,6)
Fault = arcpy.AddField_management(new_shapefile,'Fault','DOUBLE',15,6)
Rut = arcpy.AddField_management(new_shapefile,'Rut','DOUBLE',15,6)
Frict = arcpy.AddField_management(new_shapefile,'Frict','DOUBLE',15,6)
Time_Year = arcpy.AddField_management(new_shapefile,'Time_Year','TEXT',15,6)
WEL_Spring_Reflect = arcpy.AddField_management(new_shapefile,'WEL-SP-
RE','DOUBLE',15,6)
WEL_Fall_Reflect = arcpy.AddField_management(new_shapefile,'WEL-F-
RE','DOUBLE',15,6)
YEL_Spring_Reflect = arcpy.AddField_management(new_shapefile,'YEL-SP-
RE','DOUBLE',15,6)
YEL_Fall_Reflect = arcpy.AddField_management(new_shapefile,'YEL-F-
RE','DOUBLE',15,6)
YCL_Spring_Reflect = arcpy.AddField_management(new_shapefile,'YCL-SP-
RE','DOUBLE',15,6)
YCL_Fall_Reflect = arcpy.AddField_management(new_shapefile,'YCL-F-
RE','DOUBLE',15,6)
Num_Crash = arcpy.AddField_management(new_shapefile,'Num_Crash','DOUBLE',15,6)
Expose = arcpy.AddField_management(new_shapefile,'Expose','LONG',15,6)
Latitude = arcpy.AddField_management(new_shapefile,'Latitude','DOUBLE',15,6)
Longitude = arcpy.AddField_management(new_shapefile,'Longitude','DOUBLE',15,6)

# Loop
print ('Adding reference post...')
print('Creating Points...')
# Initial Search Cursor
frows = arcpy.SearchCursor(fp)
row_inserter = arcpy.InsertCursor(new_shapefile)
for each_row in frows:
   lat = each_row.LATITUDE
   lon = each_row.LONGITUDE
   rte = each_row.RTE
   mp = each_row.MP
   dire = each_row.DIR

   # Create Points
   point = arcpy.CreateObject('Point')
   point.X = lon
   point.Y = lat

   # Create insert cursor and new empty row
```

```
    new_row = row_inserter.newRow()
    # Polulate rows with Reference_post attributes
    new_row.Shape= point # setup geometry of the shape
    new_row.Latitude= lat
    new_row.Longitude = lon
    new_row.Route = rte
    new_row.Milepost = mp
    new_row.Direction = dire

    # Insert new ito the shapefile
    row_inserter.insertRow(new_row)

# Remove
del row_inserter, mp, rte, dire, lat, lon


# Calculate number of crashes in each route milepost by directions
print ('Calculating numbers of crashes...')
#outTableC = r'Z:\students\jiangao\project\shapefiles\04\crash_freq'
frequencyFeldsC = ["INITDIR","RTE","MILEPOST"]
summaryfieldC = ["AADT"]
arcpy.Frequency_analysis(crash, outTableC, frequencyFeldsC,summaryfieldC)

# Integrate number of crash and AADT in mileposts
print('Integrating Crashes and AADT...')

# Initial Search Cursor
frows = arcpy.SearchCursor(fp)
row_inserterC = arcpy.InsertCursor(new_shapefile)
for each_row in frows:
    lat = each_row.LATITUDE
    lon = each_row.LONGITUDE
    rte = each_row.RTE
    mp = each_row.MP
    dire = each_row.DIR

    crows = arcpy.SearchCursor(outTableC)
    for row in crows:
        if row.RTE == rte:
            if row.MILEPOST == mp:
                if row.INTDIR == dire:
                    numcrash = row.FREQUENCY
                    expos = row.AADT % row.FREQUENCY
                else:
```

```
            numcrash = 0
            expos = 0
        else:
          numcrash = 0
          expos = 0
      else:
        numcrash = 0
        expos = 0

      #Create Insert Cursor
      new_rowC = row_inserterC.newRow()

      # Polulate rows with crash attributes
      new_rowC.Num_crash = numcrash
      new_rowC.Expose = float(expos)

      # Insert new rows into the shapefile
      row_inserterC.insertRow(new_rowC)

  # Remove
del mp, rte, dire, row_inserterC


# Calculate marking retroreflectivity value in each route milepost by directions
print ('Compiling Marking Data...')
#outTableR = r'Z:\students\jiangao\project\shapefiles\04\retro_freq'
freqR = ["ROUTE","DIRECTION","MILEPOST","LINE_TYPE", "TIME_YEAR"]
sumR = ["REFLECT"]
arcpy.Frequency_analysis(retro, outTableR, freqR, sumR)

# Integrate Marking Retroreflectivity Data
print('Integrating Marking Retroreflectivity Data...')

frows = arcpy.SearchCursor(fp)
row_inserterM = arcpy.InsertCursor(new_shapefile)
for each_row in frows:
  lat = each_row.LATITUDE
  lon = each_row.LONGITUDE
  rte = each_row.RTE
  mp = each_row.MP
  dire = each_row.DIR

  mrows = arcpy.SearchCursor(outTableR)
  for each_rowM in mrows:
```

```
    if each_rowM.ROUTE == rte and each_rowM.MILEPOST == mp and
each_rowM.DIRECTION == dire:
        if each_rowM.TIME_YEAR == "Spring":
            if each_rowM.LINE_TYPE == "wel":
                welspre = each_rowM.REFLECT % each_rowM.REQUENCY
            elif each_rowM.LINE_TYPE == "ycl":
                yclspre = each_rowM.REFLECT % each_rowM.REQUENCY
            else:
                yelspre = each_rowM.REFLECT % each_rowM.REQUENCY
        elif each_row.TIME_YEAR == "Fall":
            if each_rowM.LINE_TYPE == "wel":
                welfre = each_rowM.REFLECT % each_rowM.REQUENCY
            elif each_rowM.LINE_TYPE == "ycl":
                yclfre = each_rowM.REFLECT % each_rowM.REQUENCY
            else:
                yelfre = each_rowM.REFLECT % each_rowM.REQUENCY
    else:
        welspre = 0
        yclspre = 0
        yelspre = 0
        welfre = 0
        yclfre = 0
        yelfre = 0


    # Create Insert Cursors
    new_rowM = row_inserterM.newRow()

    # Polulate rows with crash attributes
    if rowMI.TIME_YEAR == "Spring":
        if rowMI.LINE_TYPE == "wel":
            new_rowM.WEL-SP-RE = float(welspre)
        elif rowMI.LINE_TYPE == "ycl":
            new_rowM.YCL-SP-RE = float(yclspre)
        else:
            new_rowM.YEL-SP-RE = float(yelspre)
    else:
        if rowMI.LINE_TYPE == "wel":
            new_rowM.WEL-SP-RE = float(welfre)
        elif rowMI.LINE_TYPE == "ycl":
            new_rowM.YCL-SP-RE = float(yclfre)
        else:
            new_rowM.YEL-SP-RE = float(yelfre)
```

```
        # Insert new ito the shapefile
        row_inserterM.insertRow(new_rowM)

    # Remove
del mp, rte, dire, row_inserterM



# Integrating PCI Data by route, milepos,and directions
print('Creating PCI Table View')
arcpy.MakeTableView_management(pci, pci_table)

print('Integrating Pavement Condition Data...')
frows = arcpy.SearchCursor(fp)
row_inserterP = arcpy.InsertCursor(new_shapefile)
for each_row in frows:
    lat = each_row.LATITUDE
    lon = each_row.LONGITUDE
    rte = each_row.RTE
    mp = each_row.MP
    dire = each_row.DIR

    prows = arcpy.SearchCursor(pci_table)
    for each_rowP in prows:
        if each_rowP.RTE == rte and each_rowP.MP == mp and each_rowP.Direction == dire:
            pci = each_rowP.PCI
            iri = each_rowP.IRI
            frict = each_rowP.FRICT
            fault = each_rowP.FAULT
            rut = each_rowP.RUT



        # Create Insert Cursors
        new_rowP = row_inserterP.newRow()

        # Polulate rows with crash attributes
        new_rowP.PCI = pci
        new_rowP.IRI = iri
        new_rowP.Frict = frict
        new_rowP.Fault = fault
        new_rowP.Rut = rut

        # Insert new ito the shapefile
```

```
        row_inserterP.insertRow(new_rowP)

    # Remove
del mp, rte, dire, row_inserterP

print('All Done!')
```

Appendix B Spatial Correlation

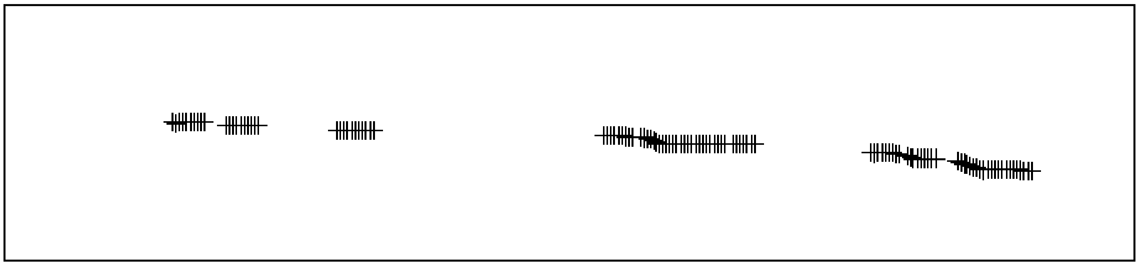

Figure B1 Sample Plot

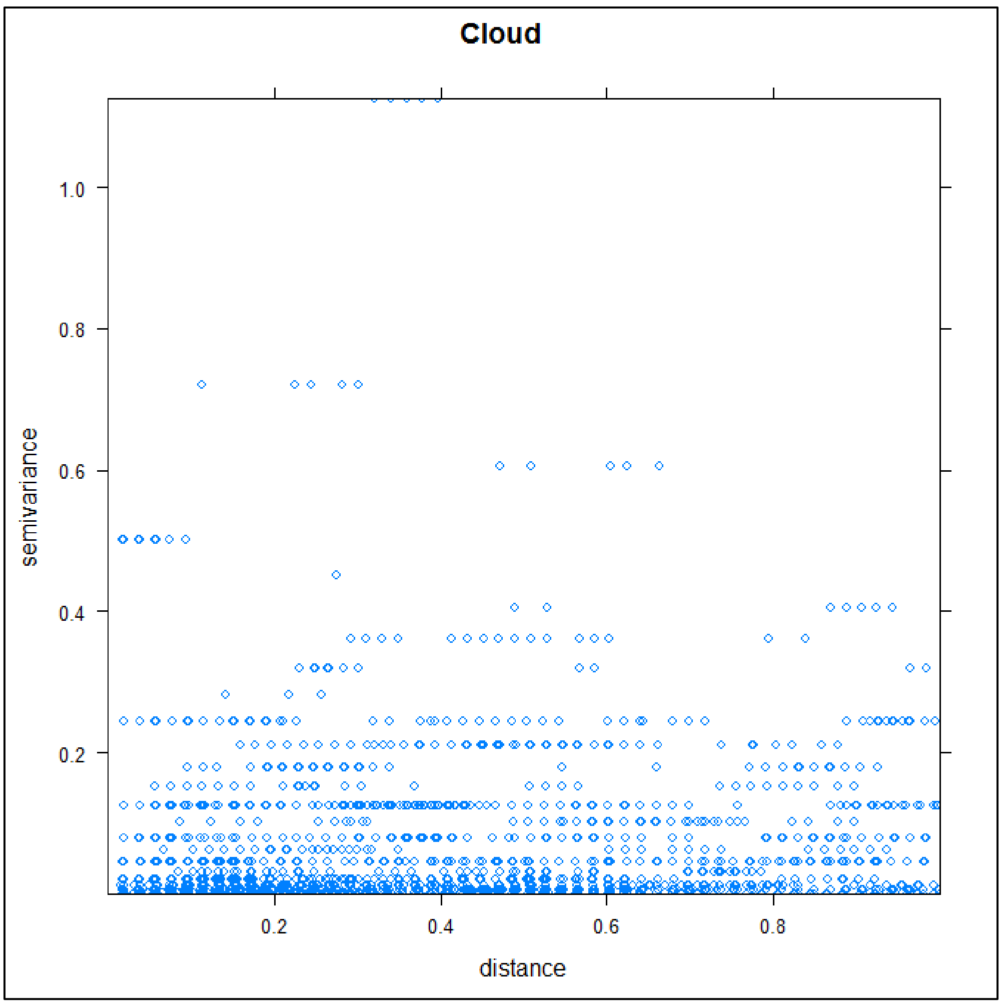

Figure B2 Cloud Semi-variogram (cutoff=1.0)

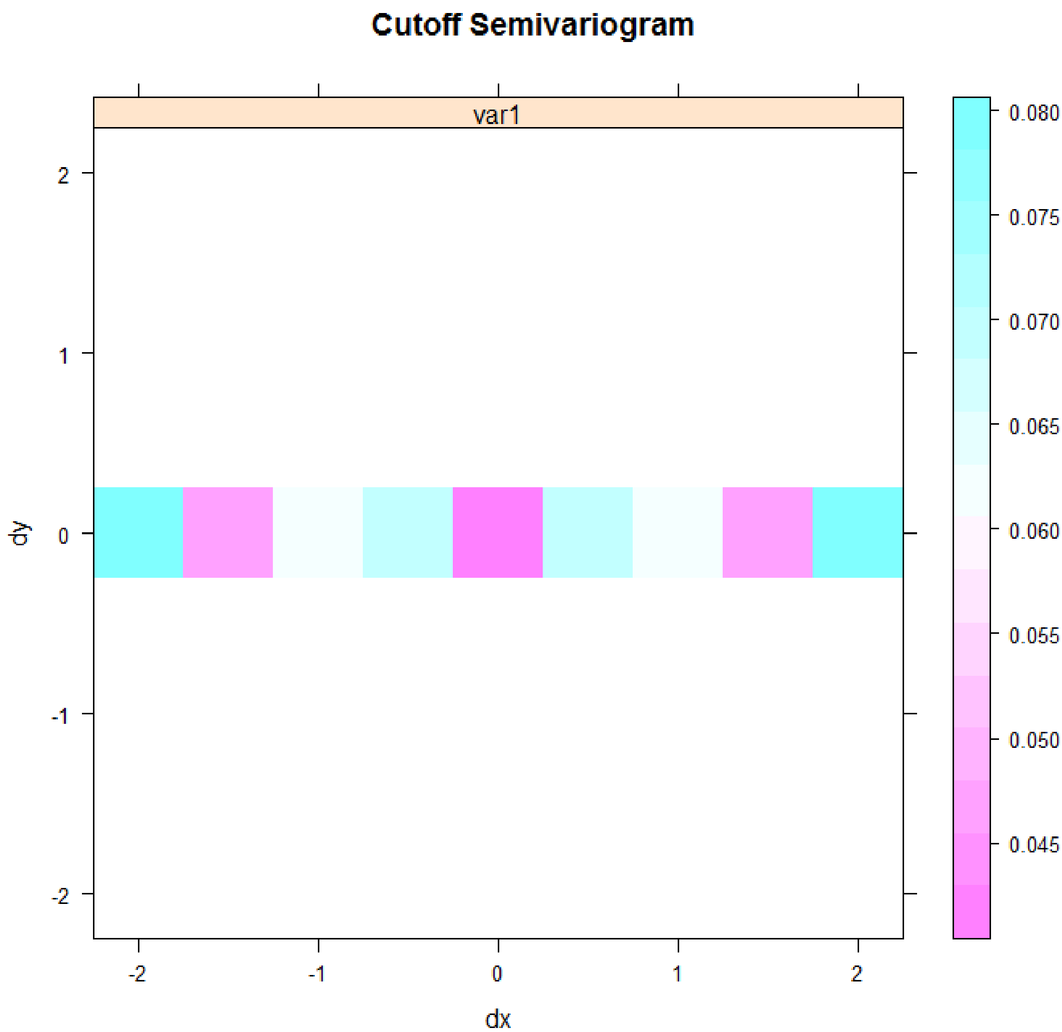

Figure B3 Map of Cutoff Semivariogram

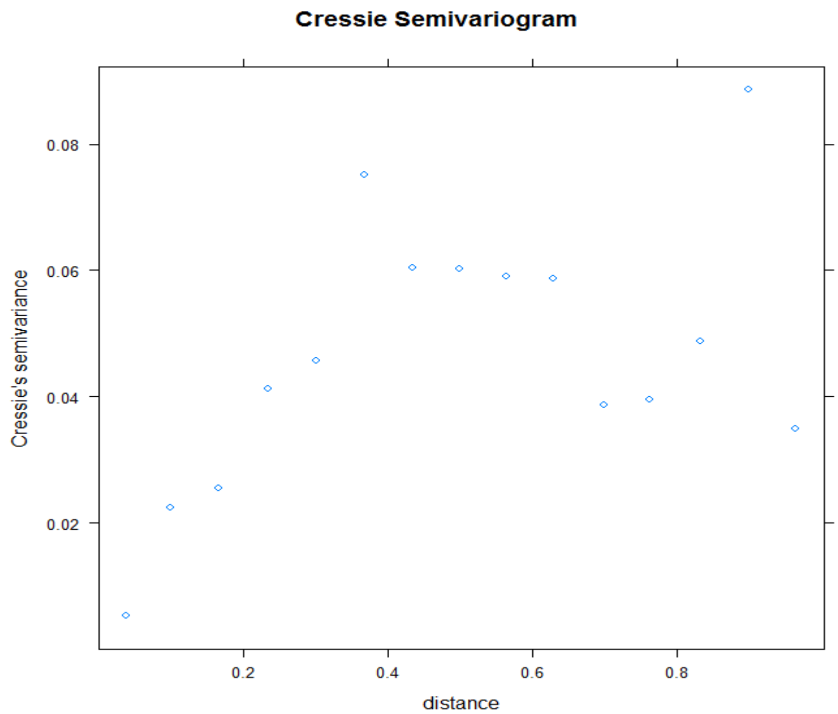

Figure B4 Cressie-Howkins Semivariogram

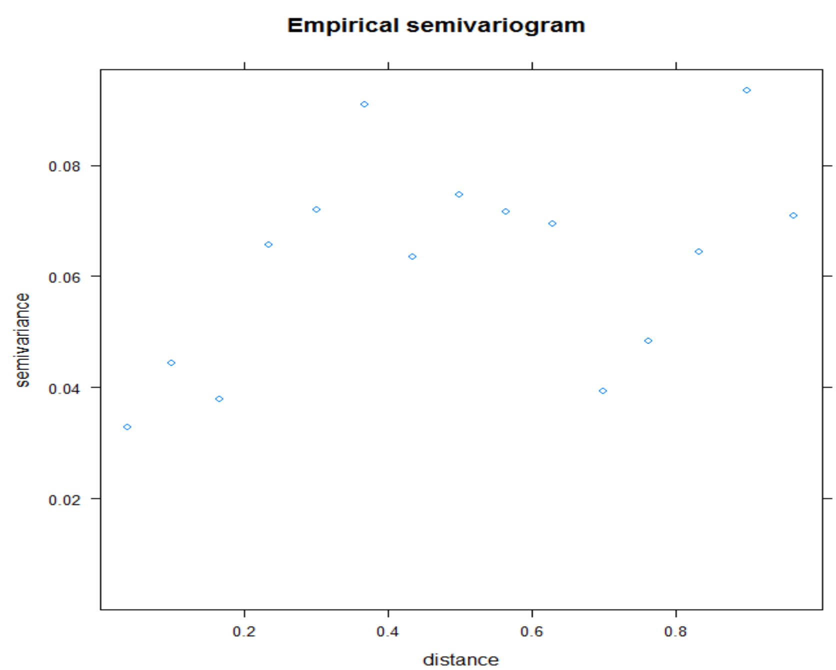

Figure B5 Empirical Semivariogram

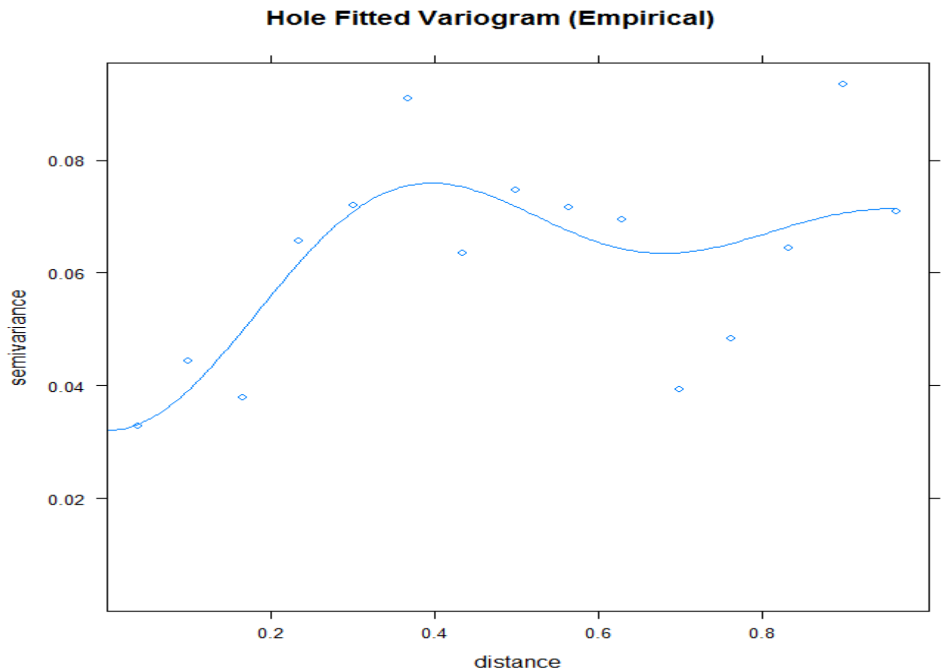

Figure B6 Hold Fitted Model Plot with Empirical Estimator

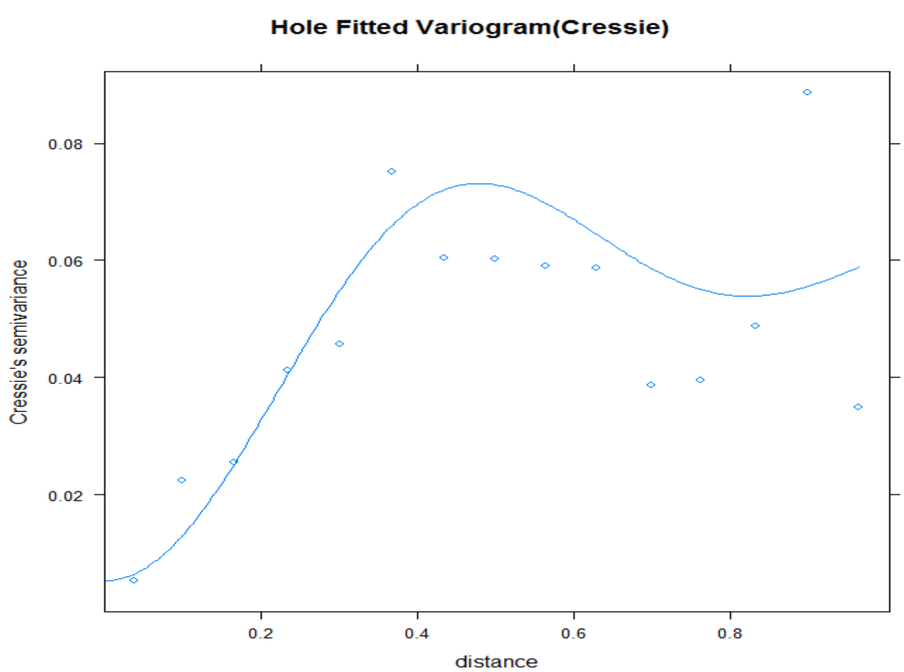

Figure B7 Hold Fitted Model Plot with Cressie Estimator

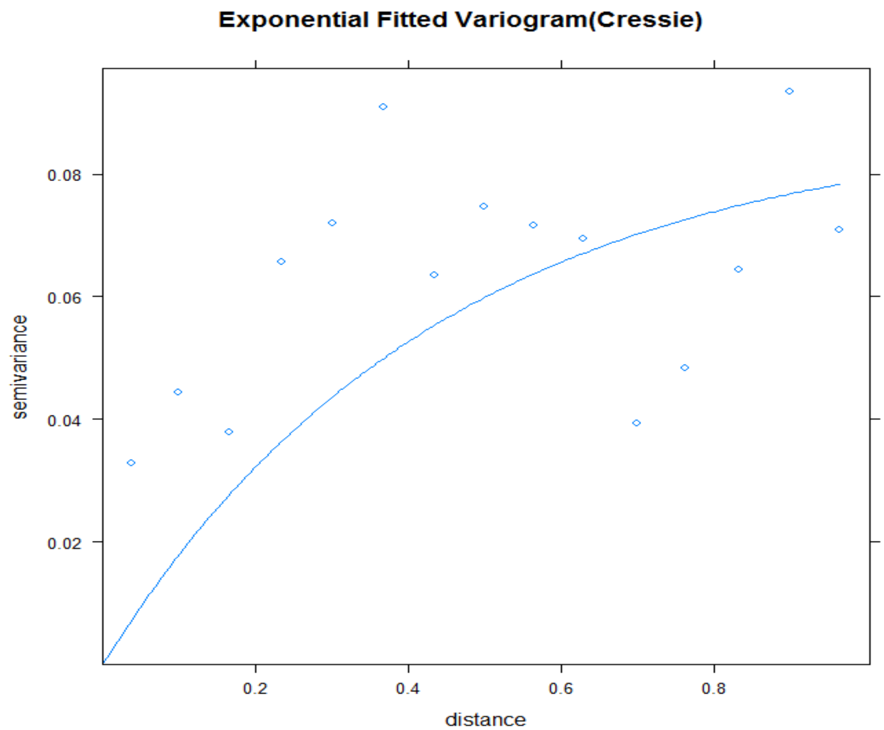

Figure B8 Exponential Fitted Model Plot with Cressie Estimator

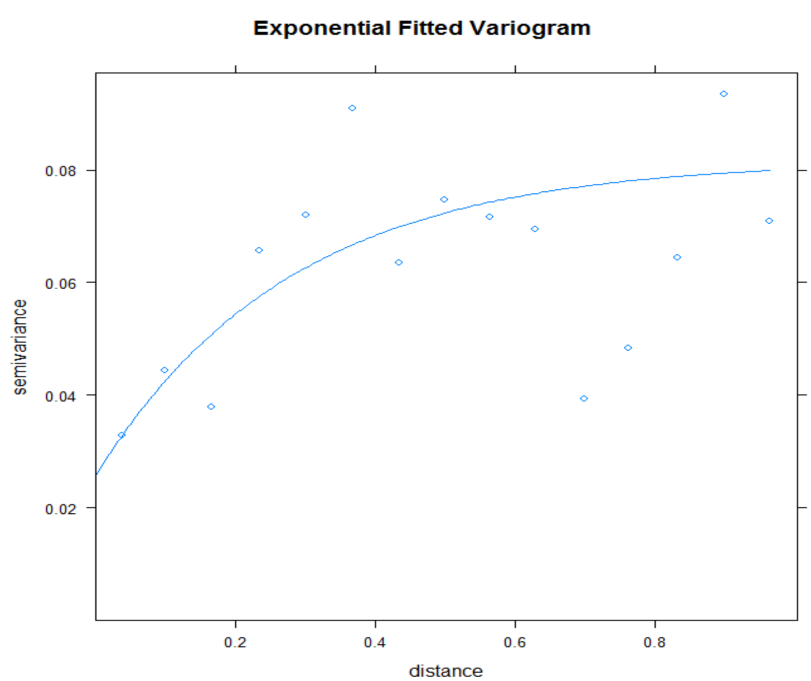

Figure B9 Exponential Fitted Model Plot with Empirical Estimator

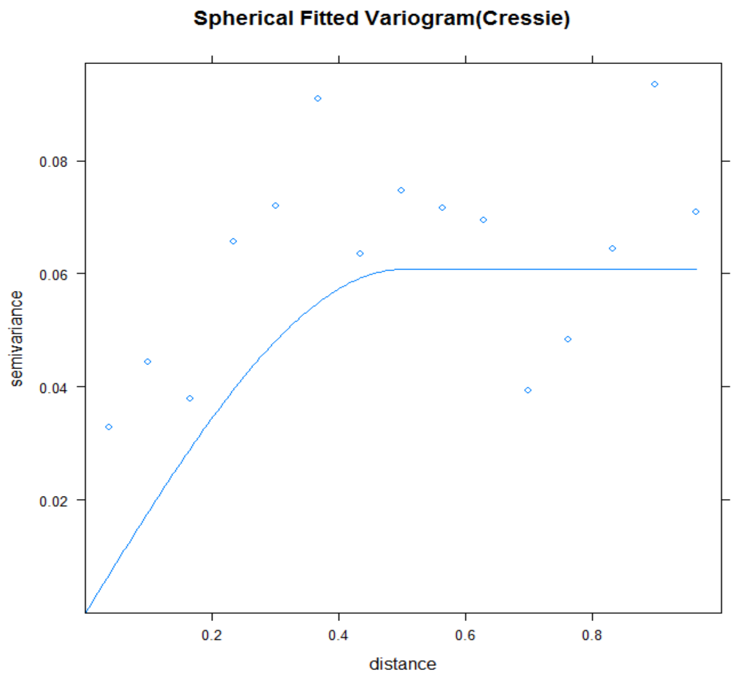

Figure B10 Spherical Fitted Model Plot with Cressie Estimator

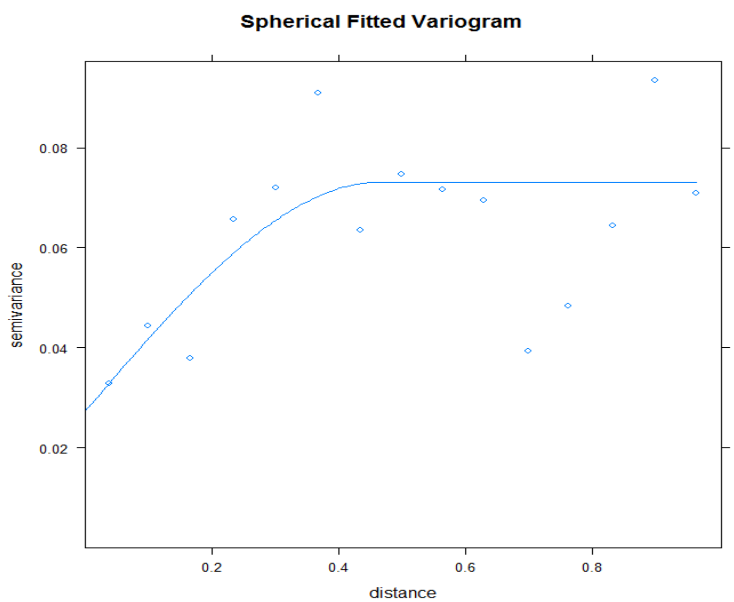

Figure B11 Exponential Fitted Model Plot with Empirical Estimator

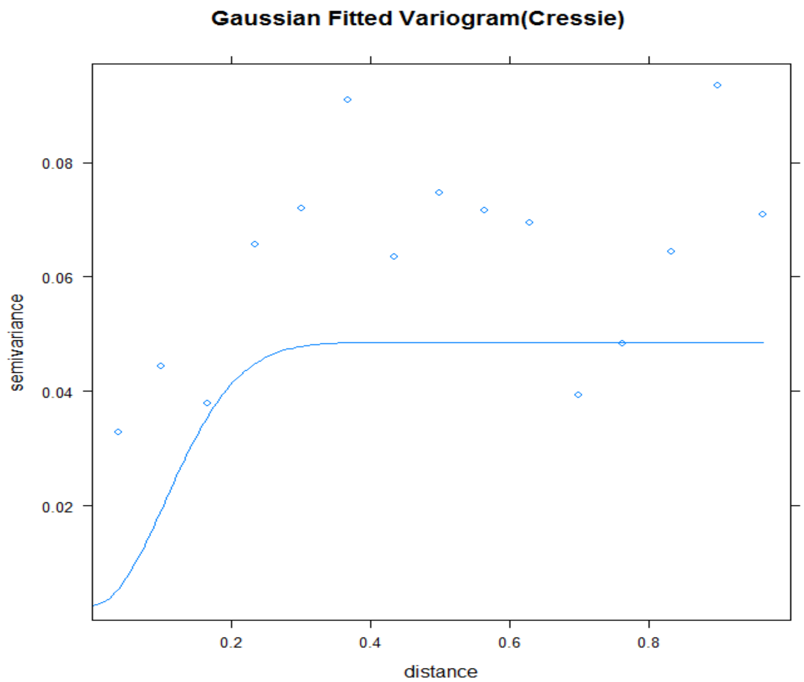

Figure B12 Gaussian Fitted Model Plot with Cressie Estimator

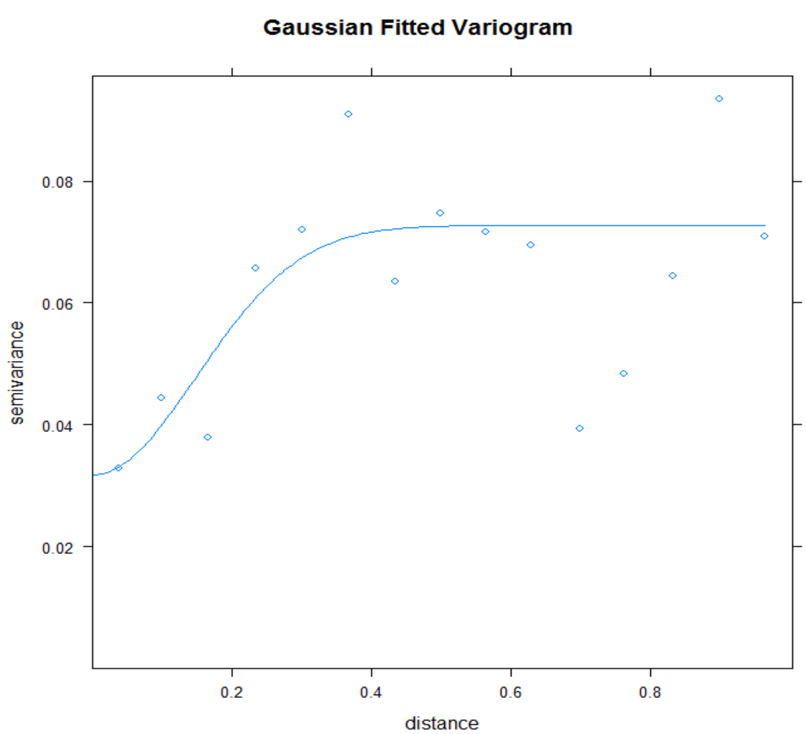

Figure B13 Gaussian Fitted Model Plot with Empirical Estimator

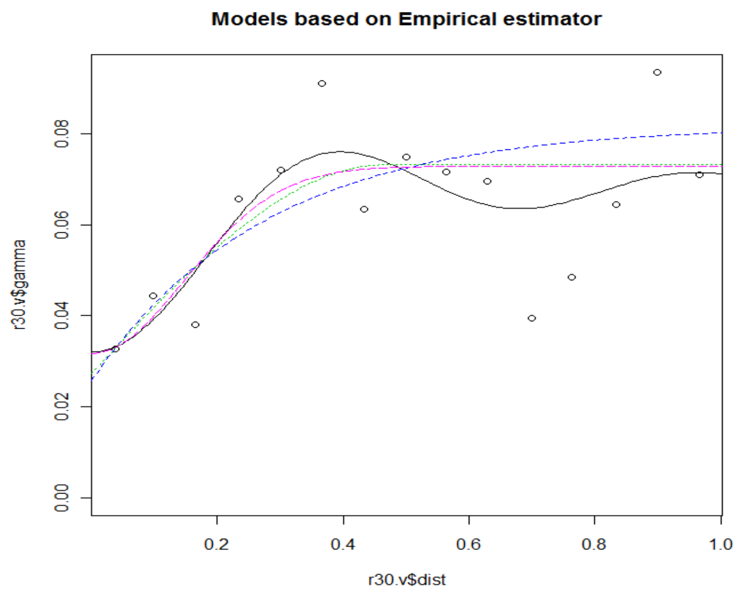

Figure B14 Models Comparison with Empirical Estimator

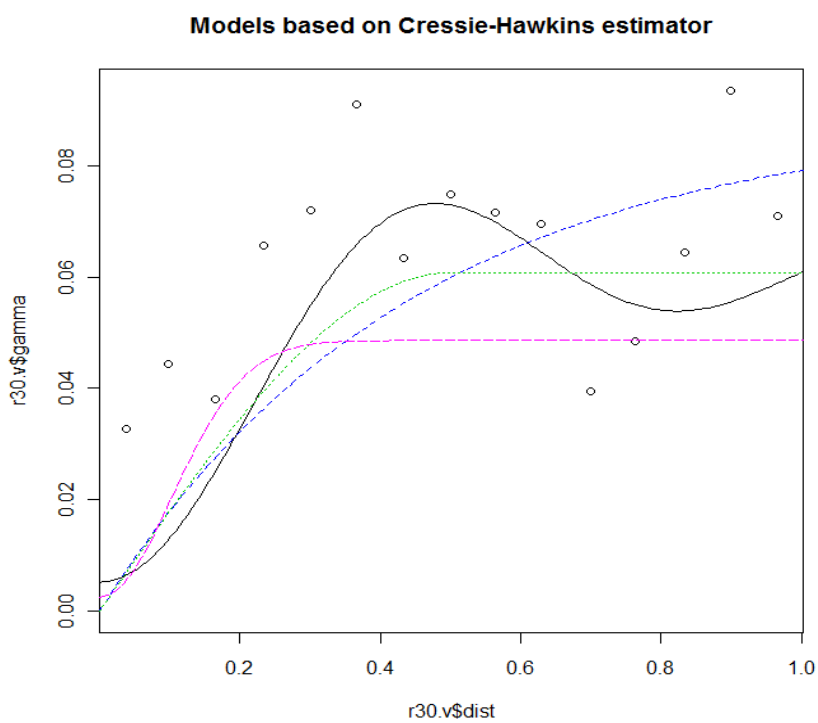

Figure B15 Models Comparison with Cressie Estimator

Table B1 Models Summary

Models Summary								
	Empirical				Cressie-Hawkins			
Model	SSE	Nugget	Sill	Range	SSE	Nugget	Sill	Range
Hole	3.492	0.005	0.056	0.107	2.698	0.032	0.036	0.088
Exponential	3.163	0.026	0.056	0.279	2.838	0.000	0.088	0.440
Spherical	2.822	0.027	0.046	0.466	1.978	0.000	0.061	0.501
Gaussian	3.018	0.032	0.041	0.211	2.496	0.003	0.046	0.148

Appendix C LIMDEP Model Results

Negative Binomial Model for all data

```
+---------------------------------------------+
| Poisson Regression                          |
| Maximum Likelihood Estimates                |
| Model estimated: Aug 10, 2011 at 01:31:26PM.|
| Dependent variable                X5        |
| Weighting variable              None        |
| Number of observations         28835        |
| Iterations completed               7        |
| Log likelihood function    -61707.76        |
| Number of parameters               3        |
| Info. Criterion: AIC =       4.28027        |
|   Finite Sample: AIC =       4.28027        |
| Info. Criterion: BIC =       4.28113        |
| Info. Criterion:HQIC =       4.28054        |
| Restricted log likelihood  -80350.34        |
| McFadden Pseudo R-squared   .2320162        |
| Chi squared                 37285.17        |
| Degrees of freedom                 2        |
| Prob[ChiSqd> value] =       .0000000     |
+---------------------------------------------+
| Poisson Regression                          |
| Chi- squared =478954.13437  RsqP=  -.9238   |
| G  - squared = 82779.40960  RsqD=   .3105   |
| Overdispersion tests: g=mu(i)  :  1.349     |
| Overdispersion tests: g=mu(i)^2:   .369     |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|   -5.05857596       .04418893  -114.476   .0000
 X4      |    -.42369909       .01195442   -35.443   .0000   2.24862147
LOGADT  |     .76886336       .00398162   193.103   .0000   8.09345290
+---------------------------------------------+
| Negative Binomial Regression                |
| Maximum Likelihood Estimates                |
| Model estimated: Aug 10, 2011 at 01:31:28PM.|
| Dependent variable                X5        |
| Weighting variable              None        |
| Number of observations         28835        |
| Iterations completed               9        |
| Log likelihood function    -45714.20        |
| Number of parameters               4        |
| Info. Criterion: AIC =       3.17102        |
|   Finite Sample: AIC =       3.17102        |
| Info. Criterion: BIC =       3.17217        |
| Info. Criterion:HQIC =       3.17139        |
| Restricted log likelihood  -61707.76        |
| McFadden Pseudo R-squared   .2591822        |
| Chi squared                 31987.11        |
| 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|   -5.38145833       .03959308  -135.919   .0000
```

```
 X4      |    -1.29146309       .01743908   -16.713   .0000   2.24862147
LOGADT  |     .77074842       .00340283   226.502   .0000   8.09345290
---------+Dispersion parameter for count data model
 Alpha   |    1.26899021       .01547431    82.006   .0000
```

Descriptive Statistics

```
All results based on nonmissing observations.
===============================================================================
Variable     Mean       Std.Dev.     Minimum      Maximum       Cases Missing
===============================================================================
All observations in current sample
X5      |  1.74701      3.88385      .000000      48.0000        28835       0
```

Model for ACI≤1.5

```
+---------------------------------------------+
| Poisson Regression                          |
| Maximum Likelihood Estimates                |
| Model estimated: Aug 10, 2011 at 01:43:00PM.|
| Dependent variable                  X5      |
| Weighting variable                None      |
| Number of observations             906      |
| Iterations completed                 7      |
| Log likelihood function      -3998.108      |
| Number of parameters                 3      |
| Info. Criterion: AIC =         8.83247      |
|   Finite Sample: AIC =         8.83250      |
| Info. Criterion: BIC =         8.84839      |
| Info. Criterion:HQIC =         8.83855      |
| Restricted log likelihood    -5067.105      |
| McFadden Pseudo R-squared      .2109680     |
| Chi squared                   2137.994      |
| Degrees of freedom                   2      |
| Prob[ChiSqd> value] =         .0000000     |
+---------------------------------------------+
| Poisson Regression                          |
| Chi- squared =111502.72930  RsqP= -6.5568   |
| G  - squared =  6314.96551  RsqD=   .2529   |
| Overdispersion tests: g=mu(i)  :  1.068     |
| Overdispersion tests: g=mu(i)^2:   .086     |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|   -2.04571310       .17372009   -11.776   .0000
 X4      |   -1.84200974       .08895010   -20.708   .0000   1.36843267
LOGADT  |     .66361644       .01578168    42.050   .0000   8.45094362
+---------------------------------------------+
| Negative Binomial Regression                |
| Maximum Likelihood Estimates                |
| Model estimated: Aug 10, 2011 at 01:43:00PM.|
| Dependent variable                  X5      |
| Weighting variable                None      |
| Number of observations             906      |
| Iterations completed                10      |
| Log likelihood function      -1999.835      |
| Number of parameters                 4      |
| Info. Criterion: AIC =         4.42348      |
|   Finite Sample: AIC =         4.42353      |
| Info. Criterion: BIC =         4.44471      |
| Info. Criterion:HQIC =         4.43158      |
| Restricted log likelihood    -3998.108      |
| McFadden Pseudo R-squared      .4998047     |
| Chi squared                   3996.547      |
| 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|     .77990616       .54169051     1.440   .1499
 X4      |   -1.66786220       .41533061    -4.016   .0001   1.36843267
 LOGADT  |     .31620081       .00994591    31.792   .0000   8.45094362
---------+Dispersion parameter for count data model
```

```
 Alpha   |    2.47848458       .15028148    16.492   .0000
```

Descriptive Statistics

```
All results based on nonmissing observations.
===============================================================================
Variable     Mean       Std.Dev.     Minimum      Maximum        Cases Missing
===============================================================================
All observations in current sample
X5      |  3.91611      7.99058      .000000      48.0000           906       0
```

Model for ACI>1.5

```
+---------------------------------------------+
| Poisson Regression                          |
| Maximum Likelihood Estimates                |
| Model estimated: Aug 10, 2011 at 02:24:01PM.|
| Dependent variable                 X5       |
| Weighting variable               None       |
| Number of observations          27929       |
| Iterations completed                7       |
| Log likelihood function     -57508.09       |
| Number of parameters                3       |
| Info. Criterion: AIC =        4.11838       |
|   Finite Sample: AIC =        4.11838       |
| Info. Criterion: BIC =        4.11926       |
| Info. Criterion:HQIC =        4.11866       |
| Restricted log likelihood   -74344.40       |
| McFadden Pseudo R-squared    .2264637       |
| Chi squared                  33672.61       |
| Degrees of freedom                  2       |
| Prob[ChiSqd> value] =        .0000000      |
+---------------------------------------------+
| Poisson Regression                          |
| Chi- squared =137081.60890  RsqP=   .3834   |
| G  - squared = 76061.33369  RsqD=   .3069   |
| Overdispersion tests: g=mu(i)  : 10.218     |
| Overdispersion tests: g=mu(i)^2: 10.194     |
+---------------------------------------------+
+--------+--------------+----------------+--------+--------+----------+
|Variable| Coefficient  | Standard Error |b/St.Er.|P[|Z|>z]| Mean of X|
+--------+--------------+----------------+--------+--------+----------+
 Constant|   -5.33495527       .04796242  -111.232   .0000
 X4      |    -.31971309       .01486877   -21.502   .0000   2.27717426
 LOGADT  |     .77262977       .00414876   186.232   .0000   8.08185612
+---------------------------------------------+
| Negative Binomial Regression                |
| Maximum Likelihood Estimates                |
| Model estimated: Aug 10, 2011 at 02:24:04PM.|
| Dependent variable                 X5       |
| Weighting variable               None       |
| Number of observations          27929       |
| Iterations completed               10       |
| Log likelihood function     -43570.57       |
| Number of parameters                4       |
| Info. Criterion: AIC =        3.12038       |
|   Finite Sample: AIC =        3.12038       |
| Info. Criterion: BIC =        3.12156       |
| Info. Criterion:HQIC =        3.12076       |
| Restricted log likelihood   -57508.09       |
| McFadden Pseudo R-squared    .2423576       |
| Chi squared                  27875.04       |
| 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|   -5.76123896       .07247317   -79.495   .0000
 X4      |    -.17940674       .02269576    -7.905   .0000   2.27717426
 LOGADT  |     .78434830       .00568427   137.986   .0000   8.08185612
---------+Dispersion parameter for count data model
```

```
 Alpha   |    1.22333346       .01529867    79.963   .0000
```

Descriptive Statistics

```
All results based on nonmissing observations.
===============================================================================
Variable     Mean       Std.Dev.     Minimum      Maximum       Cases Missing
===============================================================================
All observations in current sample
X5      |  1.67664      3.65335      .000000      48.0000       27929       0
```

ZINB Checking
All data

```
+----------------------------------------------------------------------+
| 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          .29070   Act.= 13780 Prd.=  8382.4    -61707.75752 |
| Neg. Bin.        .42473   Act.= 13780 Prd.= 12247.1    -45714.20312 |
| Z.I.Neg_Bin      .47459   Act.= 13780 Prd.= 13684.7    -46397.99197 |
| 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     -8.3582  |
| 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|   -3.20367195       .03187901  -100.495   .0000
 X4      |    -.15403620       .01230797   -12.515   .0000   2.24862147
LOGADT  |     .51228558       .00287974   177.893   .0000   8.09345290
---------+Dispersion parameter
 Alpha   |     .94962754       .01920061    49.458   .0000
---------+Zero inflation model
 Tau     |   -2.38959308       .06280429   -38.048   .0000
```

ACI≤1.5

```
+----------------------------------------------------------------------+
| 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           .05876   Act.=   371 Prd.=    53.2     -3998.10818 |
| Neg. Bin.         .12695   Act.=   371 Prd.=   115.0     -1999.83475 |
| Z.I.Neg_Bin       .41165   Act.=   371 Prd.=   373.0     -1999.29199 |
| 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      -.7153   |
| 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|     .36680966       .41692999      .880   .3790
 X4      |   -1.21992946       .31825219    -3.833   .0001   1.36843267
LOGADT  |     .30374423       .00802602    37.845   .0000   8.45094362
---------+Dispersion parameter
 Alpha   |    2.15585129       .11689362    18.443   .0000
---------+Zero inflation model
 Tau     |   -2.05580042       .32474372    -6.331   .0000
```

ACI>1.5

```
+----------------------------------------------------------------------+
| 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           .30157   Act.= 13409 Prd.=  8422.5    -57508.09418 |
| Neg. Bin.         .43679   Act.= 13409 Prd.= 12199.0    -43570.57311 |
| Z.I.Neg_Bin       .47888   Act.= 13409 Prd.= 13374.6    -44257.93334 |
| 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    -18.0023   |
| 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|   -3.41505209       .05106028   -66.883   .0000
 X4      |    -.07872994       .01559449    -5.049   .0000   2.27717426
 LOGADT  |     .51582946       .00435879   118.342   .0000   8.08185612
```

```
---------+Dispersion parameter
 Alpha   |      .88704587       .01969415    45.041   .0000
---------+Zero inflation model
 Tau     |    -2.35495654       .06398217   -36.806   .0000
```

Appendix D Economic Analysis

Table D1 Reduced Number of Crashes by Severity

Alternatives	Crashes					
	Reduced Crash	Fatal(K)	Disabling Injury (A)	Evident Injury (B)	Possible Injury (C)	PDO(O)
Reconstruction	1.520	0.0182	0.0578	0.1474	0.3435	0.9515
Major	1.515	0.0182	0.0576	0.1470	0.3424	0.9484
Minor	1.487	0.0178	0.0565	0.1442	0.3361	0.9309
Paint	0.040	0.0005	0.0015	0.0039	0.0090	0.0250
Durable	0.151	0.0018	0.0057	0.0146	0.0341	0.0945
Tape	0.202	0.0024	0.0077	0.0196	0.0457	0.1265

Table D2 Benefit from Reduced Numbers of Crashes

Alternatives	**Benefit**						
	Fatal(K)	Disabling Injury (A)	Evident Injury (B)	Possible Injury (C)	PDO(O)	Benefit(2007)	Benefit(2011)
Reconstruction	$63,840.00	$13,862.40	$7,077.12	$8,588.00	$2,569.10	95,936.62	$112,232.28
Major	$63,630.00	$13,816.80	$7,053.84	$8,559.75	$2,560.65	$95,621.04	$111,863.10
Minor	$62,454.00	$13,561.44	$6,923.47	$8,401.55	$2,513.33	$93,853.79	$109,795.66
Paint	$1,680.00	$364.80	$186.24	$226.00	$67.61	$2,524.65	$2,953.48
Durable	$6,342.00	$1,377.12	$703.06	$853.15	$255.22	$9,530.55	$11,149.39
Tape	$8,484.00	$1,842.24	$940.51	$1,141.30	$341.42	$12,749.47	$14,915.08

Economic Analysis Part II Range Analysis Tables and Figures

Range 1: 1.5<ACI

Table D3 Reconstruction NPV in Range 1

			Reconstruction			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0.0000	0.0000	0	0.00	73581.75	-73581.75
1	2.8649	0.0984	2.7665	204270.13	73581.75	125661.91
2	3.2467	0.1076	3.1391	231781.81	73581.75	146264.85
3	3.6793	0.1175	3.5618	262992.72	73581.75	168385.66
4	4.1696	0.1284	4.0412	298390.19	73581.75	192167.20
5	4.7252	0.1402	4.585	338542.77	73581.75	217778.64
					NPV	*776676.51*

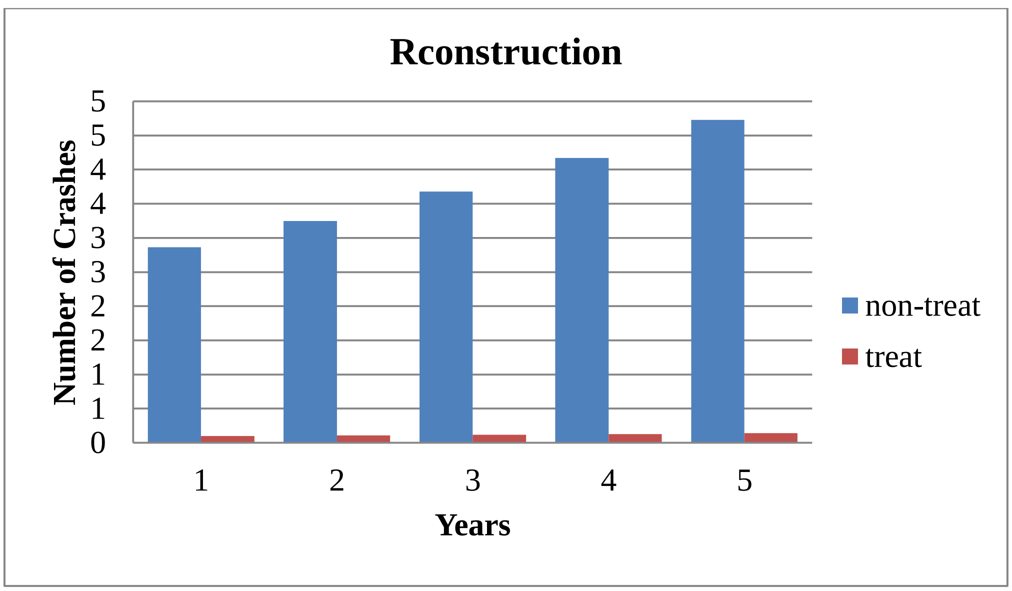

Figure D1 Reconstruction NPV in Range 1

Table D4 Major Rehabilitation NPV in Range 1

			Major			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	61645.47	-61645.47
1	2.8649	0.1871	2.6778	197720.79	61645.47	130841.65
2	3.6793	0.2233	3.456	255180.76	61645.47	178934.26
3	4.6992	0.2665	4.4327	327297.39	61645.47	236163.59
4	6.0944	0.3181	5.7763	426504.82	61645.47	311883.30
5	6.0944	0.3797	5.7147	421956.46	61645.47	296149.37
					NPV	*1092326.69*

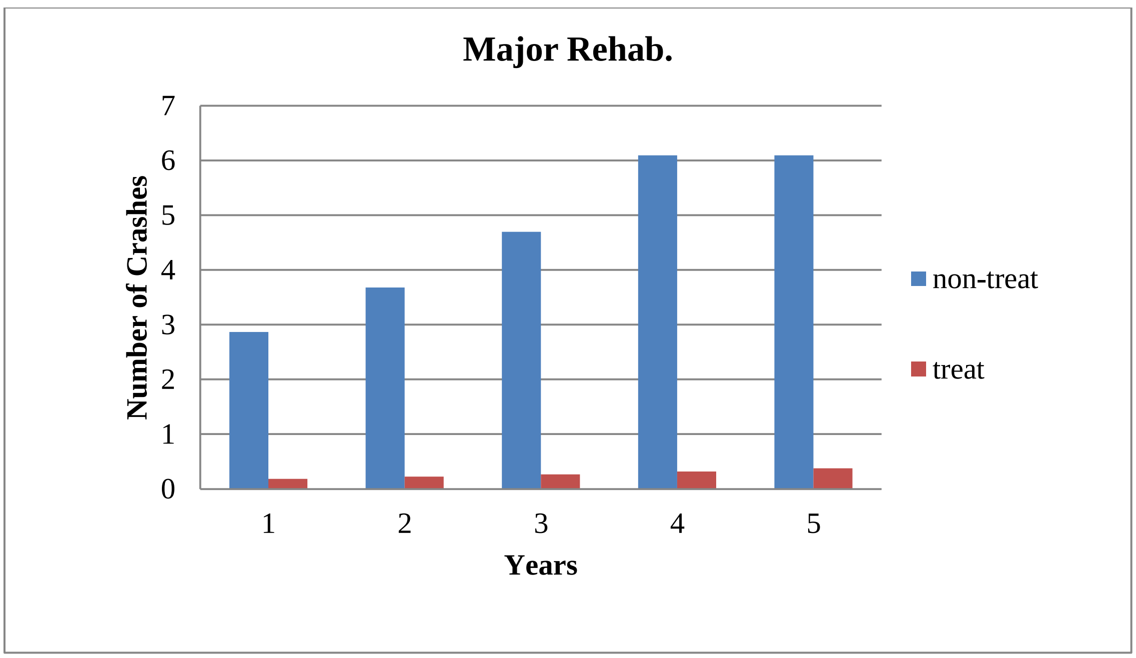

Figure D2 Major Rehabilitation NPV in Range 1

Table D5 Minor Rehabilitation NPV in Range 1

			Minor			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	54052.28	-54052.28
1	2.8649	0.3374	2.5275	186623.09	54052.28	127471.93
2	6.0944	1.595	4.4994	332222.32	54052.28	257183.84
3	6.0944	5.5871	0.5073	37457.52	54052.28	-14752.68
4	6.0944	0.4715	5.6229	415178.22	54052.28	308691.96
5	6.0944	5.5871	0.5073	37457.52	54052.28	-13639.68
					NPV	*610903.09*

Figure D3 Minor Rehabilitation NPV in Range 1

Table D6 Paint Making NPV in Range 1

			Paint			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	2376.00	-2376.00
1	2.8649	1.5704	1.2945	95582.03	2376.00	89621.18
2	6.0944	5.9936	0.1008	7442.77	2376.00	4684.52
3	6.0944	5.9936	0.1008	7442.77	2376.00	4504.34
4	6.0944	5.9936	0.1008	7442.77	2376.00	4331.10
5	6.0944	5.9936	0.1008	7442.77	2376.00	4164.52
					NPV	*104929.66*

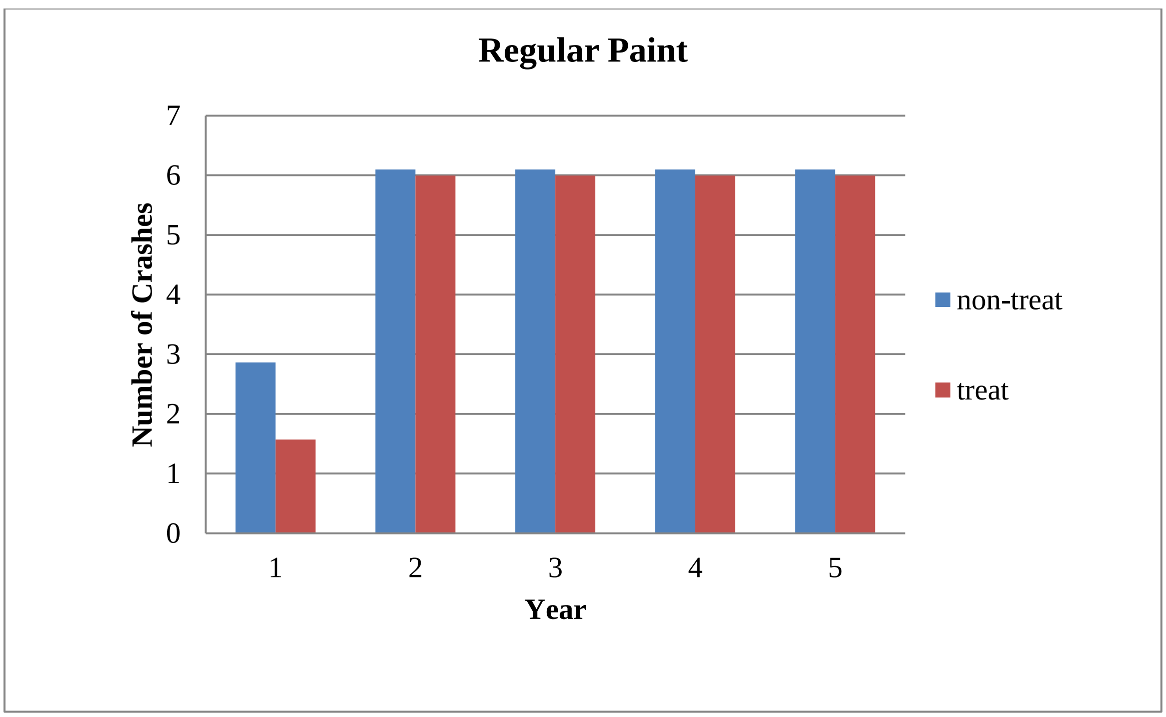

Figure D4 Paint Making NPV in Range 1

Table D7 Durable Marking NPV in Range 1

Durable						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	6298.73	-6298.73
1	2.8649	1.1898	1.6751	123684.40	6298.73	112870.84
2	6.0944	5.8344	0.26	19197.63	6298.73	11925.76
3	6.0944	5.3676	0.7268	53664.75	6298.73	42108.22
4	6.0944	5.8344	0.26	19197.63	6298.73	11026.03
5	6.0944	5.3676	0.7268	53664.75	6298.73	38931.42
					NPV	*210563.54*

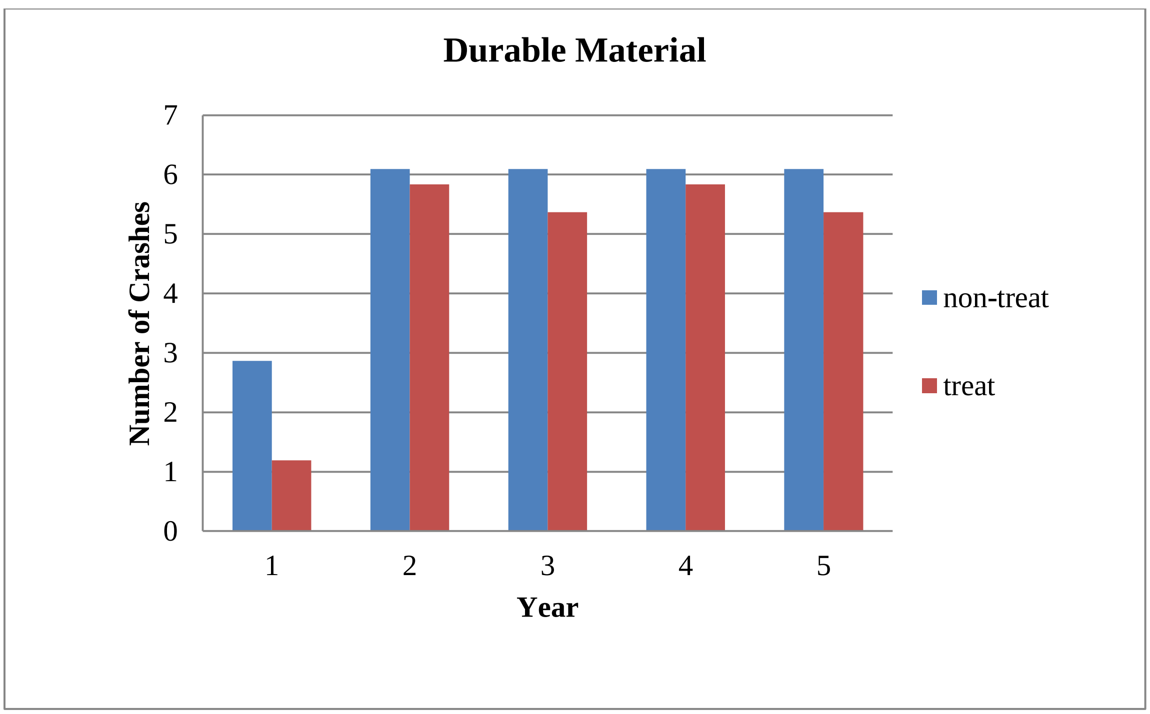

Figure D5 Durable Marking NPV in Range 1

Table D8 Tape Marking NPV in Range 1

			Tape			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	10674.28	-10674.28
1	2.8649	0.5118	2.3531	173745.91	10674.28	156799.64
2	4.6992	3.3849	1.3143	97044.00	10674.28	79853.66
3	6.0944	5.4578	0.6366	47004.65	10674.28	32297.57
4	6.0944	6.0944	0	0.00	10674.28	-9124.42
5	6.0944	6.0944	0	0.00	10674.28	-8773.48
					NPV	*240378.69*

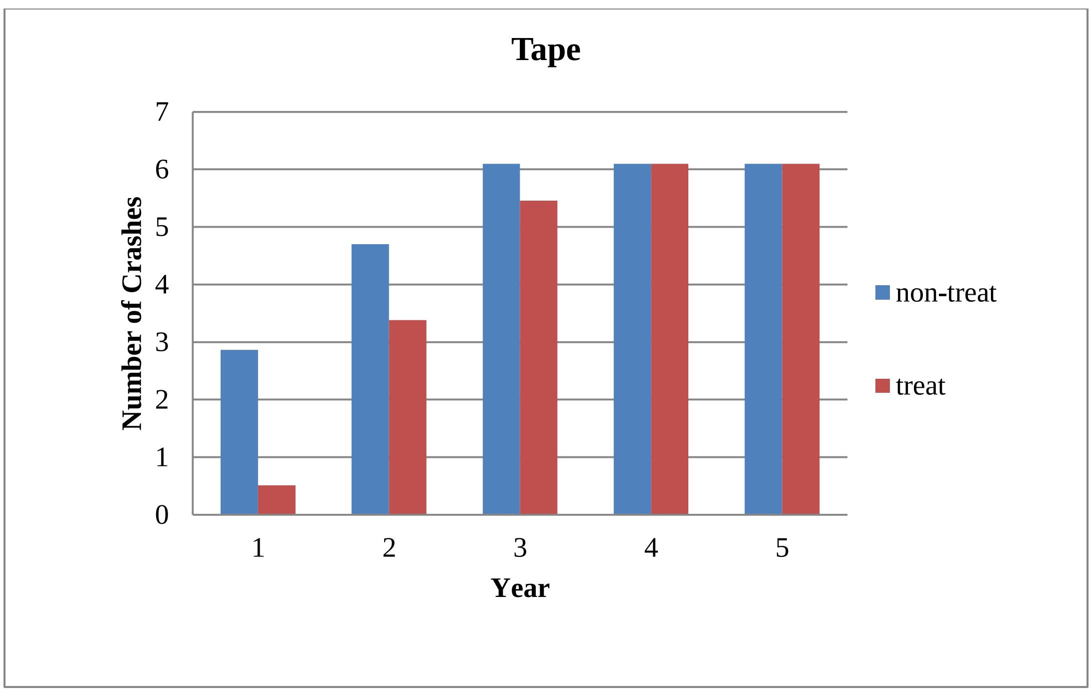

Figure D6 Tape Marking NPV in Range 1

Range 2: 1.5<ACI≤2.0

Table D9 Reconstruction NPV in Range 2

				Reconstruction		
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	73581.75	-73581.75
1	0.2409	0.0612	0.1797	13268.51	73581.75	-57993.50
2	0.359	0.0669	0.2921	21567.80	73581.75	-48089.83
3	0.4629	0.0731	0.3898	28781.67	73581.75	-39827.11
4	0.8216	0.0798	0.7418	54772.31	73581.75	-16078.39
5	0.988	0.0872	0.9008	66512.39	73581.75	-5810.50
					NPV	-241381.06

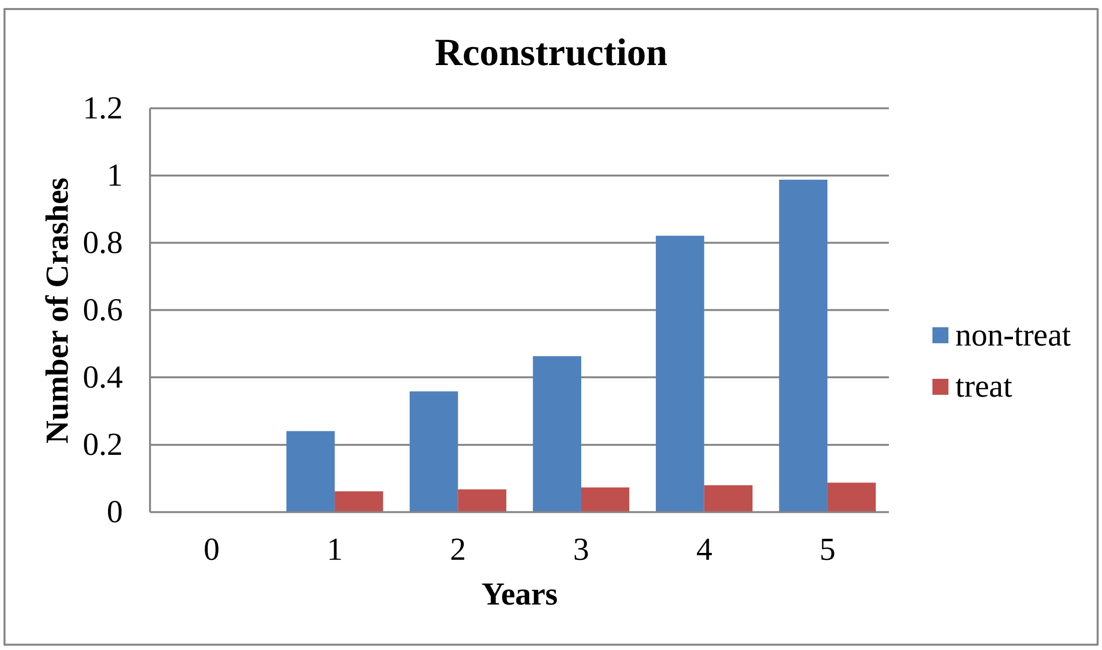

Figure D7 Reconstruction NPV in Range 2

Table D10 Major Rehabilitation NPV in Range 2

			Major			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	61645.47	-61645.47
1	0.2409	0.0741	0.1668	12316.02	61645.47	-47432.17
2	0.4629	0.0884	0.3745	27651.97	61645.47	-31428.91
3	0.988	0.1055	0.8825	65161.18	61645.47	3125.45
4	2.011	0.1259	1.8851	139190.18	61645.47	66285.54
5	3.5365	0.1503	3.3862	250026.94	61645.47	154835.84
					NPV	*83740.28*

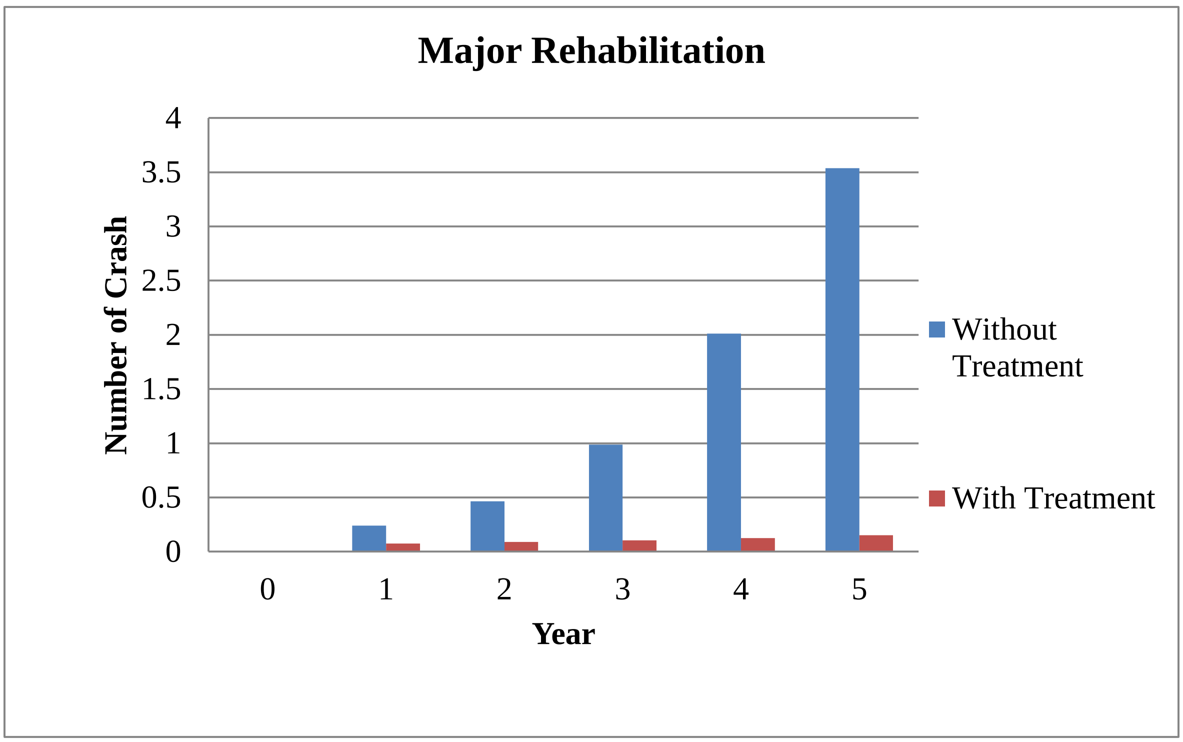

Figure D8 Major Rehabilitation NPV in Range 2

Table D11 Minor Rehabilitation NPV in Range 2

				Minor		
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	54052.28	-54052.28
1	0.2409	0.1336	0.1073	7922.71	54052.28	-44355.35
2	2.468	0.2409	2.2271	164442.44	54052.28	102061.91
3	5.258	2.468	2.79	206005.30	54052.28	135085.69
4	5.258	0.2404	5.0176	370484.67	54052.28	270487.73
5	5.258	2.468	2.79	206005.30	54052.28	124894.31
					NPV	*534122.00*

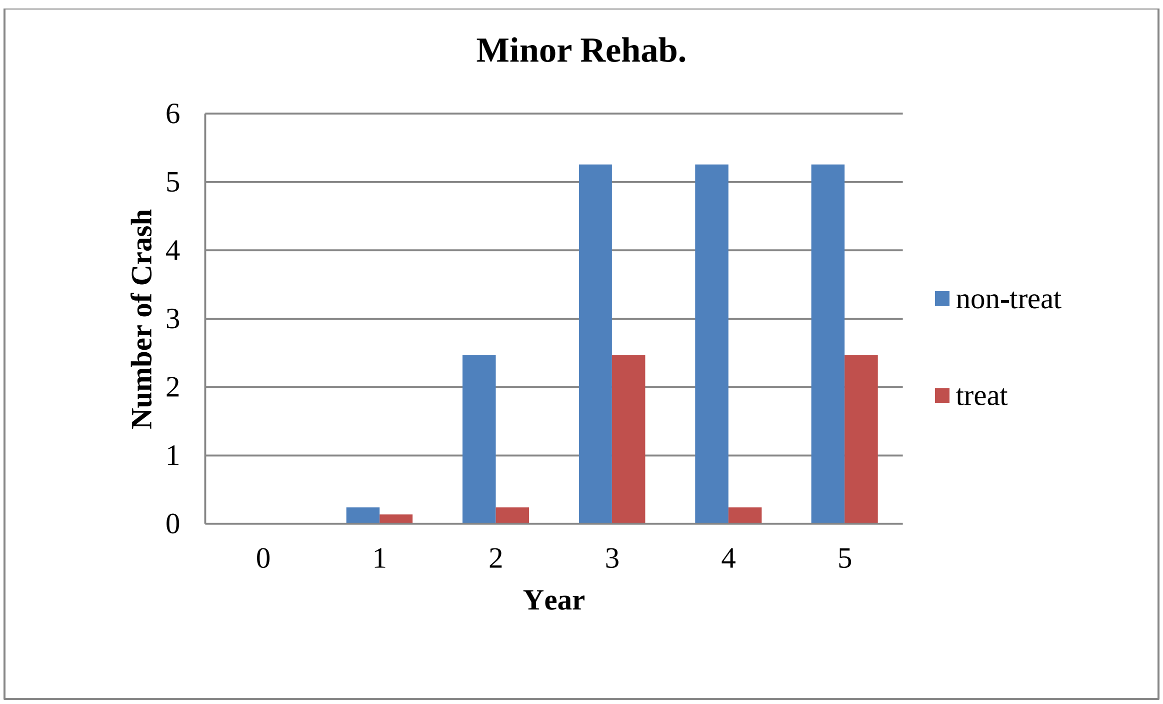

Figure D9 Minor Rehabilitation NPV in Range 2

Table D12 Paint Making NPV in Range 2

			Paint			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	2376.00	-2376.00
1	0.249	0.2381	0.0109	804.82	2376.00	-1510.75
2	5.258	5.171	0.087	6423.82	2376.00	3742.44
3	5.258	5.171	0.087	6423.82	2376.00	3598.50
4	5.258	5.171	0.087	6423.82	2376.00	3460.09
5	5.258	5.171	0.087	6423.82	2376.00	3327.01
					NPV	*10241.30*

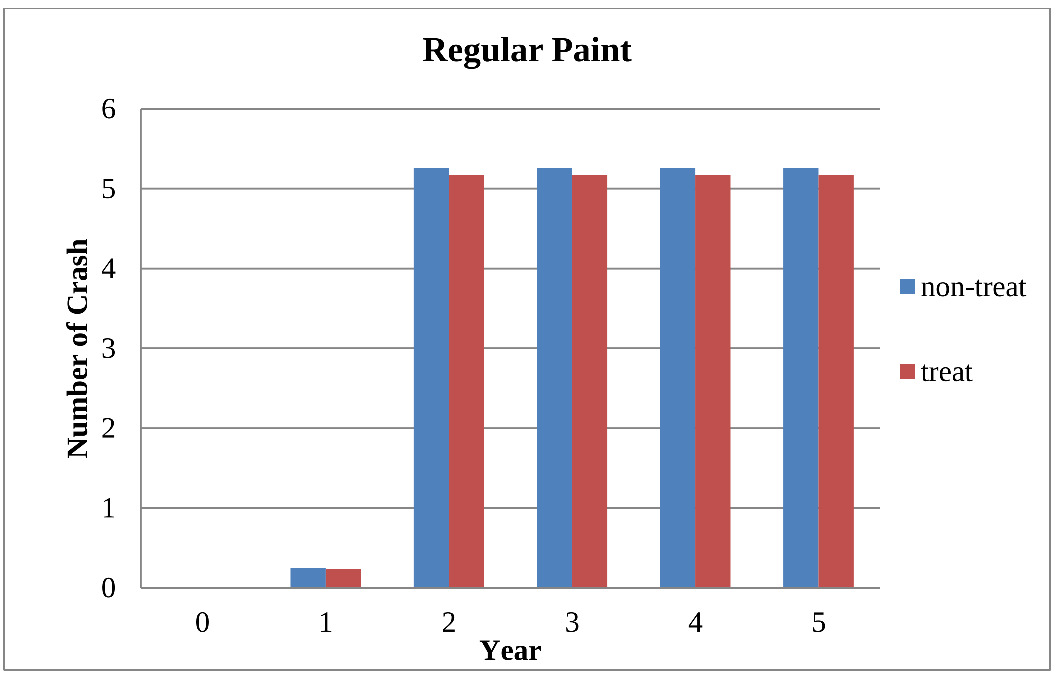

Figure D10 Paint Making NPV in Range 2

Table D13 Durable Marking NPV in Range 2

			Durable			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	6298.73	-6298.73
1	0.2409	0.2271	0.0138	1018.95	6298.73	-5076.71
2	4.2875	4.0397	0.2478	18296.82	6298.73	11092.90
3	5.258	3.7165	1.5415	113819.78	6298.73	95585.82
4	5.258	5.258	0	0.00	6298.73	-5384.18
5	5.258	4.8373	0.4207	31063.24	6298.73	20354.62
					NPV	*110273.72*

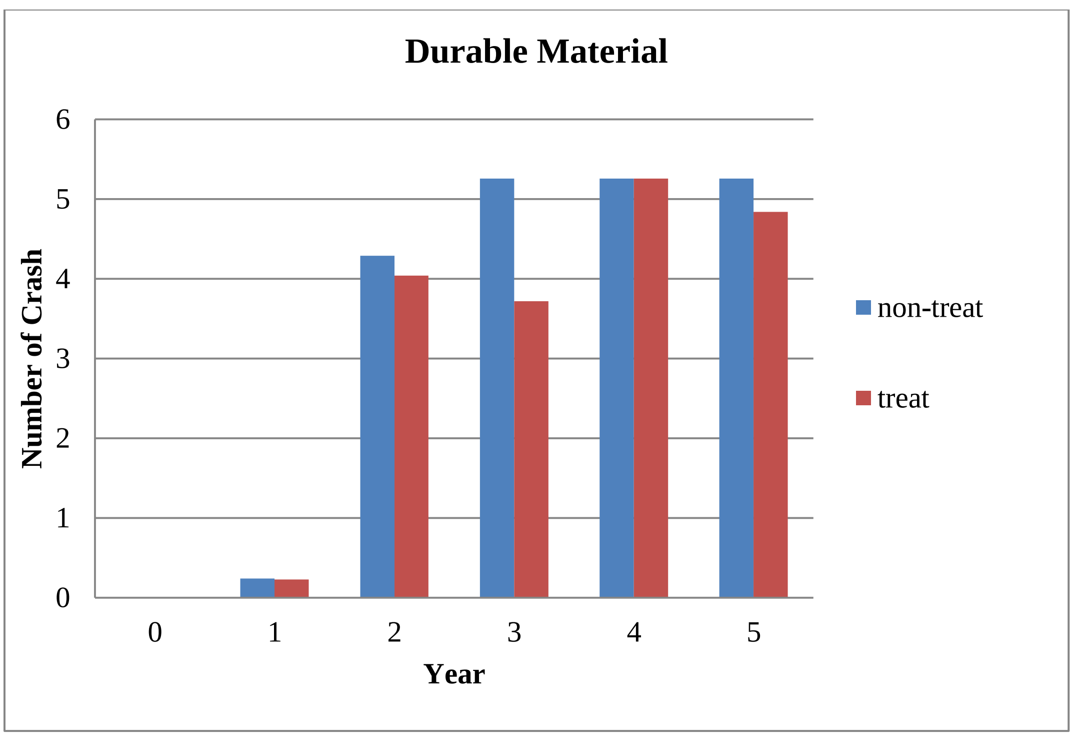

Figure D11 Durable Marking NPV in Range 2

Table D14 Tape Marking NPV in Range 2

			Tape			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	10674.28	-10674.28
1	0.2409	0.1903	0.0506	3736.15	10674.28	-6671.28
2	0.988	0.3712	0.6168	45542.68	10674.28	32237.79
3	3.5142	1.567	1.9472	143775.46	10674.28	118326.46
4	4.9808	4.0397	0.9411	69488.03	10674.28	50274.24
5	5.258	5.258	0	0.00	10674.28	-8773.48
					NPV	*174719.46*

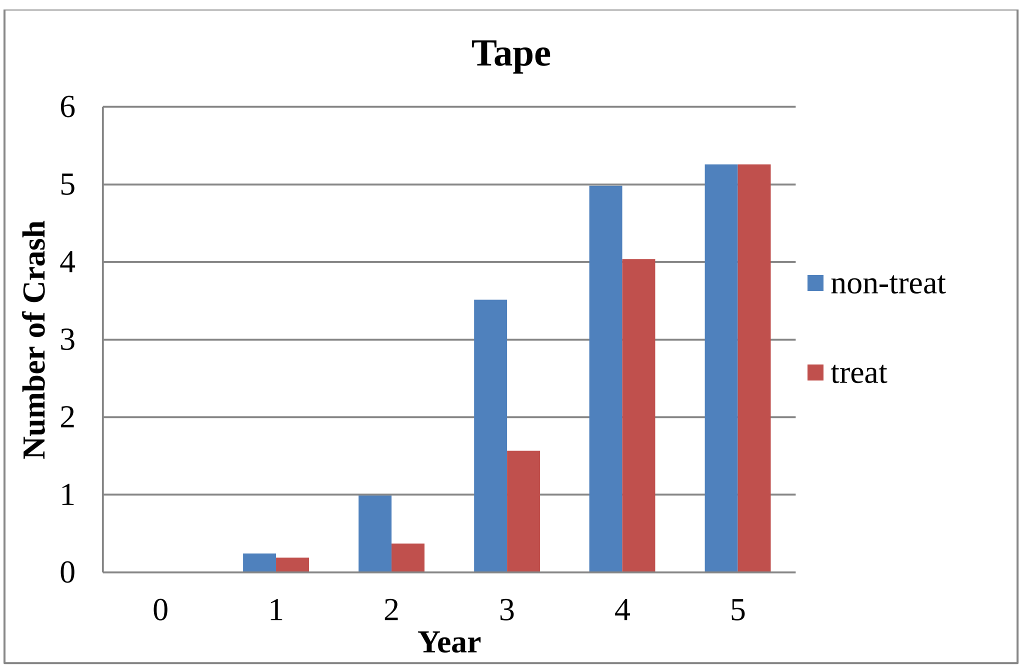

Figure D12 Tape Marking NPV in Range 2

Range 3: 2.0≤ACI<2.25

Table D15 Reconstruction NPV in Range 3

			Reconstruction			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	73581.75	-73581.75
1	0.1918	0.0708	0.121	8934.28	73581.75	-62161.03
2	0.2096	0.0773	0.1323	9768.64	73581.75	-58998.81
3	0.2289	0.0845	0.1444	10662.07	73581.75	-55935.37
4	0.2501	0.0923	0.1578	11651.48	73581.75	-52938.25
5	0.2733	0.1008	0.1725	12736.89	73581.75	-50010.04
					NPV	*-353625.25*

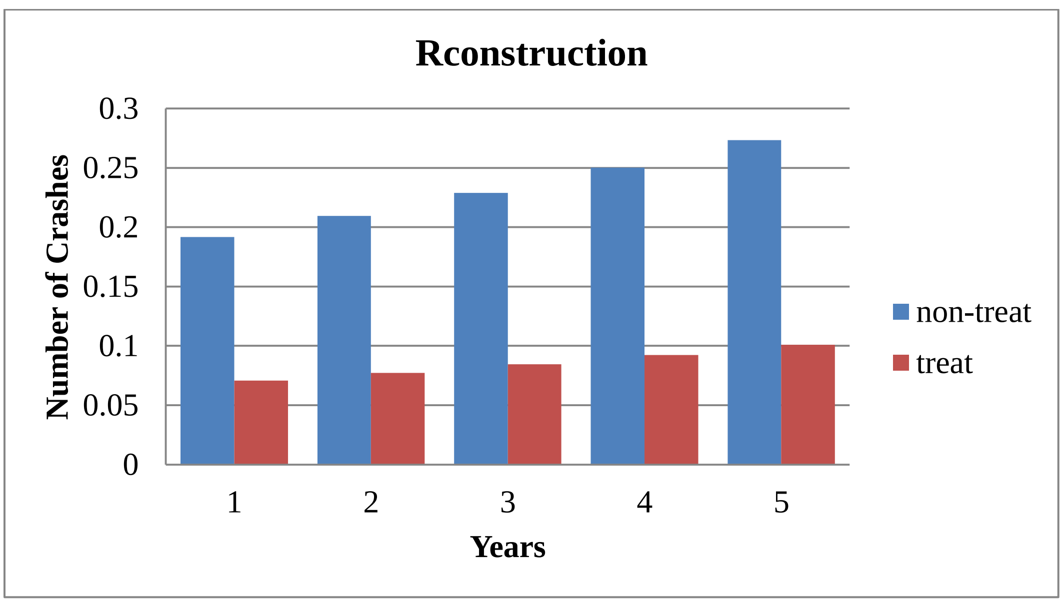

Figure D13 Reconstruction NPV in Range 3

Table D16 Major Rehabilitation NPV in Range 3

			Major			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	61645.47	-61645.47
1	0.1918	0.0708	0.121	8934.28	61645.47	-50683.84
2	0.2289	0.0773	0.1516	11193.69	61645.47	-46645.51
3	0.2733	0.0845	0.1888	13940.43	61645.47	-42409.61
4	0.3261	0.0923	0.2338	17263.10	61645.47	-37938.24
5	0.8058	0.1008	0.705	52055.10	61645.47	-7882.58
					NPV	*-247205.25*

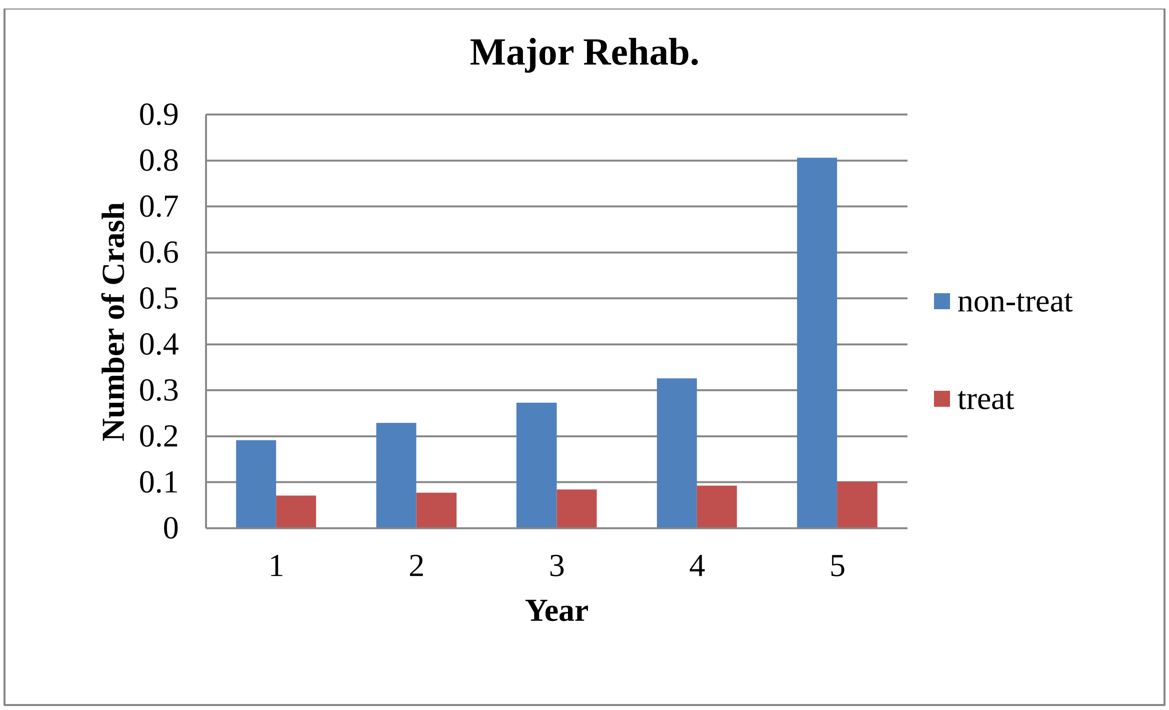

Figure D14 Major Rehabilitation NPV in Range 3

Table D17 Minor Rehabilitation NPV in Range 3

			Minor			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	54052.28	-54052.28
1	0.1918	0.1064	0.0854	6305.68	54052.28	-45910.19
2	0.3459	0.1918	0.1541	11378.29	54052.28	-39454.51
3	4.2821	0.3459	3.9362	290637.31	54052.28	210323.23
4	5.5141	4.2821	1.232	90967.22	54052.28	31555.04
5	5.5141	5.5141	0	0.00	54052.28	-44427.03
					NPV	*58034.25*

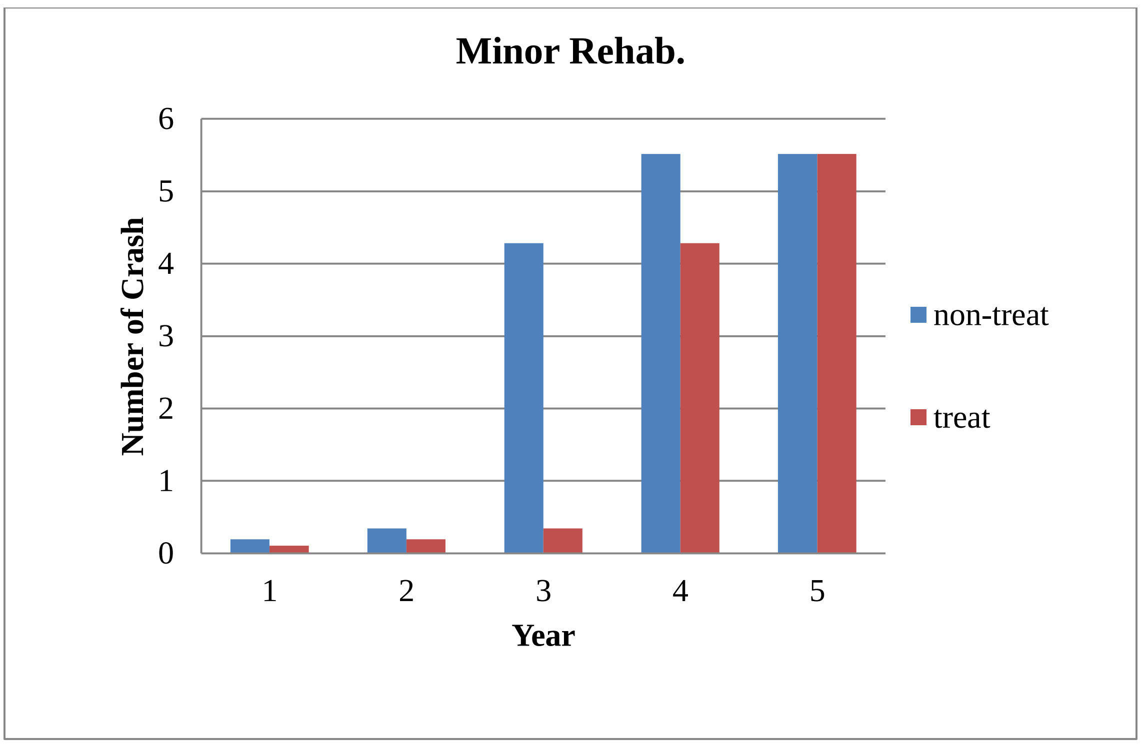

Figure D15 Minor Rehabilitation NPV in Range 3

Table D18 Paint Making NPV in Range 3

				Paint		
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	2376.00	-2376.00
1	0.1918	0.1896	0.0022	162.44	2376.00	-2128.42
2	5.5141	5.4229	0.0912	6733.94	2376.00	4029.16
3	5.5141	5.4229	0.0912	6733.94	2376.00	3874.19
4	5.5141	5.4229	0.0912	6733.94	2376.00	3725.18
5	5.5141	5.4229	0.0912	6733.94	2376.00	3581.91
					NPV	*10706.02*

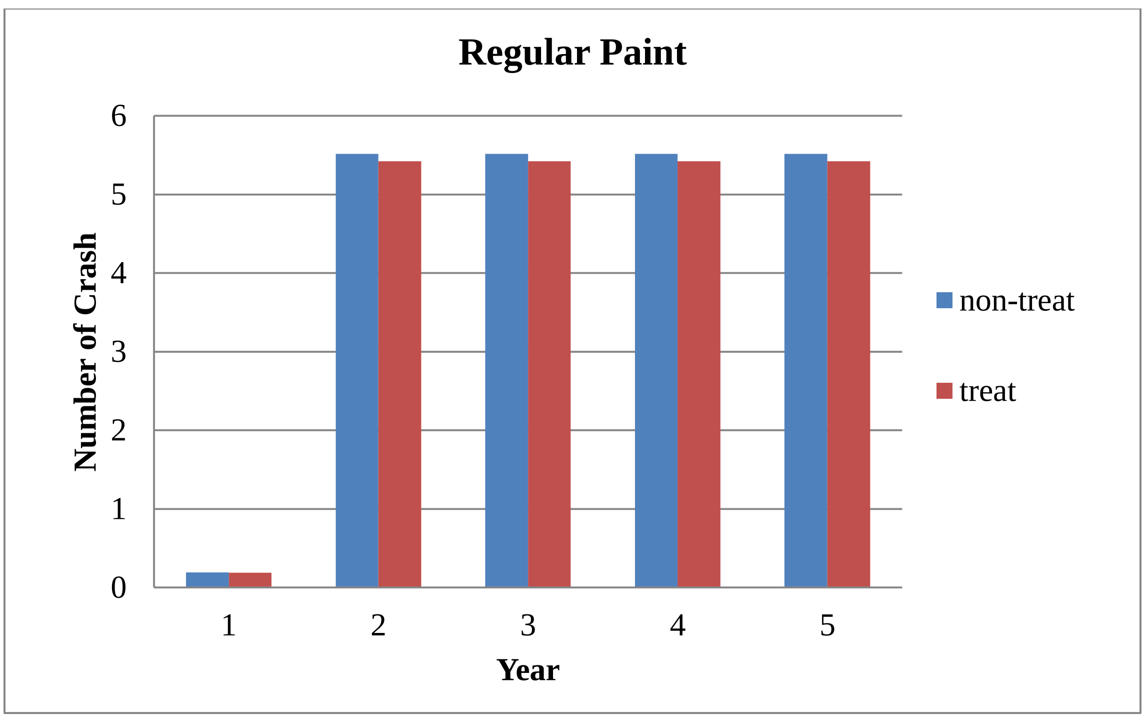

Figure D16 Paint Making NPV in Range 3

Table D19 Durable Marking NPV in Range 3

			Durable			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	6298.73	-6298.73
1	0.1918	0.1808	0.011	812.21	6298.73	-5275.50
2	2.3611	1.8584	0.5027	37117.87	6298.73	28494.03
3	5.5141	1.1559	4.3582	321796.53	6298.73	280476.40
4	5.5141	5.5141	0	0.00	6298.73	-5384.18
5	5.5141	5.0729	0.4412	32576.90	6298.73	21598.74
					NPV	*313610.75*

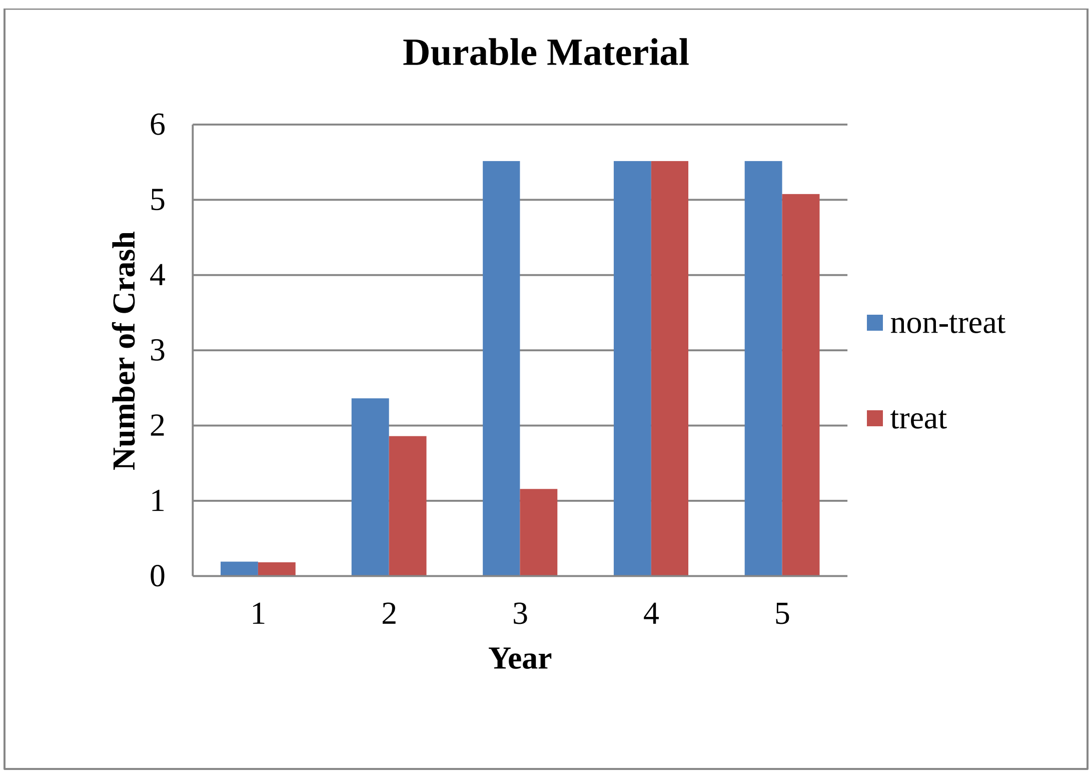

Figure D17 Durable Marking NPV in Range 3

Table D20 Tape Marking NPV in Range 3

Tape						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	10674.28	-10674.28
1	0.1918	0.1515	0.0403	2975.63	10674.28	-7402.55
2	0.2733	0.2158	0.0575	4245.63	10674.28	-5943.65
3	0.8058	0.3075	0.4983	36792.99	10674.28	23219.44
4	3.6242	1.8584	1.7658	130381.42	10674.28	102326.17
5	5.4087	4.2821	1.1266	83184.79	10674.28	59598.36
					NPV	*161123.49*

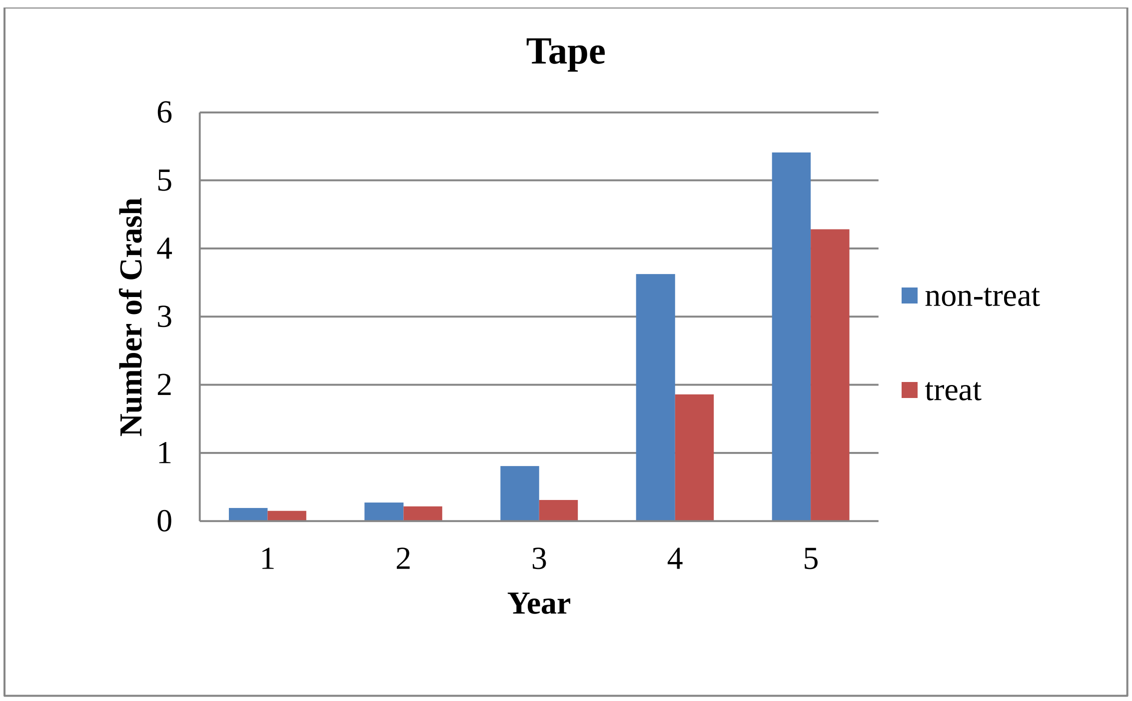

Figure D18 Tape Marking NPV in Range 3

Range 4: 2.25<ACI≤2.50

Table D21 Reconstruction NPV in Range 4

			Reconstruction			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	73581.75	-73581.75
1	0.1569	0.0778	0.0791	5840.51	73581.75	-65135.81
2	0.1714	0.085	0.0864	6379.52	73581.75	-62132.24
3	0.1873	0.0929	0.0944	6970.22	73581.75	-59217.41
4	0.2046	0.1015	0.1031	7612.60	73581.75	-56390.71
5	0.2235	0.1109	0.1126	8314.05	73581.75	-53645.29
					NPV	*-370103.21*

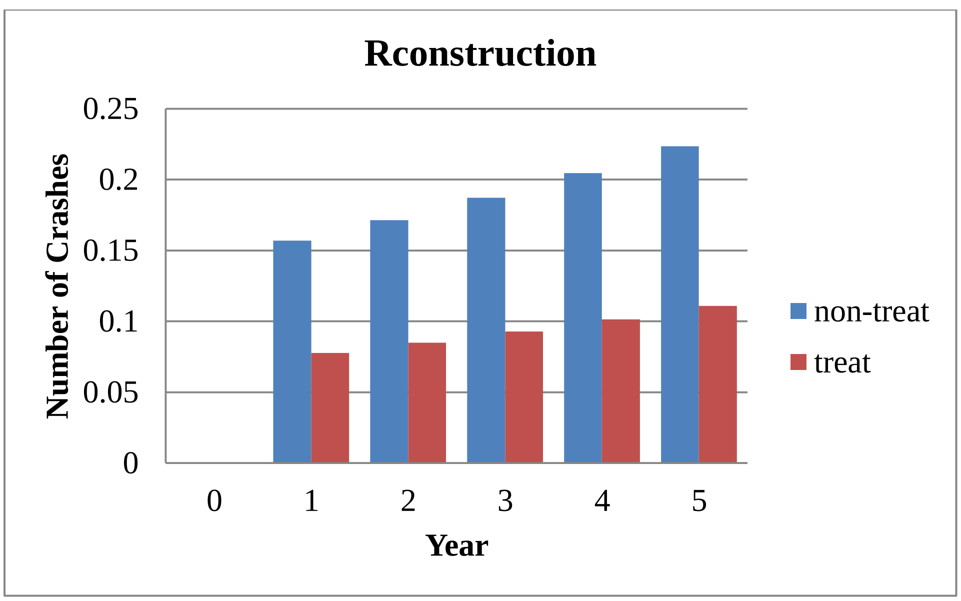

Figure D19 Reconstruction NPV in Range 4

Table D22 Major Rehabilitation NPV in Range 4

			Major			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	61645.47	-61645.47
1	0.1569	0.0778	0.0791	5840.51	61645.47	-53658.62
2	0.1873	0.0929	0.0944	6970.22	61645.47	-50550.35
3	0.2235	0.1109	0.1126	8314.05	61645.47	-47411.44
4	0.2668	0.1323	0.1345	9931.08	61645.47	-44205.68
5	0.3184	0.1579	0.1605	11850.84	61645.47	-40927.56
					NPV	*-298399.11*

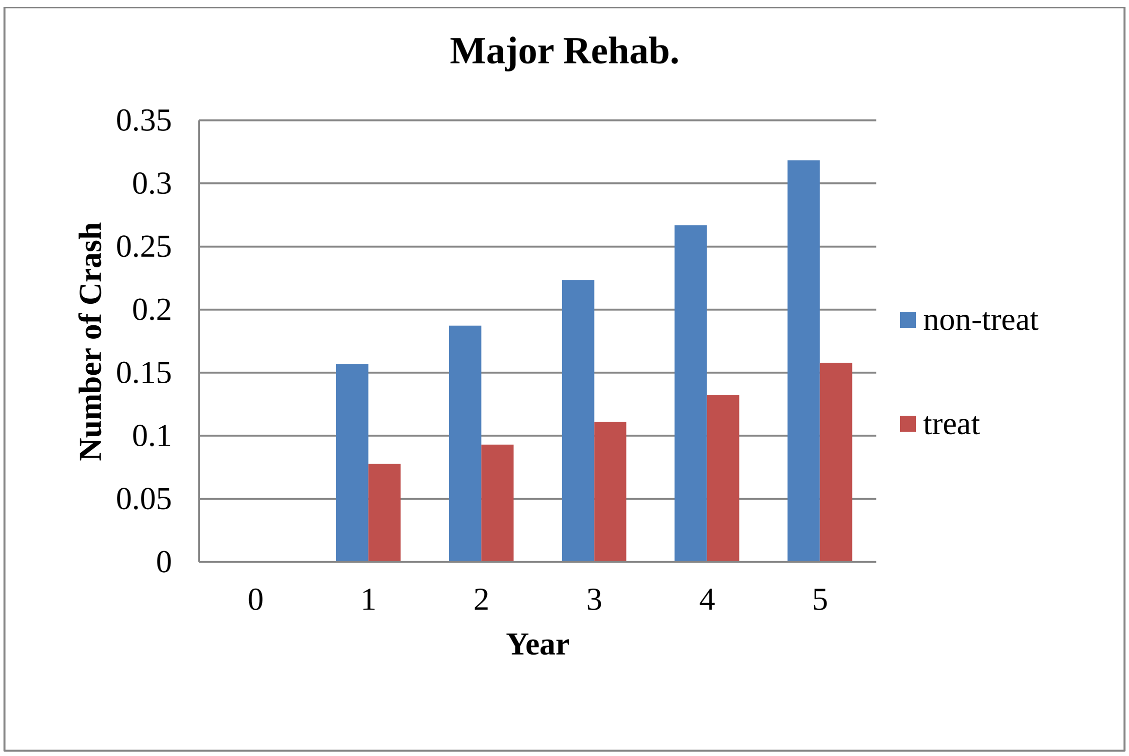

Figure D20 Major Rehabilitation NPV in Range 4

Table D23 Minor Rehabilitation NPV in Range 4

Minor						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	54052.28	-54052.28
1	0.1569	0.087	0.0699	5161.21	54052.28	-47010.65
2	0.283	0.1569	0.1261	9310.85	54052.28	-41365.97
3	2.3949	0.283	2.1119	155936.42	54052.28	90574.63
4	5.6707	0.1569	5.5138	407122.60	54052.28	301805.99
5	5.6707	0.283	5.3877	397811.75	54052.28	282545.23
					NPV	*532496.94*

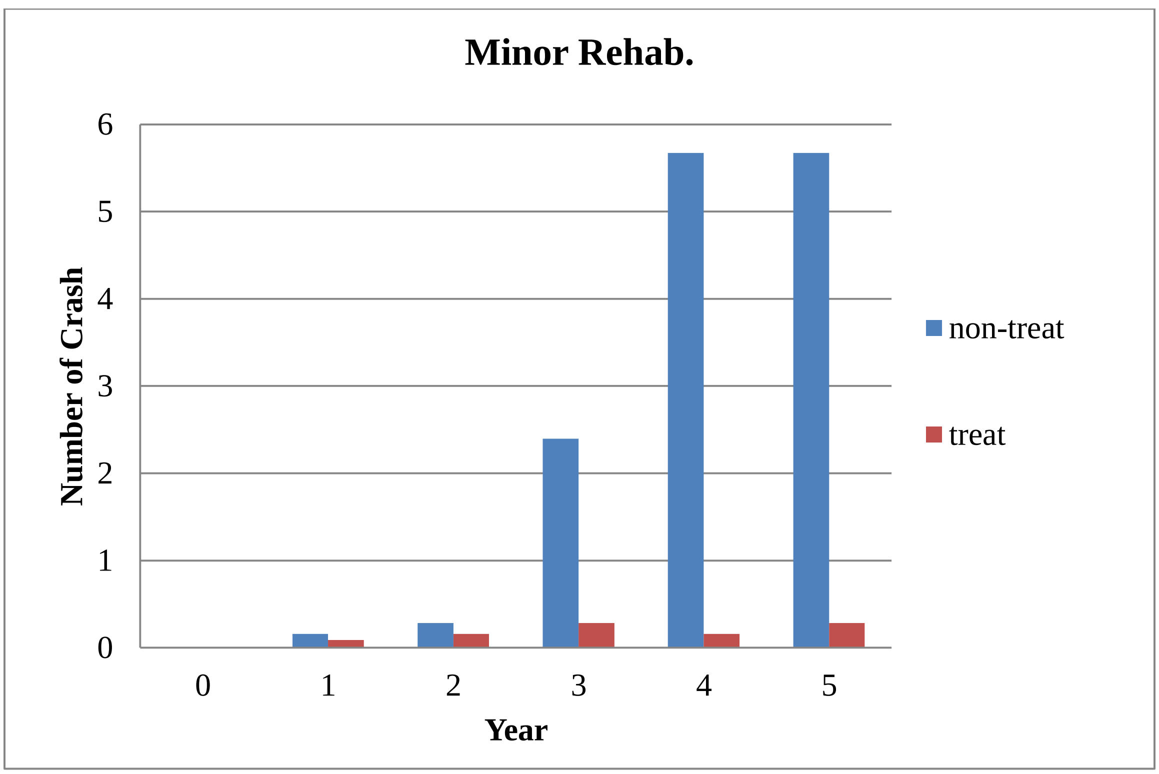

Figure D21 Minor Rehabilitation NPV in Range 4

Table D24 Paint Marking NPV in Range 4

			Paint			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	2376.00	-2376.00
1	0.1569	0.1551	0.0018	132.91	2376.00	-2156.82
2	5.6707	5.5769	0.0938	6925.91	2376.00	4206.65
3	5.6707	5.5769	0.0938	6925.91	2376.00	4044.86
4	5.6707	5.5769	0.0938	6925.91	2376.00	3889.28
5	5.6707	5.5769	0.0938	6925.91	2376.00	3739.70
					NPV	*11347.67*

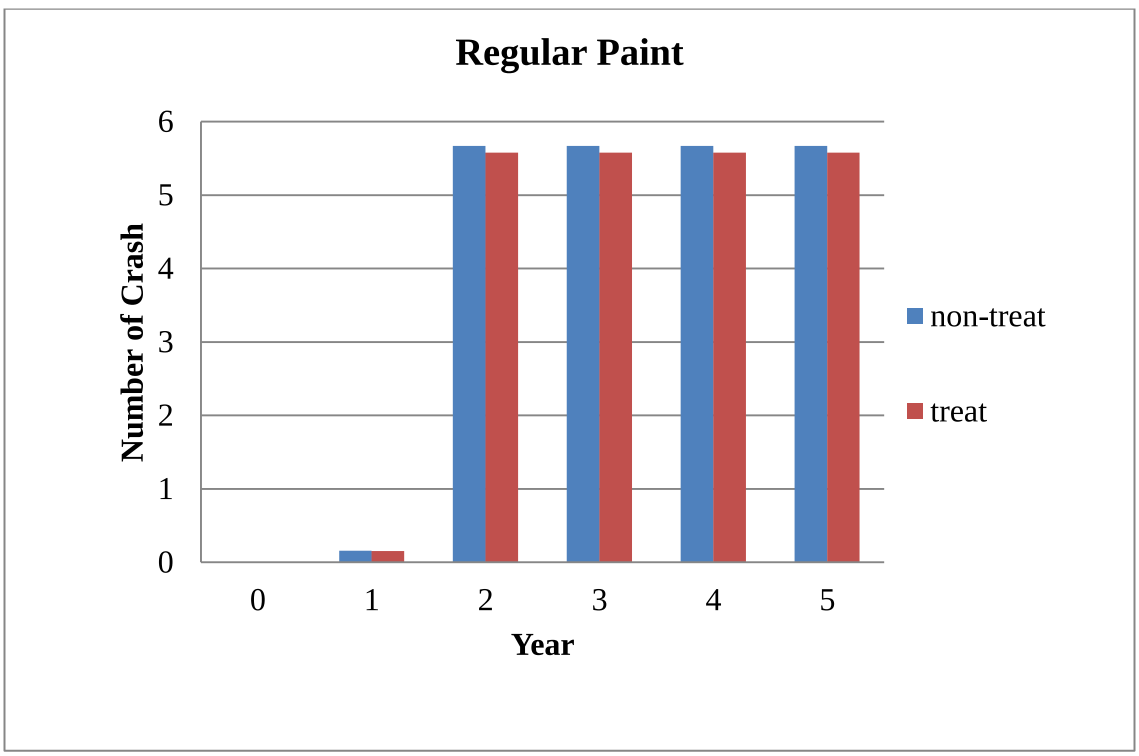

Figure D22 Paint Marking NPV in Range 4

Table D25 Durable Marking NPV in Range 4

Durable						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	6298.73	-6298.73
1	0.1569	0.1479	0.009	664.53	6298.73	-5417.50
2	0.38	0.3583	0.0217	1602.26	6298.73	-4342.15
3	5.6707	0.3378	5.3329	393765.48	6298.73	344456.53
4	5.6707	5.384	0.2867	21169.08	6298.73	12711.23
5	5.6707	4.9532	0.7175	52978.07	6298.73	38367.01
					NPV	*379476.41*

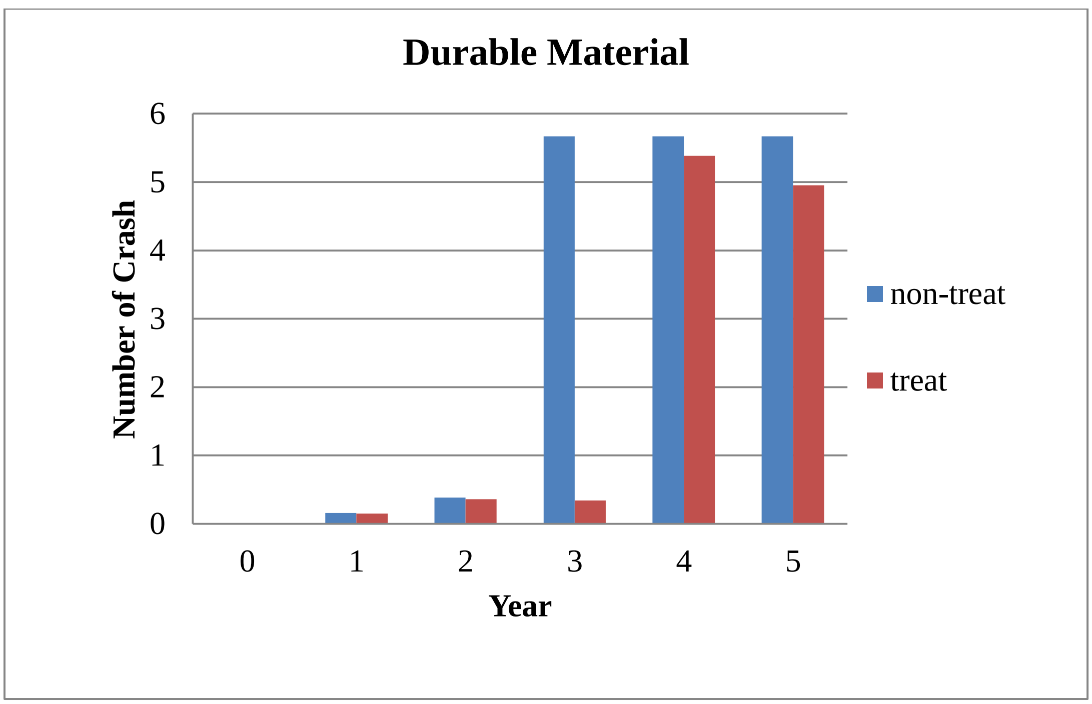

Figure D23 Durable Marking NPV in Range 4

Table D26 Tape Marking NPV in Range 4

Tape						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	10674.28	-10674.28
1	0.1569	0.1239	0.033	2436.62	10674.28	-7920.83
2	0.2235	0.1766	0.0469	3462.96	10674.28	-6667.27
3	0.3184	0.2515	0.0669	4939.70	10674.28	-5098.02
4	1.3635	0.3583	1.0052	74220.98	10674.28	54319.98
5	4.0375	2.3949	1.6426	121284.70	10674.28	90913.70
					NPV	*114873.28*

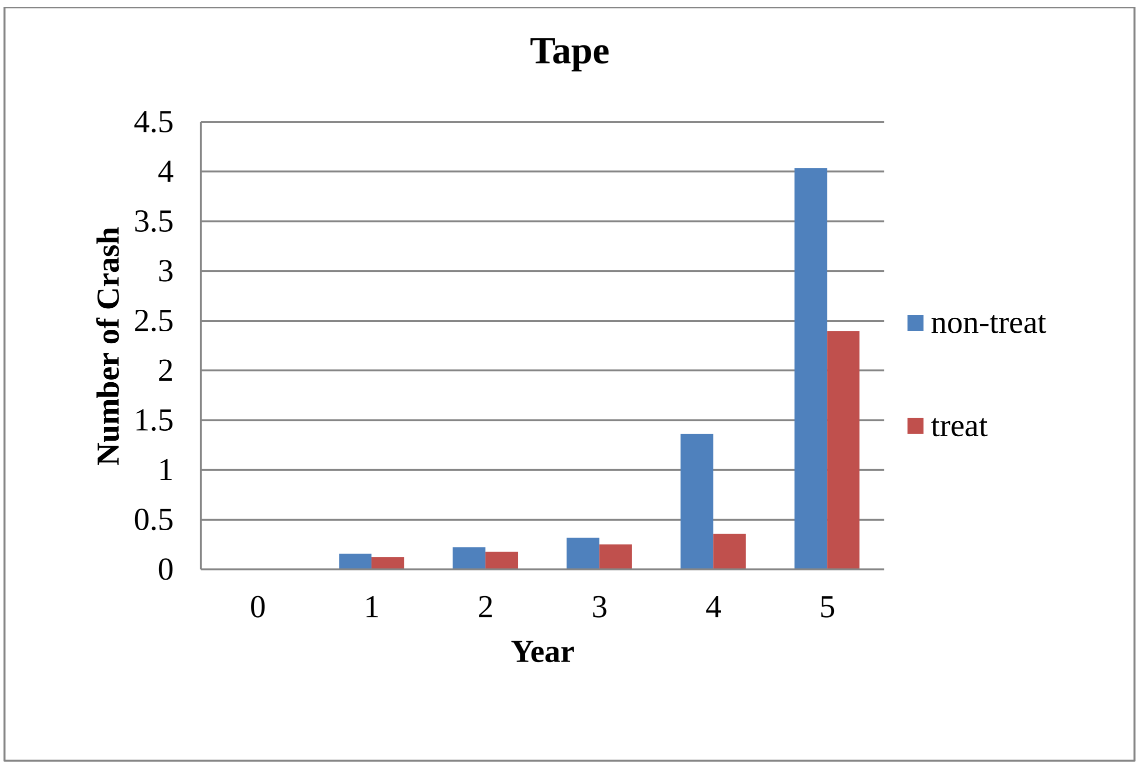

Figure D24 Tape Marking NPV in Range

Range 5: 2.50<ACI≤2.75

Table D27 Reconstruction NPV in Range 5

				Reconstruction		
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	73581.75	-73581.75
1	0.1251	0.0796	0.0455	3359.58	73581.75	-67521.31
2	0.1366	0.0869	0.0497	3669.70	73581.75	-64637.62
3	0.1493	0.095	0.0543	4009.35	73581.75	-61849.61
4	0.1631	0.1037	0.0594	4385.92	73581.75	-59148.89
5	0.1782	0.1133	0.0649	4792.02	73581.75	-56540.14
					NPV	*-383279.32*

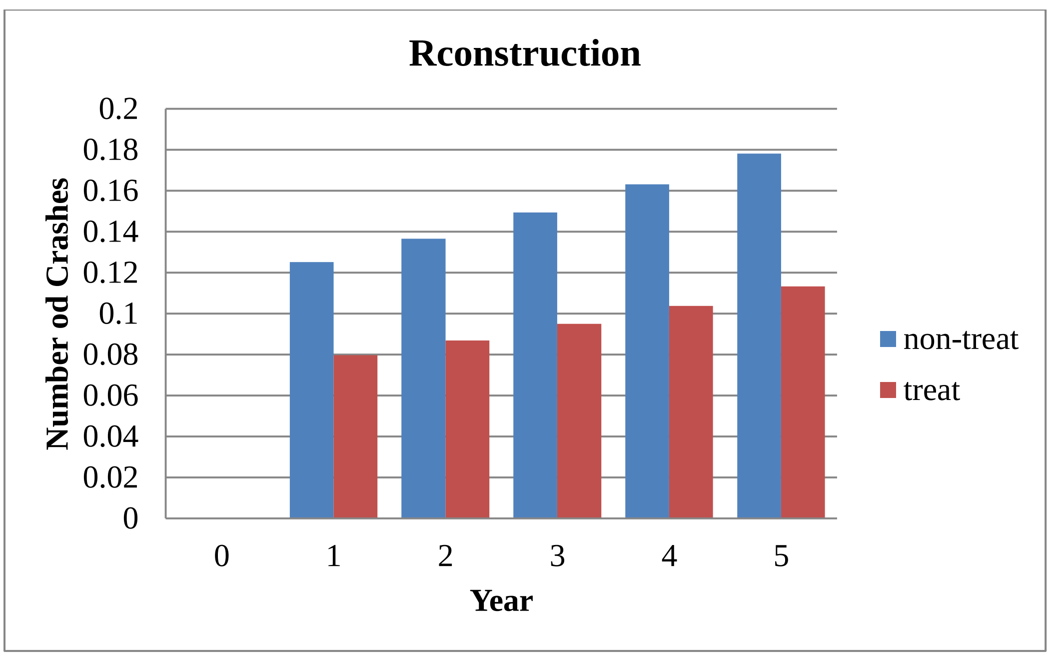

Figure D25 Reconstruction NPV in Range 5

Table D28 Major Rehabilitation NPV in Range 5

			Major			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	61645.47	-61645.47
1	0.1251	0.0796	0.0455	3359.58	61645.47	-56044.12
2	0.1493	0.1133	0.036	2658.13	61645.47	-54537.11
3	0.1782	0.1353	0.0429	3167.61	61645.47	-51986.61
4	0.2127	0.1615	0.0512	3780.46	61645.47	-49463.26
5	0.2538	0.1927	0.0611	4511.44	61645.47	-46960.01
					NPV	*-320636.58*

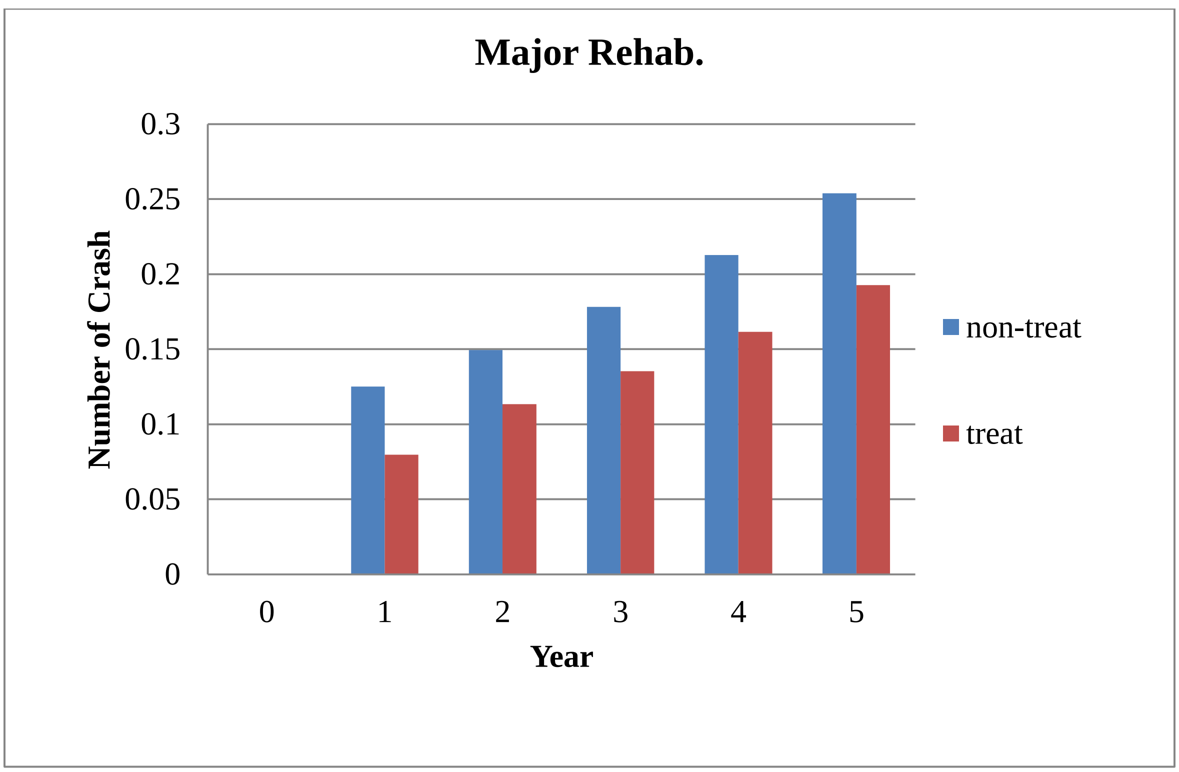

Figure D26 Major Rehabilitation NPV in Range 5

Table D29 Minor Rehabilitation NPV in Range 5

			Minor			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	54052.28	-54052.28
1	0.1251	0.0796	0.0455	3359.58	54052.28	-48742.98
2	0.2256	0.1435	0.0821	6062.02	54052.28	-44369.69
3	0.4068	0.2588	0.148	10927.88	54052.28	-38337.44
4	4.7341	0.1435	4.5906	338956.26	54052.28	243537.11
5	5.7663	0.2588	5.5075	406657.43	54052.28	289815.73
					NPV	*347850.45*

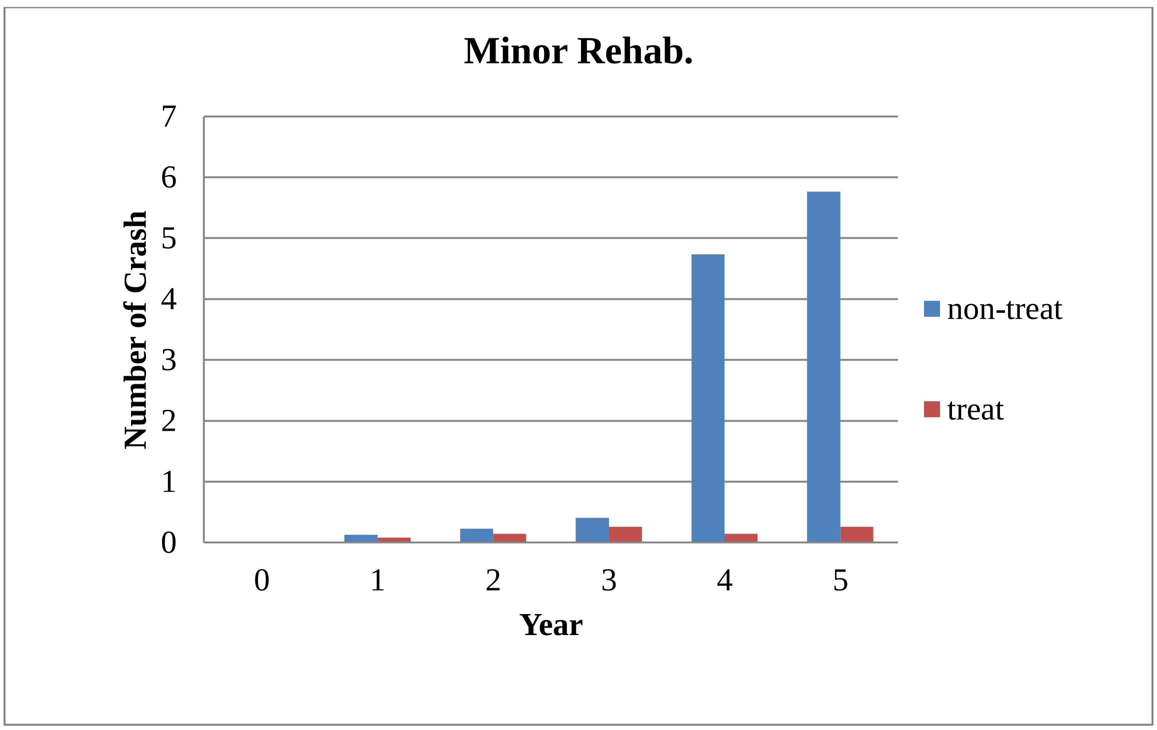

Figure D27 Minor Rehabilitation NPV in Range 5

Table D30 Paint Making NPV in Range 5

			Paint			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	2376.00	-2376.00
1	0.1251	0.1236	0.0015	110.76	2376.00	-2178.12
2	5.7663	5.6709	0.0954	7044.05	2376.00	4315.88
3	5.7663	5.6709	0.0954	7044.05	2376.00	4149.88
4	5.7663	5.6709	0.0954	7044.05	2376.00	3990.27
5	5.7663	5.6709	0.0954	7044.05	2376.00	3836.80
					NPV	*11738.71*

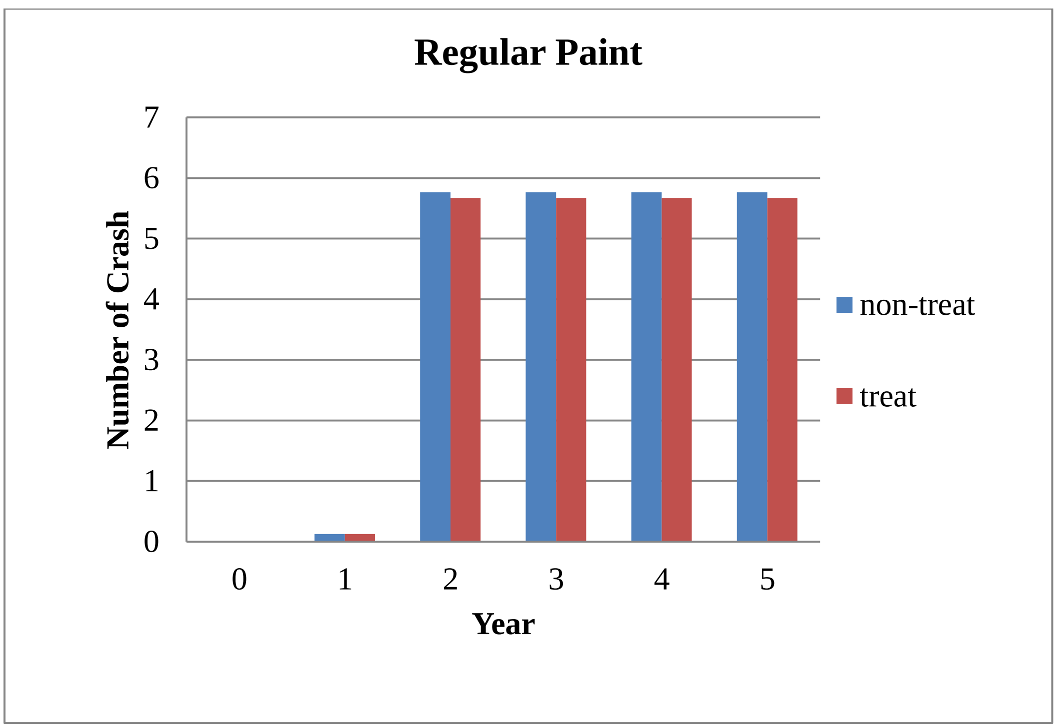

Figure D28 Paint Making NPV in Range 5

Table D31 Durable Marking NPV in Range 5

			Durable			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	6298.73	-6298.73
1	0.1251	0.1179	0.0072	531.63	6298.73	-5545.29
2	0.3029	0.2856	0.0173	1277.38	6298.73	-4642.52
3	4.7341	0.4485	4.2856	316435.96	6298.73	275710.87
4	5.7663	4.6119	1.1544	85237.46	6298.73	67477.16
5	5.7663	4.2429	1.5234	112483.33	6298.73	87276.00
					NPV	*413977.49*

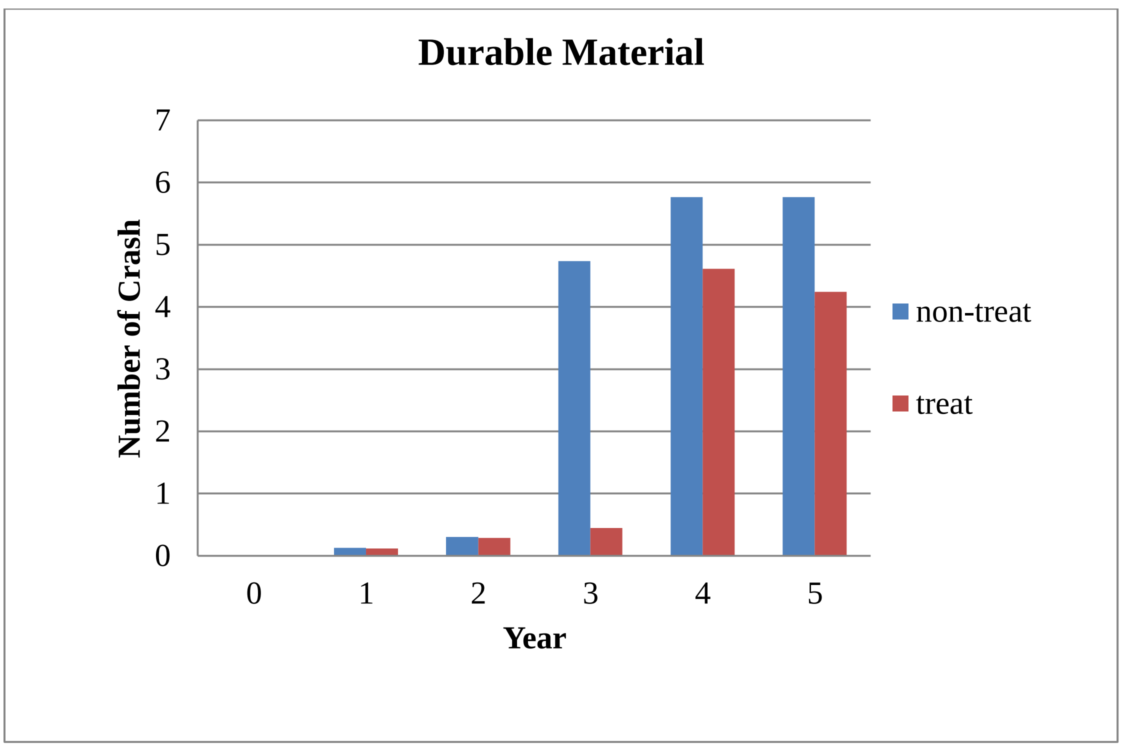

Figure D29 Durable Marking NPV in Range 5

Table D32 Tape Marking NPV in Range 5

Tape						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	10674.28	-10674.28
1	0.1251	0.0988	0.0263	1941.91	10674.28	-8396.51
2	0.1782	0.1407	0.0375	2768.89	10674.28	-7308.98
3	0.2538	0.2005	0.0533	3935.51	10674.28	-5990.74
4	0.3616	0.2856	0.076	5611.61	10674.28	-4327.59
5	2.5209	0.4068	2.1141	156098.86	10674.28	119528.40
					NPV	*82830.31*

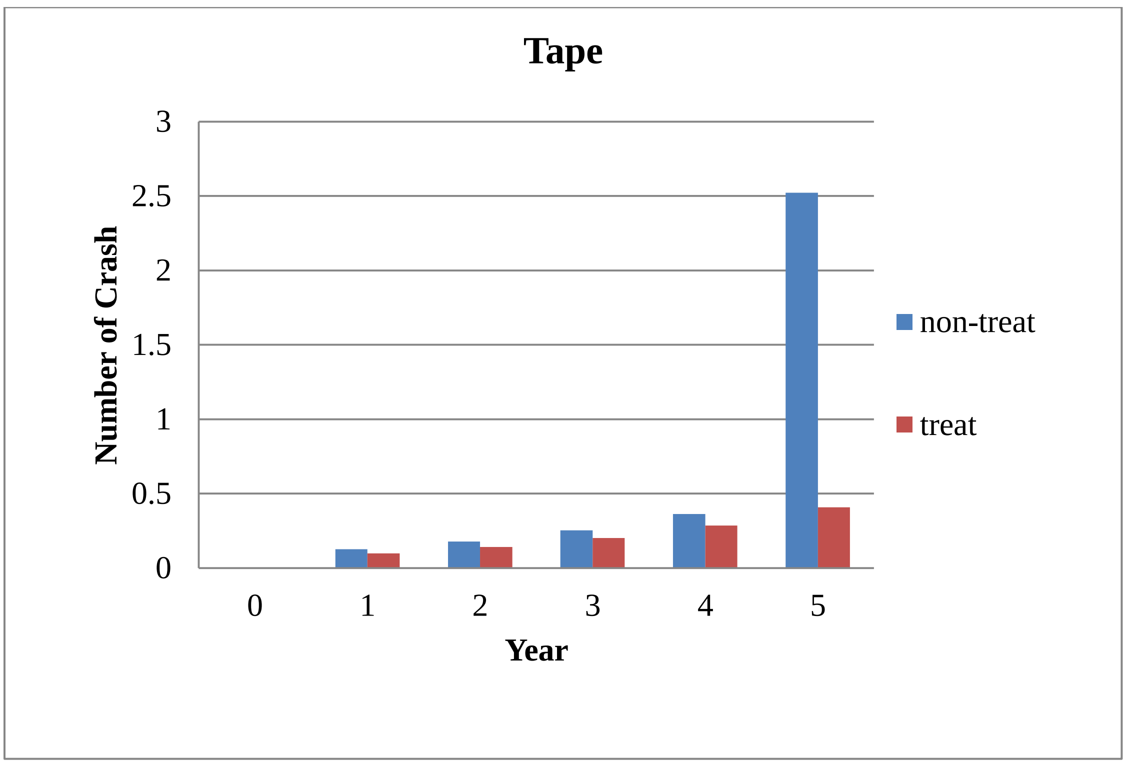

Figure D30 Tape Marking NPV in Range 5

Range 6: 2.75<ACI≤3.0

Table D33 Reconstruction NPV in Range 6

			Reconstruction			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	73581.75	-73581.75
1	0.1251	0.0796	0.0455	3359.58	73581.75	-67521.31
2	0.1366	0.0869	0.0497	3669.70	73581.75	-64637.62
3	0.1493	0.095	0.0543	4009.35	73581.75	-61849.61
4	0.1631	0.1037	0.0594	4385.92	73581.75	-59148.89
5	0.1782	0.1133	0.0649	4792.02	73581.75	-56540.14
					NPV	*-383279.32*

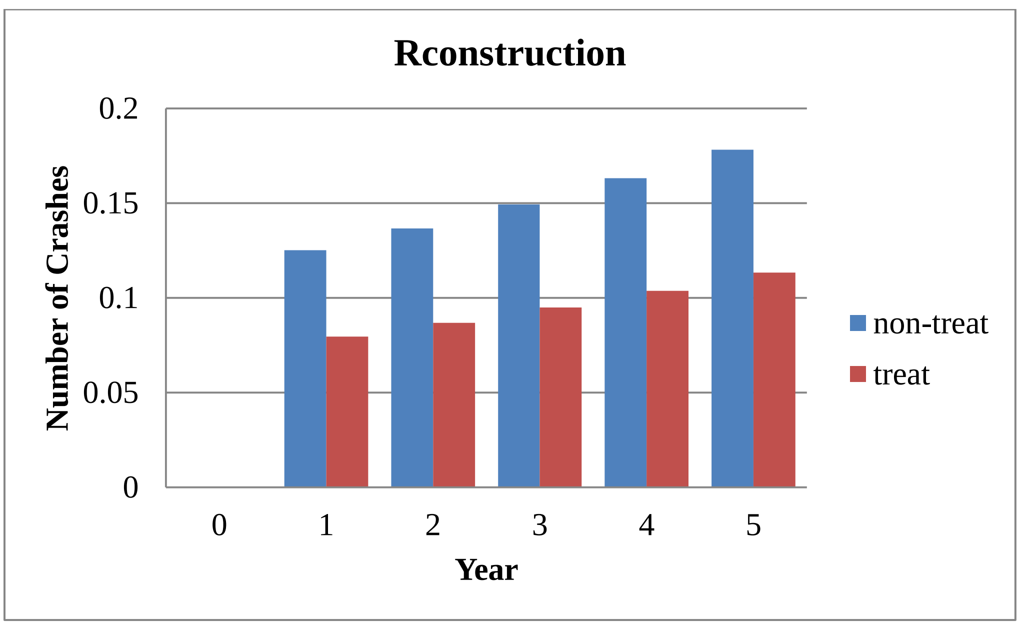

Figure D31 Reconstruction NPV in Range 6

Table D34 Major Rehabilitation NPV in Range 6

			Major			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	61645.47	-61645.47
1	0.0813	0.0672	0.0141	1041.10	61645.47	-58273.43
2	0.097	0.0802	0.0168	1240.46	61645.47	-55847.83
3	0.1157	0.0957	0.02	1476.74	61645.47	-53489.78
4	0.1381	0.1142	0.0239	1764.70	61645.47	-51186.33
5	0.1649	0.1363	0.0286	2111.74	61645.47	-48932.39
					NPV	*-329375.24*

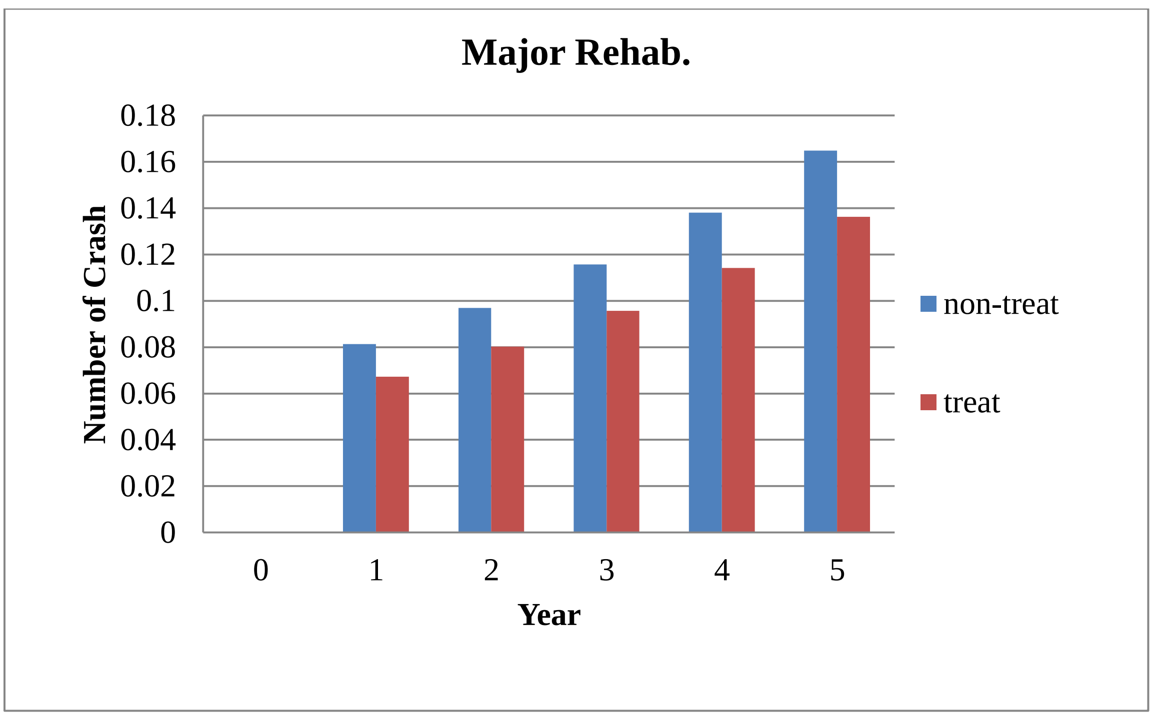

Figure D32 Major Rehabilitation NPV in Range 6

Table D35 Minor Rehabilitation NPV in Range 6

			Minor			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	54052.28	-54052.28
1	0.0813	0.0672	0.0141	1041.10	54052.28	-50972.29
2	0.1465	0.1211	0.0254	1875.46	54052.28	-48240.40
3	0.2643	0.2184	0.0459	3389.12	54052.28	-45039.37
4	3.0273	0.1311	2.8962	213846.80	54052.28	136593.02
5	5.4225	0.2184	5.2041	384255.27	54052.28	271402.79
					NPV	*209691.47*

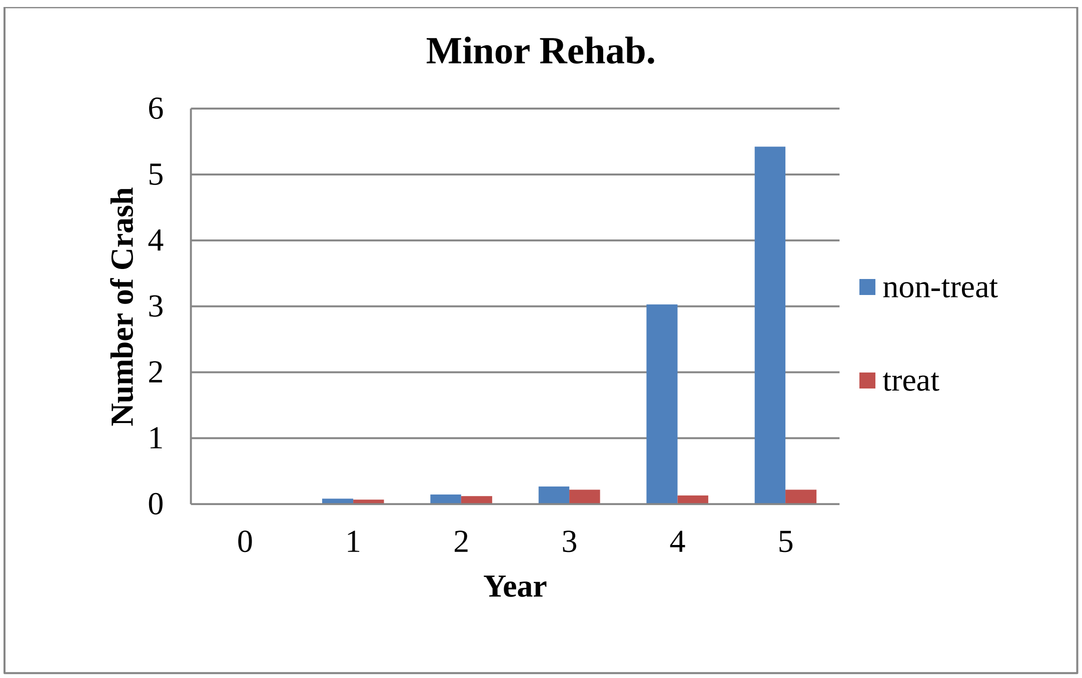

Figure D33 Minor Rehabilitation NPV in Range 6

Table D36 Paint Making NPV in Range 6

Paint						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	2376.00	-2376.00
1	0.0813	0.0803	0.001	73.84	2376.00	-2213.62
2	5.4225	5.3328	0.0897	6623.18	2376.00	3926.76
3	5.4225	5.3328	0.0897	6623.18	2376.00	3775.73
4	5.4225	5.3328	0.0897	6623.18	2376.00	3630.51
5	5.4225	5.3328	0.0897	6623.18	2376.00	3490.87
					NPV	*10234.25*

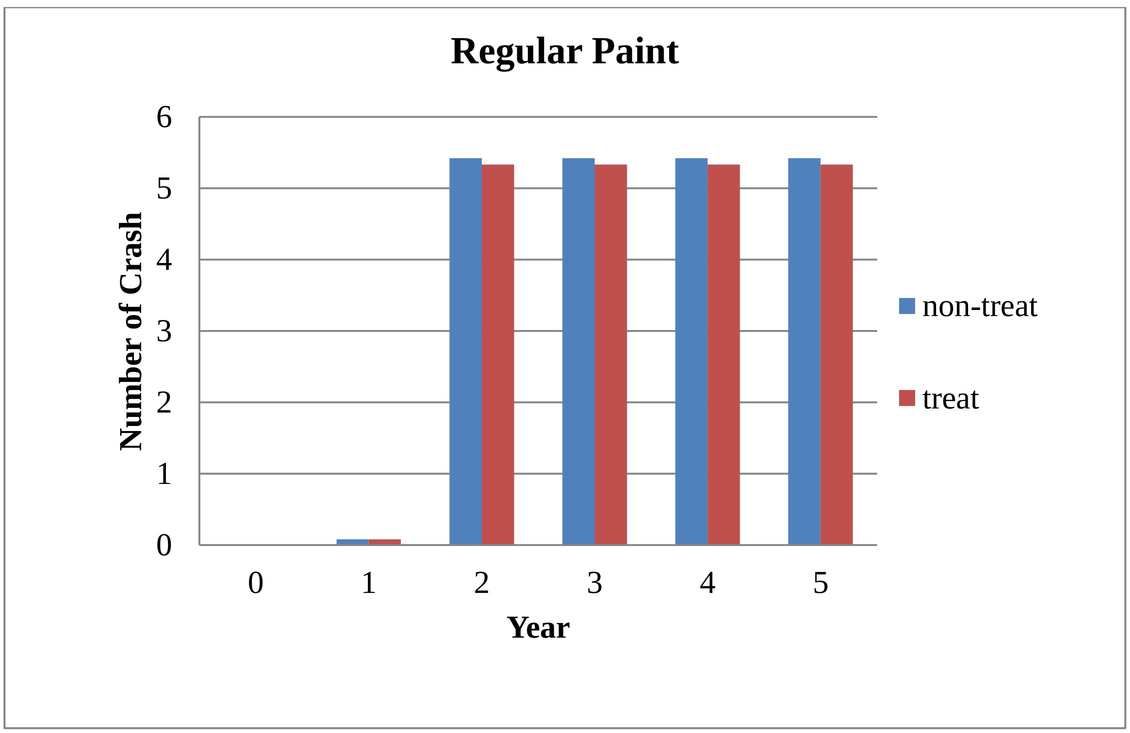

Figure D34 Paint Making NPV in Range 6

Table D37 Durable Marking NPV in Range 6

			Durable			
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	6298.73	-6298.73
1	0.0813	0.0767	0.0046	339.65	6298.73	-5729.88
2	0.1968	0.1858	0.011	812.21	6298.73	-5072.60
3	3.0273	0.1751	2.8522	210597.97	6298.73	181621.28
4	5.4225	2.4673	2.9552	218203.18	6298.73	181136.81
5	5.4225	1.1389	4.2836	316288.29	6298.73	254788.82
					NPV	*600445.70*

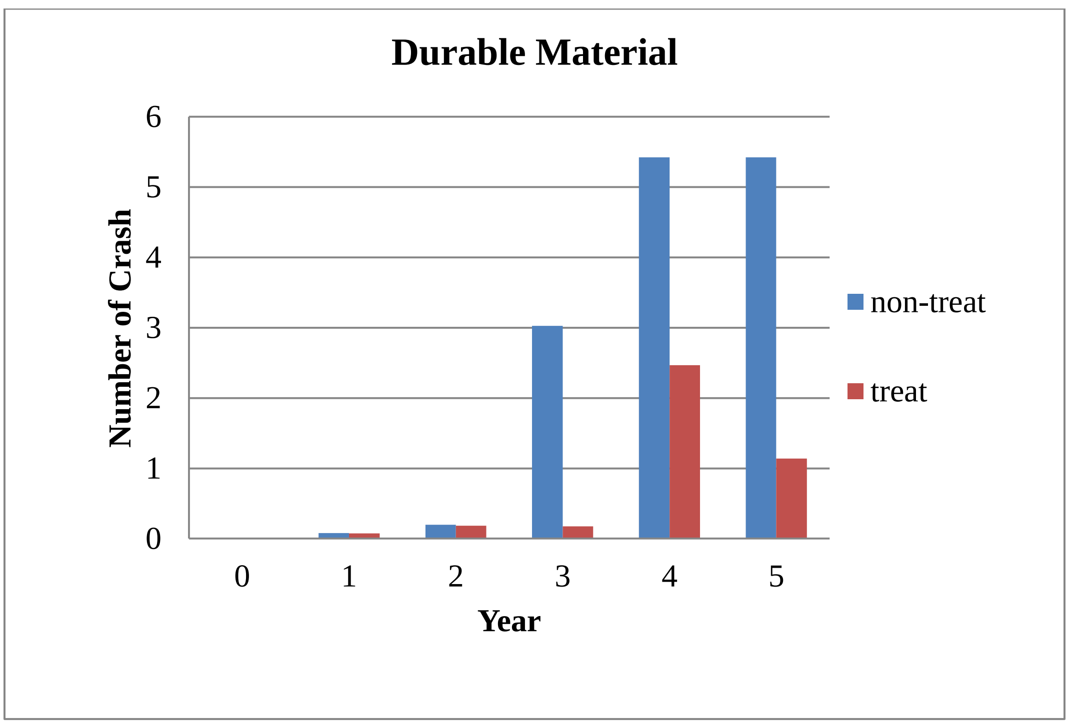

Figure D35 Durable Marking NPV in Range 6

Table D38 Tape Marking NPV in Range 6

Tape						
year	non-treat	treat	reduce	Benefit	Cost (EUAC)	PV
0	0	0	0	0.00	10674.28	-10674.28
1	0.0813	0.0672	0.0141	1041.10	10674.28	-9262.67
2	0.1157	0.0957	0.02	1476.74	10674.28	-8503.64
3	0.1649	0.1363	0.0286	2111.74	10674.28	-7612.07
4	0.2349	0.1941	0.0408	3012.55	10674.28	-6549.28
5	0.3346	0.2766	0.058	4282.55	10674.28	-5253.54
					NPV	*-47855.48*

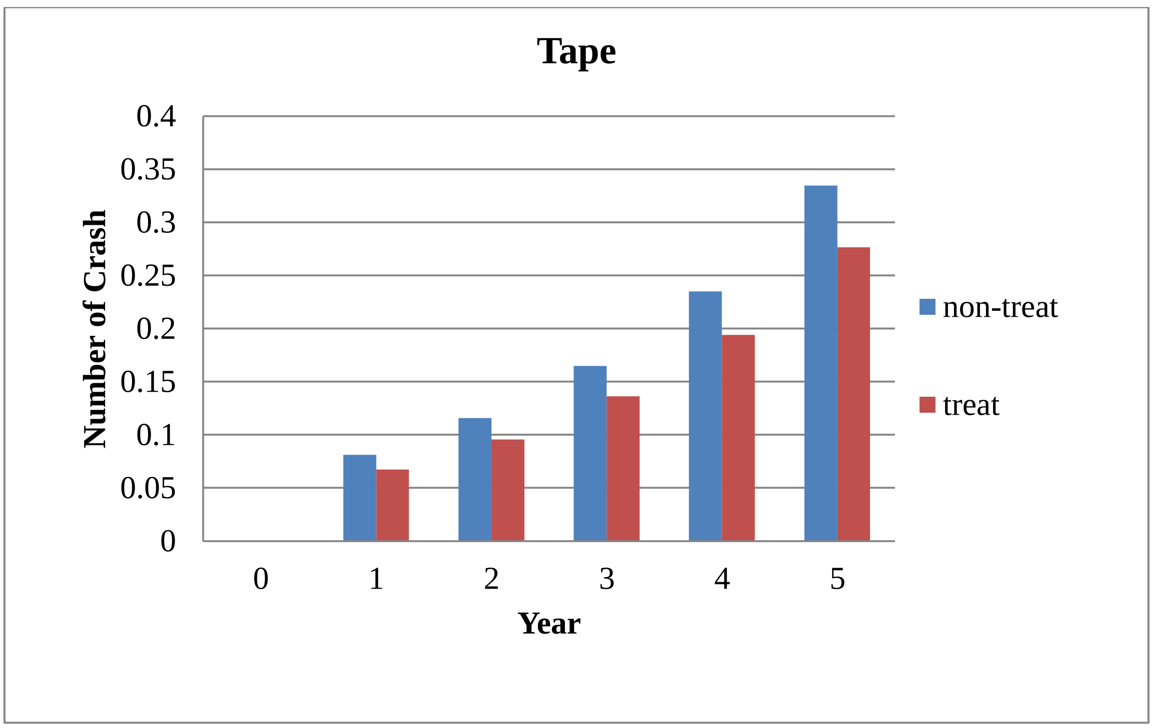

Figure D36 Tape Marking NPV in Range 6