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Incorporating safety into transportation planning for small and medium-sized communities

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Incorporating safety into transportation planning for small and medium-sized communities

by

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ABSTRACT

The City of Ames, in Iowa is a typical small-sized urban area. In 2008, the city had an estimated population of 56,500 and covered an area of 21.6 square miles. In 2003, the Ames Area Metropolitan Planning Organization (AAMPO) was designated with a planning area of 36 square miles. Ames hosts Iowa State University with an enrollment of 27,900 as of Fall 2009. During the period 2002–2008, on average 1,000 traffic crashes (of property damage over $1,000 worth) occurred. To meet the requirement of future development and solve the transportation problem facing today, city planners and engineers are seeking additional ways to explicitly consider safety in the transportation planning process.

Historically, the approach to safety problem identification and mitigation has been reactive; "black spots or hot spots" have been identified by ranking locations based on the crash frequency and severity, mainly at the corridor-level and without considering the exposure rate (vehicle miles traveled) and socio-demographics of the study area. To address safety in planning process, a larger study analysis area at the Transportation Analysis Zone (TAZ) level or the network planning-level should be used to address the needs of development of the community in the future and incorporate safety into long-range transportation planning process.

This thesis examines how existing planning models (for example, the PLANSAFE models presented in NCHRP Report 546) can be used for forecasting safety in the future in small and medium-sized communities, due to changes in socio-demographics, traffic demand, road network and countermeasures. The thesis also evaluates the applicability of the Empirical Bayes (EB) method to network-level analysis for small planning areas. Finally, application of US Road Assessment Program (usRAP) protocols at the local urban road network is investigated. It is anticipated that incorporating safety methods into the long-range transportation planning process can assist city decision-makers in setting and monitoring progress towards transportation safety goals.

Key Words: Transportation Planning, Safety, Small and Medium-Size Communities.

CHAPTER 1. INTRODUCTION

1.1 Problem Statement and Background Summary

According to the US Department of Transportation (US DOT), over 40,000 crash fatalities occurred in the United States every year during the period 2002-2007. In 2009, the number of crash fatalities dropped to 33,808. Still, the Federal Highway Administration (FHWA) stresses that, "Safety should be considered first, every time and at every stage of a project. Make safety your first consideration in every investment decision". Safety-related legislation (e.g., SAFETEA-LU) mandates planning by state departments of transportation that "considers the results of state, regional, or local transportation and highway safety planning processes." Although there is an increasing interest in developing safety performance measures and incorporating safety into transportation planning process, a few tools are available that planning agencies could use. Moreover, there is no national guidance on how to measure and incorporate safety into transportation planning process for small and medium-sized communities. This thesis investigates the applicability of three safety analysis methodologies to planning for small area planning agencies, where the lack of guidance is particularly challenging.

The City of Ames, Iowa is a typical small-sized urban area. In 2008, the city had an estimated population of 56,500 and covered an area of 21.6 square miles. In 2003, the Ames Area Metropolitan Planning Organization (AAMPO) was designated with a planning area of 36 square miles. Ames hosts Iowa State University with an enrollment of 27,900 as of Fall 2009. During the period 2002–2008, on average 1,000 traffic crashes (of property damage over $1,000) occurred per year. City planners and engineers are seeking additional ways to explicitly consider safety in the transportation planning process.

The City of Ames is representative of hundreds of small and medium-sized communities across the United States. For these communities, safety has traditionally been considered separately from the regional transportation planning process, and has typically been incorporated only at the project design level or addressed by enforcement agencies. "Incorporating safety considerations and strategies into the transportation planning process includes not only a consideration of safety-related capital projects and system operations strategies, but also a concern for public education, enforcement and emergency response to incidents" (Washington et al., 2006).

The historically reactive approach to identifying safety problems and mitigating them involves selecting "black spots or hot spots" by ranking locations based on the crash frequency and severity. The approach mainly focuses on the corridor-level without taking the exposure rate (vehicle miles traveled) and socio-demographics information, which is very important in the transportation planning process, of the study area in to consideration. A larger study analysis unit at the Transportation Analysis Zone (TAZ) level or the network planning-level should be used to address the needs of development of the community in the future and incorporate safety into long-range transportation planning process.

In this thesis, existing planning tools (for example, the PLANSAFE models presented in NCHRP Report 546) are examined for forecasting safety in small and medium-sized communities, particularly as related to changes in socio-demographics characteristics, traffic demand, road network and countermeasures. The thesis also evaluates the applicability of the Empirical Bayes (EB) method to network-level analysis. EB has been adopted in recent model-based ranking safety studies (Hauer et al. 2002; Miranda-Moreno and Fu, 2006; Persaud and Lyon, 2007). In addition, application of US Road Assessment Program (usRAP) protocols at the local urban road network is investigated. This thesis evaluated the applicability of these methods and examined whether incorporating safety methods into the long-range transportation planning process can assist city decision-makers in setting and monitoring progress towards transportation safety goals.

1.2 Research Objective and Tasks

The main objective of this thesis was to develop a safety planning tool useful for screening the network of the City of Ames for safety problems. The plan for this thesis included the following tasks.

Task 1: Literature Review

Synthesize the state-of-the practice at the state and regional level, and document best practices in safety programming. Document and assess the state-of-the practice in safety planning/programming across metropolitan and small urban areas in the state and nationwide.

Task 2: Data Collection and Descriptive Data Analysis

Compile crash data for the City of Ames and quantify the trends (increasing or decreasing) in fatal, injury and other crashes during the analysis period.

The analysis period (7 years) and analysis network (all roads) were defined in consultation with traffic engineers and planners with the City of Ames. The Iowa Traffic Safety Data Service at Iowa State University provided crash data which were analyzed for the selected network during the analysis period.

Task 3: Calibrate safety network-based predictive PLANSAFE models

Using local data, safety prediction models were developed to predict the frequency of crashes as a function of traffic and zonal characteristics to make use of variables typically available and used in transportation planning models. Variables in the models included: 2002-2008 geocoded crash data for the City of Ames from Iowa DOT statewide crash database, as well as the Geographic Information Management System (GIMS) 2008 road network data from Iowa DOT. Additionally, socio-demographic data, such as population of a block and median household income were acquired from the US Census Bureau 2000. The models were estimated and calibrated using the log-linear regression method, which is the standard form of the models included in PLANSAFE (Washington et al., 2006). The safety network-based predictive models can be linked to the planning process through GIS-based tools. GIS enable both data management and visualization of the data entries and model predictions.

Task 4: Empirical Bayes Statistical Data Analysis

The applicability of statistical data analysis using the Empirical Bayes (EB) method was tested for network-level analysis. The EB method uses both datasets from the observed road segments and the similar sites which have the typical crash frequency and road characteristic as the observed road segments to predict a more sensible and precise estimation (Hauer et al. 2002).

Task 5: usRAP protocols application

The US Road Assessment Program (usRAP) is an effort sponsored by the AAA Foundation for Traffic Safety (AAAFTS). One of the usRAP protocols, risk mapping, is potentially applicable to regional planning. The objective of this portion of the research was to investigate the applicability of usRAP risk mapping to small and medium-sized urban areas.

Task 6: Conclusions and Recommendations

This task was to make recommendations to the City of Ames and Iowa DOT regarding the use of the three tools studied for identifying candidate locations for safety enhancement and incorporating safety into planning.

The outcome of this thesis is a systematic process and framework to consider road safety issues explicitly in the small and medium-sized communities' transportation planning process, and quantify the safety impacts of new developments and policy programs. The proposed quantitative screening process can provide decision support for planners in City of Ames and could provide guidance to other small and medium-sized communities as well.

CHAPTER 2. LITERATURE REVIEW

2.1 Overview

In this chapter, I first reviewed the strategies and methods of how to incorporate safety into the transportation planning process that were provided in *NCHRP Report 546. Incorporating Safety into Long-Range Transportation Planning (*Washington et al., 2006*)*. Next, I examined some of the existing safety forecasting tools such as the PLANSAFE models presented in the report and other safety analysis tools like Empirical Bayes (EB) and US Road Assessment Program (usRAP). These safety tools can be used for forecasting safety in the future for small and medium-sized communities, due to changes in socio-demographics, traffic demand, road network and countermeasures.

Fourteen safety tools were introduced in NCHRP Report 546. These fourteen tools ranged in coverage from corridor-level to project-level, and planning-level safety analysis; from road segments to intersections and from motor vehicle crashes only to crashes involving bicyclists and pedestrians.

After examining each safety tool, I made the following summary:

- Most safety tools can only analyze safety performance at the corridor-level or project-level; only PLANSAFE was designed to perform safety analysis at the TAZ/planning level.

- Most safety tools require the development of Safety Performance Functions (SPFs) based on historical crash data. These tools perform safety analysis by using statistical approaches such as Empirical Bayes (EB).

- Geographic Information System (GIS) software is helpful in incorporating safety into transportation planning process. A significant amount of spatial analysis is necessary during this analysis process such as the usRAP protocol risk mapping.

The PLANSAFE models are used to forecast safety in the future and inform safety-related decision making at the planning-level (TAZs level). The comparison of PLANSAFE with the other (previous or existing) transportation safety analysis tools/models showed that PLANSAFE is a macroscopic model with the smallest analysis unit of a Traffic Analysis Zone (TAZ), and the largest unit of an entire region (aggregated TAZs). Hence the data used to develop PLANSAFE are different from those required for small-scale projects like the road segment level planning. By using road network data, crash data and socio-demographics data as inputs, eight models can be estimated and calibrated that range in granularity from a model of total crash frequency to a model of frequency of crashes involving bicycles.

To increase the precision of estimation in the Safety Performance Functions (SPFs) and correct for the "regression-to-the-mean" bias by using the crash count/frequency method only, one statistical approach, known as Empirical Bayes (EB) has been adopted in this thesis.

The EB method uses both datasets from the observed road segments (i.e., Ames road network) and similar sites, which have similar crash frequency and road characteristics to the observed road segments. Typically, engineers use the crash data and road attributes for the similar sites to develop Safety Performance Functions (SPFs). SPFs are statistical functions, which present the relationship between crash frequency and road attributes, such as the relationship between crash frequency and Annual Average Daily Traffic (AADT) for a two lane rural road. SPFs are used to predict the crash frequency in the future with the change of road attributes or the crash frequency of a similar road.

In addition, the United States Road Assessment Program (usRAP) and in specific, the risk-mapping tool and star ratings were reviewed. This tool documents the risk of fatal and serious injury crashes and shows where the risk is high and low. usRAP uses four types of risk maps to document the safety performance of rural state roads based on the following safety measures: crash density, crash rate, crash rate ratio and potential crash savings. The application of this tool to small and medium-sized communities is evaluated for the first time.

Details on the review of the available tools for incorporating safety into planning process are provided in Chapter 4 (PLANSAFE), Chapter 5 (Empirical Bayes) and Chapter 6 (usRAP style risk mapping).

Lastly, I studied other Metropolitan Planning Organizations (MPOs), which have similar characteristics to the City of Ames in order to collect information on how these small and medium-sized communities incorporate safety into their transportation planning processes. Details are provided in section 2.5.

2.2 PLANSAFE

The PLANSAFE Models provided in *NCHRP Report 546. Incorporating Safety into Long-Range Transportation Planning (*Washington et al. 2006*)* are used to forecast safety in future periods and help the safety related decision making for a planning-level (TAZs level) transportation planning project.

Compare to the previous/existing transportation safety analysis tools/models, PLANSAFE is macroscopic with the smallest analysis unit of a Traffic Analysis Zone (TAZ), and largest unit of an entire region (aggregated TAZs). Hence the data used to develop PLANSAFE are different from small scale projects like the road segment level planning.

By using road network data, crash data and census data as inputs, the PLANSAFE could have eight outputs, from total accident frequency model to accidents involving bicycles frequency model.

In February 2010, *PLANSAFE: Forecasting the Safety Impacts of Socio-Demographic Changes and Safety Countermeasures* software program published as a result of NCHRP 8-44-2 (Washington et al., 2010). As claimed in the user manual “the software is as a planning-level decision support tool, and as such, does not compete directly with any of the project and site level tools currently available, such as Safety Analyst, Interactive Highway Design Model, Intersection Magic, etc.” This software program allows users to do safety planning analysis at planning-level, apply different scenarios and generate project reports. The detail application of this software for City of Ames is in Chapter 4 PLANSAFE.

2.3 Empirical Bayes (EB)

EB and other statistical methods are widely used to estimate the safety performance of the planning transportation network. The EB method has been applied in past studies (Miaou and Song 2005, Persaud and Lyon 2007) researches use to do a before and after comparison of crash frequency or rate. Other studies have identified high risk locations by using the ranking of the EB results of the road network to estimate and improve safety performance (Miranda-Moreno and Fu 2006, Cafiso et al., 2007).

To apply EB, the safety prediction models like Safety Performance Functions (SPFs) need to be developed first. SPFs are usually estimated and calibrated in two types, segments and intersections, by using different types of road like functional class and number of lanes. The SPFSs prediction results derive from the number of fatal crash to fatal crash plus injury and Property Damage Only (PDO) crashes (Schwetz et al., 2004 and Tarko, 2006). Also to calibrate the SPFs, some variables such as the Annual Average Daily Traffic (AADT), length of the segment, lane width, median width and other road features are used in the model (Tarko et al., 2008). Because of the non-linear relationship between segment length and crashes (Lordand Persaud, 2004), Poisson regression model or Negative Binomial regression model are used to built SPFs (Miranda-Moreno et al., 2005).

The EB statistical method presented in *Estimating Safety by the Empirical Bayes Method* by Ezra Hauer provided a completed tutorial of how to apply this theory into daily practice. This report was used as the main reference for conducting the EB analysis in this thesis. The EB method uses both datasets from the observed road segments and similar sites, which these similar sites have similar crash frequency and road characteristics to the observed road segments. The EB method could increase the precision of estimation in the SPFs which are calibrated based on the similar sites along. Also the EB method could correct the "regression-to-mean" bias caused by using the crash count/frequency method for the observed road segments only. In this tutorial, the author first introduced the EB theory and how to build the SPFs for segments and intersections. Then the author gave 10 numerical examples of how to apply this theory in practice from the basic abridged EB procedure "A road segment with one year of accident counts" example to a more complicated "Accidents by severity" example until the full EB procedure like "Accounting for changing ADTs".

2.4 usRAP

US Road Assessment Program (usRAP), sponsored by the AAA Foundation for Traffic Safety (AAAFTS) was originally developed by European Road Assessment Program (EuroRAP). Both the usRAP and EuroRAP are under the umbrella of the International Road Assessment Program (iRAP) which is "a not-for-profit organization dedicated to saving lives through safer roads" as stated in the iRAP report: Safer Roads Investment Plans: The iRAP Methodology.

According to the usRAP website (www.usrap.us), usRAP pilot program has archived phase I, II and III by May 2010. The primary objectives of usRAP include, "reduce death and serious injury on U.S. roads rapidly through a program of systematic assessment of risk that identifies major safety shortcomings, which can be addressed by practical road improvement measures" and "ensure that assessment of risk lies at the heart of strategic decisions on route improvements, crash protection, and standards of route management" as listed in the final report of usRAP phase III.

In these three phases of the usRAP pilot program, three safety assessment protocols, risk mapping, star rating and performance tracking are introduced and applied to the following states, FL, IA, MI, NJ, IL, KY, NM, and UT. The detailed information could be found in the final report of usRAP phase I, II, III. The investigation of applicability of usRAP risk mapping tool to small and medium sized urban area safety planning is presented in Chapter 6 usRAP style risk mapping.

2.5. Review of MPOs State-of-the Practice

2.5.1 Ames Area MPO

Ames Area MPO (AAMPO), website: http://www.aampo.org

Area: 36 Sq. Miles. Designation year: 2003. Population: 56,510, by July 1st 2008. (Iowa Data Center)

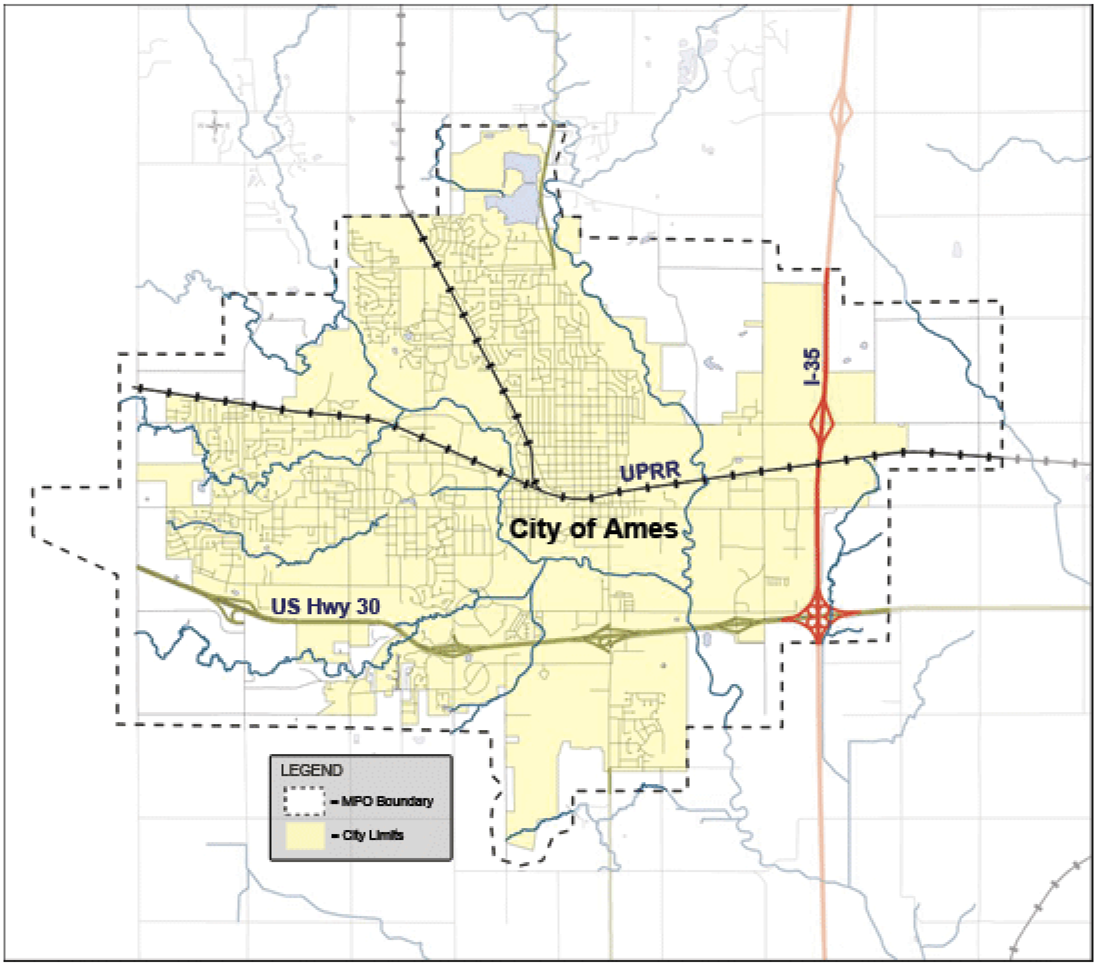

Figure 2.1. Ames Area MPO study Area.

The AAMPO Final 2035 Long Range Transportation Plan includes the following statement:

Chapter 2.2 Goals and Objectives

1. Develop a Safe and Connected Multi-Modal Network

a.) Increase the connectivity of all modes including automobile, public transit, bicycle, air travel, freight rail, truck and pedestrian.

b.) Incorporate strategies to promote safety and security across the entire network.

Also in Chapter 10 Safety and Security the plan included the descriptive crash data analysis such as the crash counts by severities, GIS-based crash map like the crash density map and safety candidate locations by using the Iowa DOT's Safety Improvement Candidate Location Listing (SICL). At the end of that chapter, it provided two recommendations, roundabouts and access management to resolve the safety problems for City of Ames.

2.5.2 Other MPOs

Using the MPO Database from FHWA (Website: http://www.planning.dot.gov/mpo.asp) and after limiting the search to areas less than 1,000 sq miles and population up to 140,000, I got total 149 records. After having reviewed these MPOs which has similar area, population with Ames and/or some other characteristics like a university town, I selected 5 MPOs to describe in more detail in this study as described below.

1. Johnson County COG (JCCOG)

Major City: Iowa City, IA. Area: 89 Sq. Miles Populations: 88980

Website: http://www.jccog.org/whatwedo/transportation/index.htm

In the Johnson County Council of Governments *Long Range Multi-Modal Transportation Plan*, there are several places where considering safety into the planning process is mentioned, such as including safe routes to school program, and helping persons to be able to drive safety for a longer period in their life-span, constructing pedestrian infrastructure with improvement in safety, etc.

They also make a map with top collision locations, which shows the ten intersections and top mid-block collision location, 2001-2004. And many of these locations have had or undergoing construction projects to mitigate safety concerns.

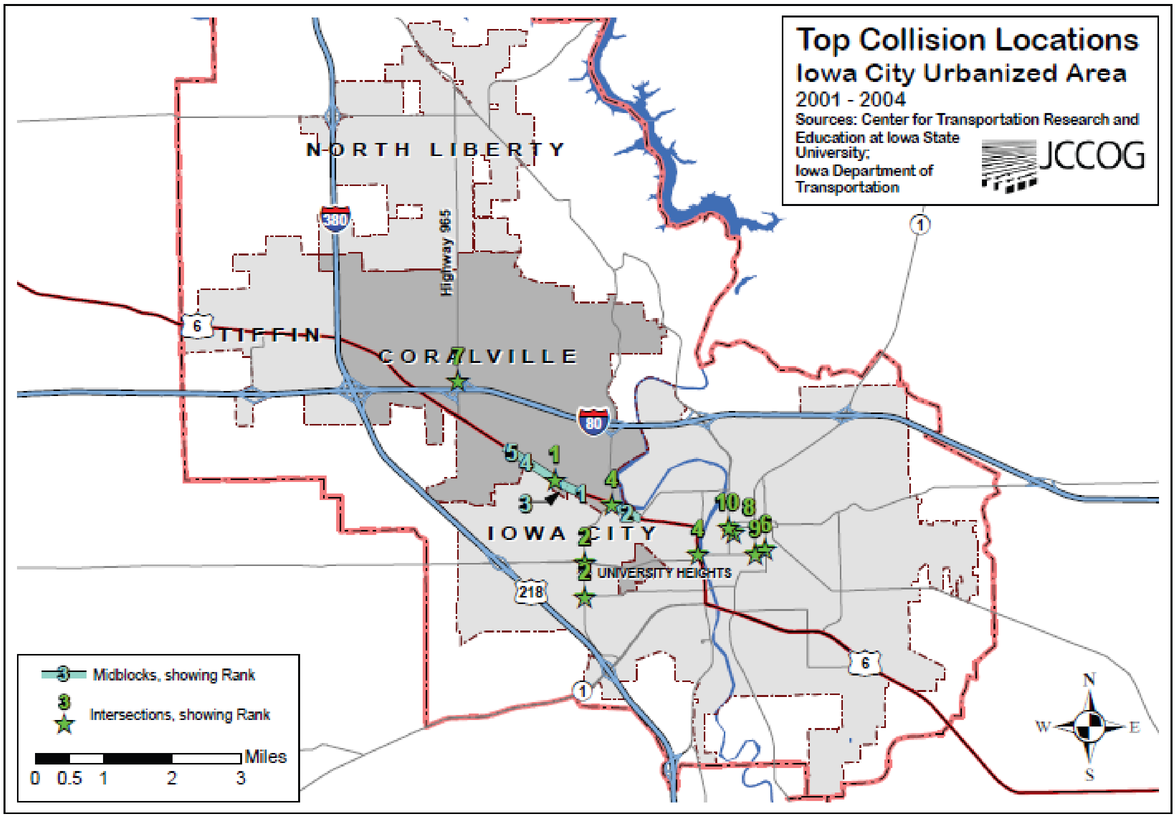

Figure 2.2. Top Collision Locations. From JCCOG

2. Corvallis Area MPO (CAMPO)

Major City: Corvallis, OR. Area: 38 Sq. Miles Population: 59277

Website: http://www.corvallisareampo.org/TransportationPlan.html

From the *Corvallis Area MPO Transportation Improvement Program (TIP) FY2008-2011*, the Corvallis Area MPO considered several methods for incorporating safety into the transportation improvement process, such as safety and educational activities for pedestrian and bicyclists, conduct safety projects like intersection improvements and pavement skid treatments. They also had three projects about establishing safe routes to school that were conducted in 2008.

In Corvallis *Area Metropolitan Transportation Plan: Destination 2030*, they set the first goal of the plan as "To provide for safe, convenient and efficient movement of people and goods throughout the planning area”. Beside that they also used one section in the plan to evaluate safety and conducted crash analysis for the existing transportation system.

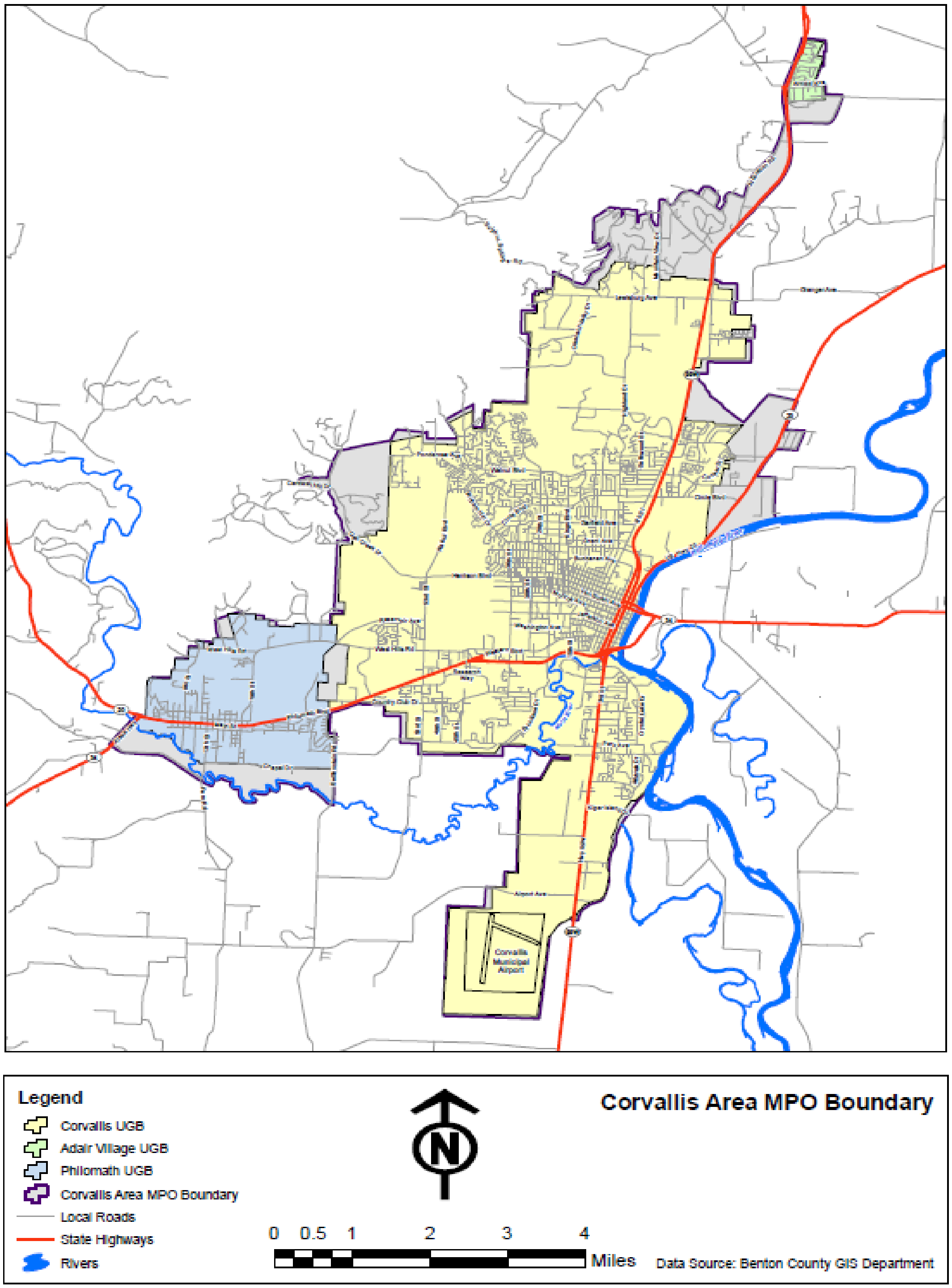

Figure 2.3. Corvallis Area MPO Boundary. From CAMPO.

3. Wenatchee Valley Transportation Council (WVTC)

Major City: Wenatchee, WA. Area: 41 Sq. Miles Population: 56627

Website: http://www.wvtc.org/

WVTC 2009 Regional Transportation Plan, Part D. Incorporating safety into planning process is discussed in an entire chapter in that Plan and include the subjects of state highways, county Roads, city streets, high accident corridor identification, public transit and walking & bicycling.

Figure 2.4. Map of NCRTPO Planning Area. From WVTC.

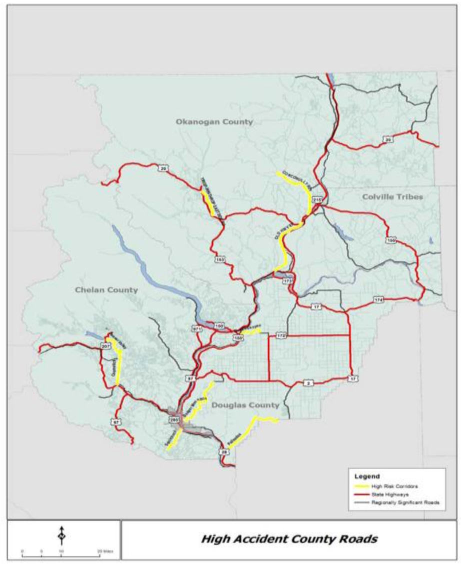

Figure 2.5. County Road High Accidents Corridors From WVTC

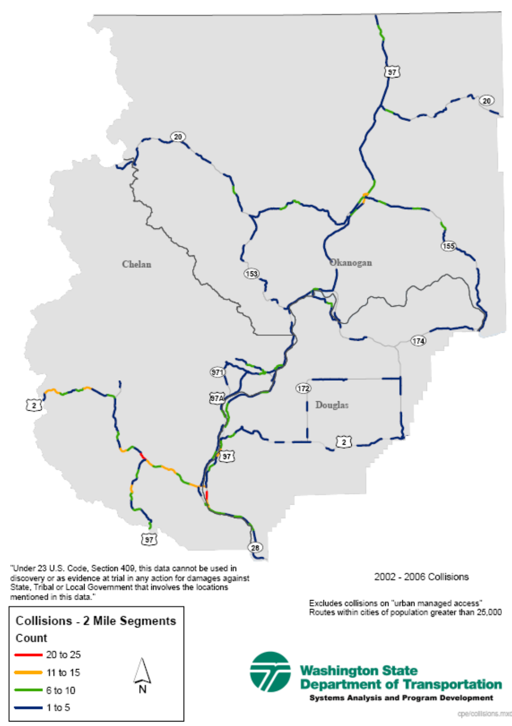

Figure 2.6. State Highway Accident Corridors. From WVTC

4. Lewis-Clark Valley MPO (LCVMPO)

Major City: Asotin, WA, ID. Area: 43 Sq. Miles Population: 50856.

Website: http://lewisclarkmpo.org/

Both of the Long Range Transportation Plan (LRTP) and Transportation Improvement Program (TIP) were not available but the plan included the following objective:

“Increase the safety of the transportation system for motorized and non-motorized users”, as directed in SAFETEA-LU.

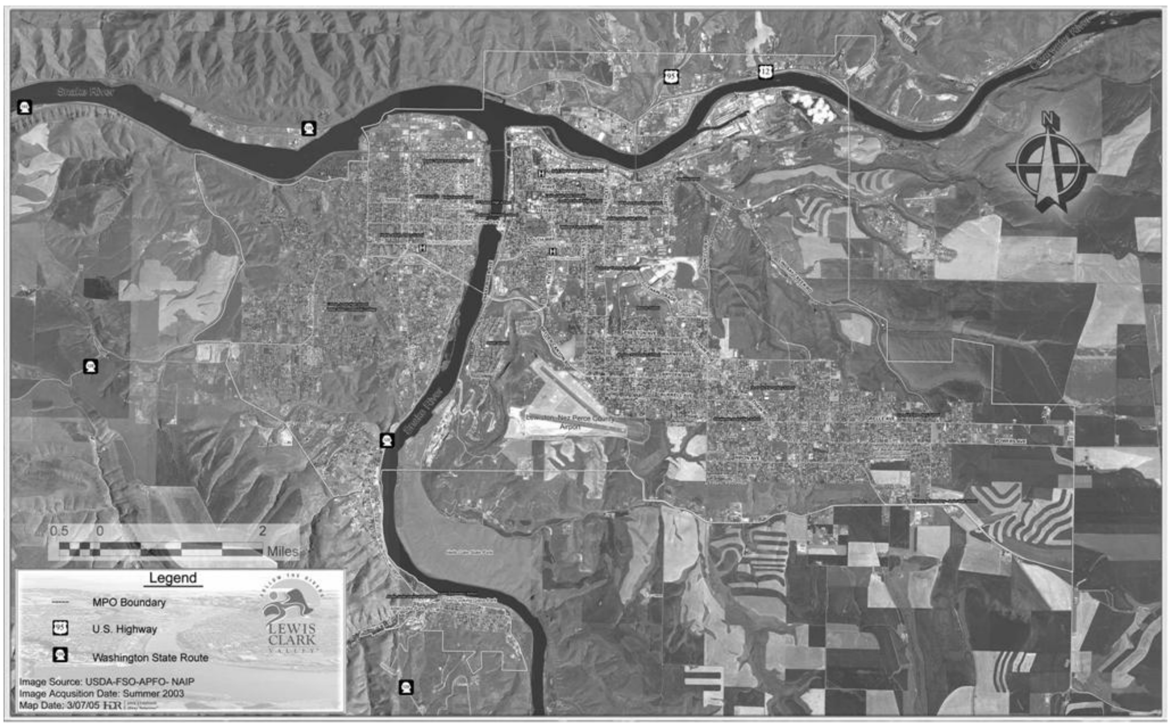

Figure 2.7 LCVMPO boundary.

5. Bend MPO

Major City: Bend, OR. Area: 46 Sq. Miles Population: 59027.

Website:
http://www.ci.bend.or.us/depts/community_development/bend_metropolitan/index.html

In the Metropolitan Transportation Plan (MTP), Bend MPO set three goals and one objective for safety and efficiency as following:

Goal 1

Address traffic congestion and problem areas by evaluating the broadest range of transportation solutions, including but not limited to:

• Operational improvements to maximize the efficiency of existing facilities;

• Construction of new transportation corridors;

• Transportation Demand Management (TDM) - bicycle, pedestrian and carpool strategies; and

• Transportation Systems Management (TSM) – Intelligent Transportation Systems (ITS), intersection operations and access management.

Goal 2

Serve the existing, proposed and future land uses with an efficient and safe transportation network

Goal 3

Design and construct the transportation system to enhance safety for all modes.

<u>Objective</u>

1) In cases where improving safety will also improve efficiency, these projects should receive funding priority

Chapter 12 addressed transportation safety. In that chapter, they included safety related regulations from federal, state and regional area. They also provided a crash analysis and suggest safety improvements as well as using Intelligent Transportation Systems (ITS) solutions to help incorporating safety into planning process.

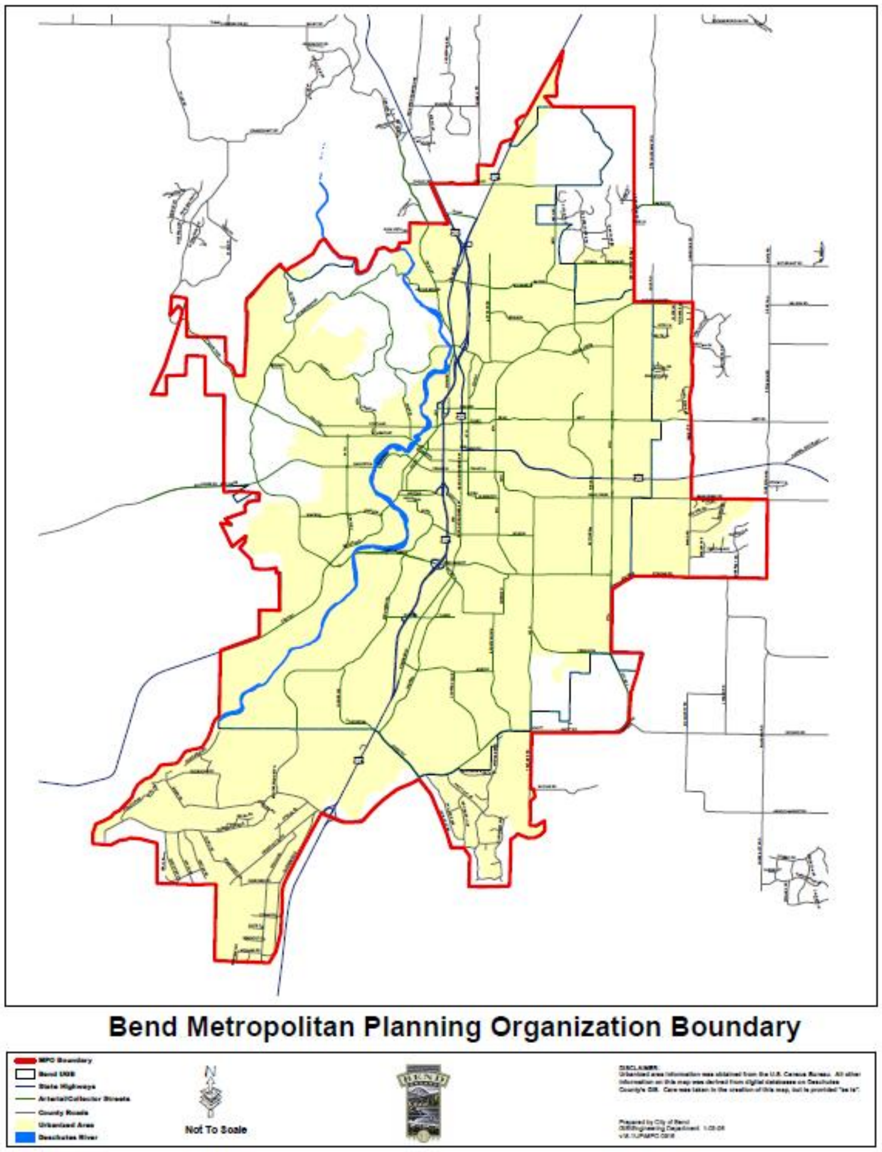

Figure 2.8 Bend MPO Boundary. From Bend MPO.

2.5.3 Summary

A summary of these MPOs safety planning performance based on other MPOs' Transportation Improvement Plan (TIP) and/or Long Range Transportation Plan (LRTP) is shown in the matrix below.

Table 2.1 Summary of MPOs safety planning performance

	MPOs' TIP and LRTP					
Criteria	AAMPO	JCCOG	CAMPO	WVTC	LCVMPO	BENDMPO
Mention Safety Planning	X	X	X	X		X
Tool or Methodology of Safety Planning						
Safety Performance Listed in Goals/Objectives	X	X	X	X	X	X
Consider all Modes of Transportation	X	X	X	X		X
Candidate Sites to be improved	X	X	X	X	X	X
GIS-based Crash Map	X	X		X		

2.6 Summary/Conclusions

After reviewing the NCHRP Report 546 and the TIPs and LRTPs of MPOs similar in size to Ames, I concluded that most MPOs emphasize safety in the transportation planning process. Safety is a solid part of the MPO's planning objectives and goals. These objectives and goals are also incorporated into the planning process through the Transportation Improvement Program (TIP), Metropolitan Transportation Plan (MTP) and the Long Range Transportation Plan (LRTP). However, no specific guidance has yet been provided to metropolitan planning organizations (MPOs) on how safety should be considered (qualitatively or quantitatively), nor where or at what level it should be considered (project, corridor or region wide). The lack of guidance is particularly challenging to small planning agencies. "How safety is reflected in state and MPO plans is reflective of how safety is addressed in the planning process. Plans need to be proactive on safety and not simply mention safety" (Transportation Planner's Safety Desk Reference 2007). A new tool or toolbox should be developed to incorporate statistical analysis at the planning-level, GIS-based spatial analysis and mapping, and safety evolution before and after for applying certain safety improvements. More details about these tools used in this study could be found in Chapters 4, 5 and 6.

CHAPTER 3. DATA COLLECTION AND DESCRIPTIVE ANALYSIS

3.1 Overview

This chapter describes the data used in this thesis. Sources of data included the following. Geocoded crash data for the City of Ames were provided for the years 2002-2008 from the Iowa DOT statewide crash database (Office of Traffic and Safety). A 2008 snapshot of road network data and attributes were obtained from the Geographic Information Management System (GIMS; Office of Transportation Data). Socio-economic and demographic data, such as block population and median household income were acquired from the 2000 decennial census (US Census Bureau). Geographic Information System (GIS) files of Metropolitan Planning Organization (MPO) boundary and city boundary were provided by the City of Ames.

3.2 Crash Data

In addition to geographic coordinates, the study crash data included many crash attributes related to severity, drivers, vehicles and environmental conditions at the time of the crash. In Iowa, the minimum threshold for reporting crashes for property damage only crashes is $1,000 and all injury and fatal crashes must be reported. A summary of the crash data used in this study is shown below.

Table 3.1 Crash Statistics, City of Ames, 2002-2008.

Year	Total Crashes	Fatalities	Major Injuries	Minor/Possible Injuries
2002	1000	0	21	292
2003	1079	2	20	291
2004	1114	1	11	310
2005	1035	2	13	237
2006	963	4	19	296
2007	1077	3	23	329
2008	1248	0	17	343
Total	7516	12	124	2098

Source: Iowa DOT statewide geocoded crash database.

Table 3.2 City of Ames Crashes as a percentage of Statewide Crashes, 2002-2008

Year	2002	2003	2004	2005	2006	2007	2008	Total
Ames	1000	1079	1114	1035	963	1077	1248	7516
Iowa	59666	59440	59192	58644	54815	60112	61194	413063
Percentage %	1.68	1.82	1.88	1.76	1.76	1.79	2.04	1.82

Source: Iowa DOT statewide geocoded crash database.

Table 3.3 Total crashes count by zone.

ZONE	CRASHES	Percentage %
Agricultural Zone	203	2.70
Campus town Service Center	247	3.29
Community Commercial Node	114	1.52
Community Commercial/Residential	10	0.13
Convenience Commercial Node	4	0.05
Downtown Service Center	167	2.22
General Industrial Zone	176	2.34
Government/Airport District	1818	24.19
Highway-Oriented Commercial Zone	1602	21.31
Hospital-Medical District	36	0.48
Neighborhood Commercial Zone	46	0.61
Planned Industrial Zone	40	0.53
Planned Regional Commercial Zone	141	1.88
Planned Residence District	109	1.45
Residential High Density Zone	574	7.64
Residential Low Density Park Zone	16	0.21
Residential Low Density Zone	1174	15.62
Residential Medium Density Zone	143	1.90
South Lincoln Mixed-Use District	73	0.97
Suburban Residential Floating Zoning Residential Low Density	20	0.27
Suburban Residential Floating Zoning Residential Medium Density	2	0.03
Urban Core Residential Medium Density Zone	325	4.32
Village Residential District	53	0.71
Other	423	5.63
Total	7516	100.00

The highlighted records are the top 3 zones by crash number.

3.3 Road Network Data, MPO Boundary and City Boundary

The research road network and attribute data included many fields such as: functional class, road type, annual average daily traffic (AADT), segment length, and segment width. Figure 3.1 depicts Ames road network, city and MPO boundaries.

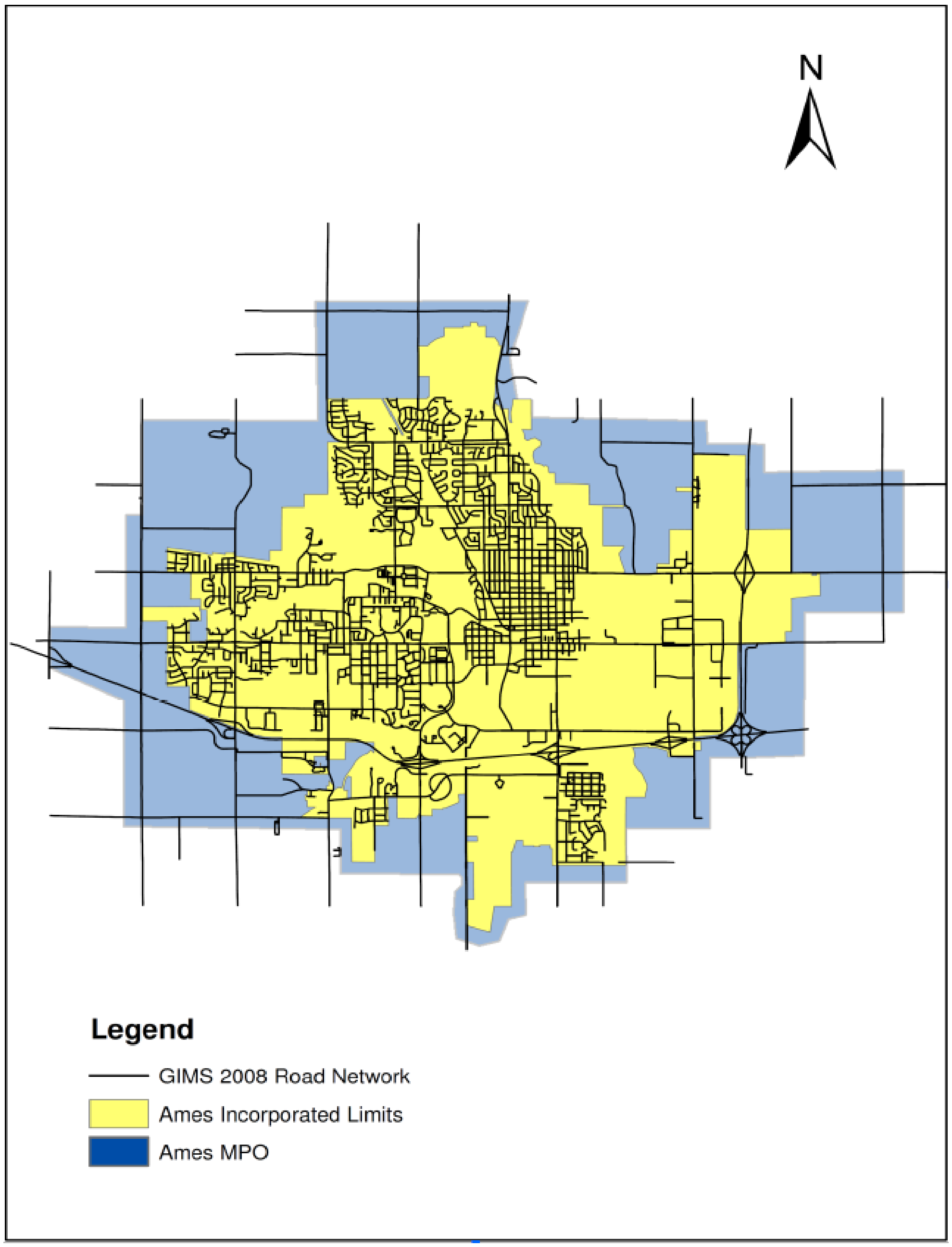

Figure 3.1 Ames road network and boundaries

A summary of road network and attribute data used in usRAP-style risk mapping (Chapter 6) is presented in table 3.4.

Table 3.4 Risk Mapping Data Summary (Ames Metropolitan Area 2002-2008)

Road Type	Sections	Road Miles	Average Length (mi)	Average AADT (vel/day)	Annual VMT (Million)	Total Crashes				Fatal Crashes	Major Injury Crashes
						Total Frequency	Annual Frequency	Annual Density	Annual Rate per M VMT		
Two-lane Local	790	167.4	0.212	683	41.7	1691	242	1.44	5.79	2	21
Two-lane Collector	66	35.8	0.542	3217	42	631	90	2.52	2.15	2	5
Two-lane Arterial	41	17.2	0.420	7189	45.1	607	87	5.04	1.92	0	9
Four-lane Undivided	55	18.1	0.329	9557	63.1	2236	319	17.65	5.06	6	28
Four-lane Divided	44	12.7	0.289	10064	46.7	1508	215	16.96	4.61	0	25
Freeway	3	12.5	4.167	19080	87.1	569	81	6.50	0.93	2	19
Ramp	33	8.5	0.258	2908	0.9	168	24	2.82	26.67	0	3
Total	1032	272.2	0.264	2102	326.6	7410	1059	3.89	3.24	12	110

Note: As only non-zero AADT road segments are used in the usRAP style risk mapping analysis, total and major injury crash frequencies differ slightly between tables 3.1 and 3.4.

3.4. Socio-demographic data used in the PLANSAFE models

A summary of the socio-economic and demographic data from the 2000 US Census is presented in Table 4.1 in Chapter 4. These data were used to estimate and calibrate the PLANSAFE models.

3.5 GIS based crash maps

GIS based crash maps, such as maps showing the total crash frequency (Figure 3.2) and the fatality and injury crash frequency (Figure 3.3), were developed so that “black spots” can be identified visually. For example, in Figure 3.3, most injury crashes occurred along Lincoln Way, Duff Ave. and 220th St (13th St). More detailed and informative maps such as crash density and rate maps are present in Chapter 6.

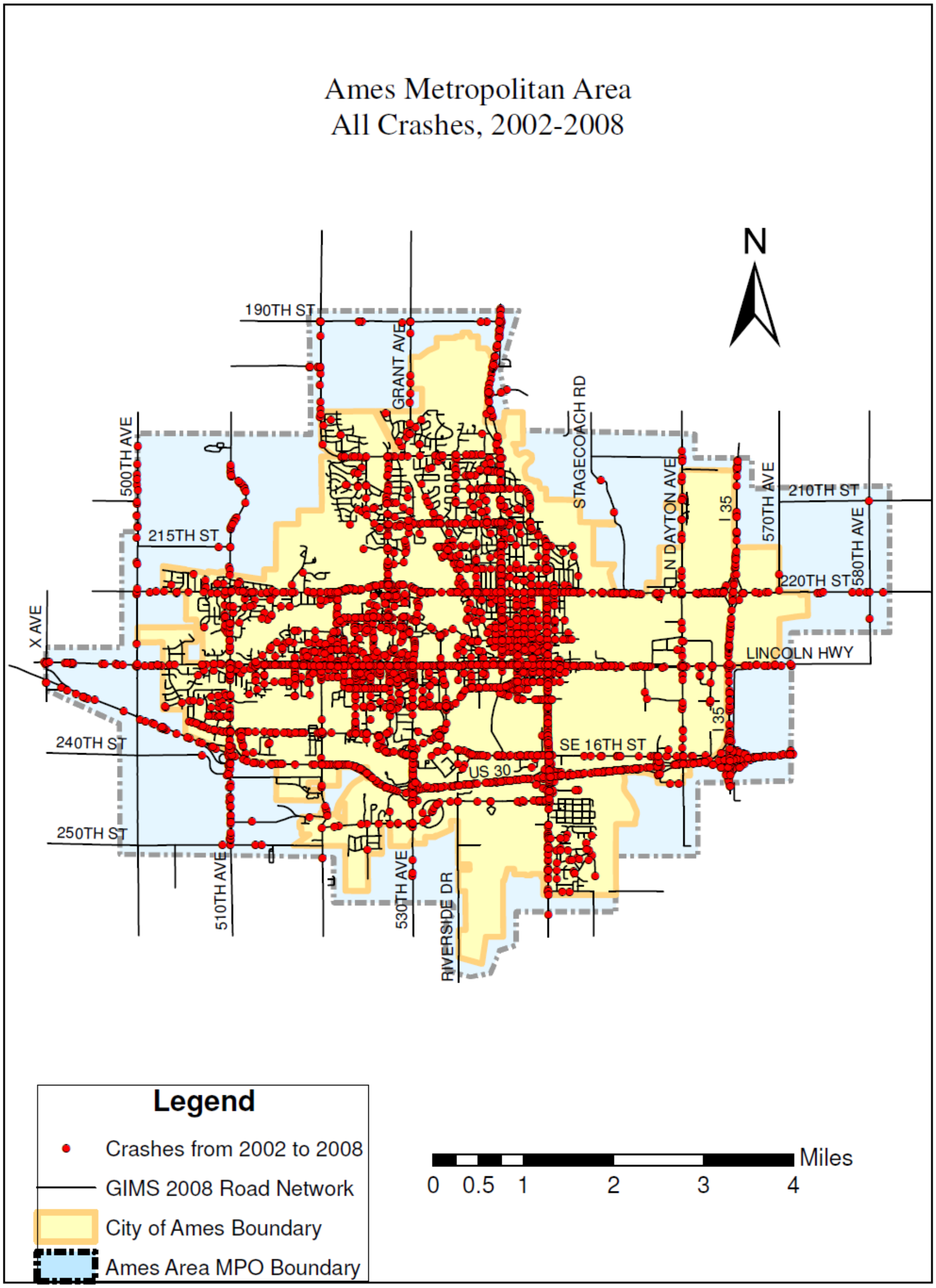

Figure 3.2. Total crash frequency map of Ames Metropolitan Area, 2002 to 2008.

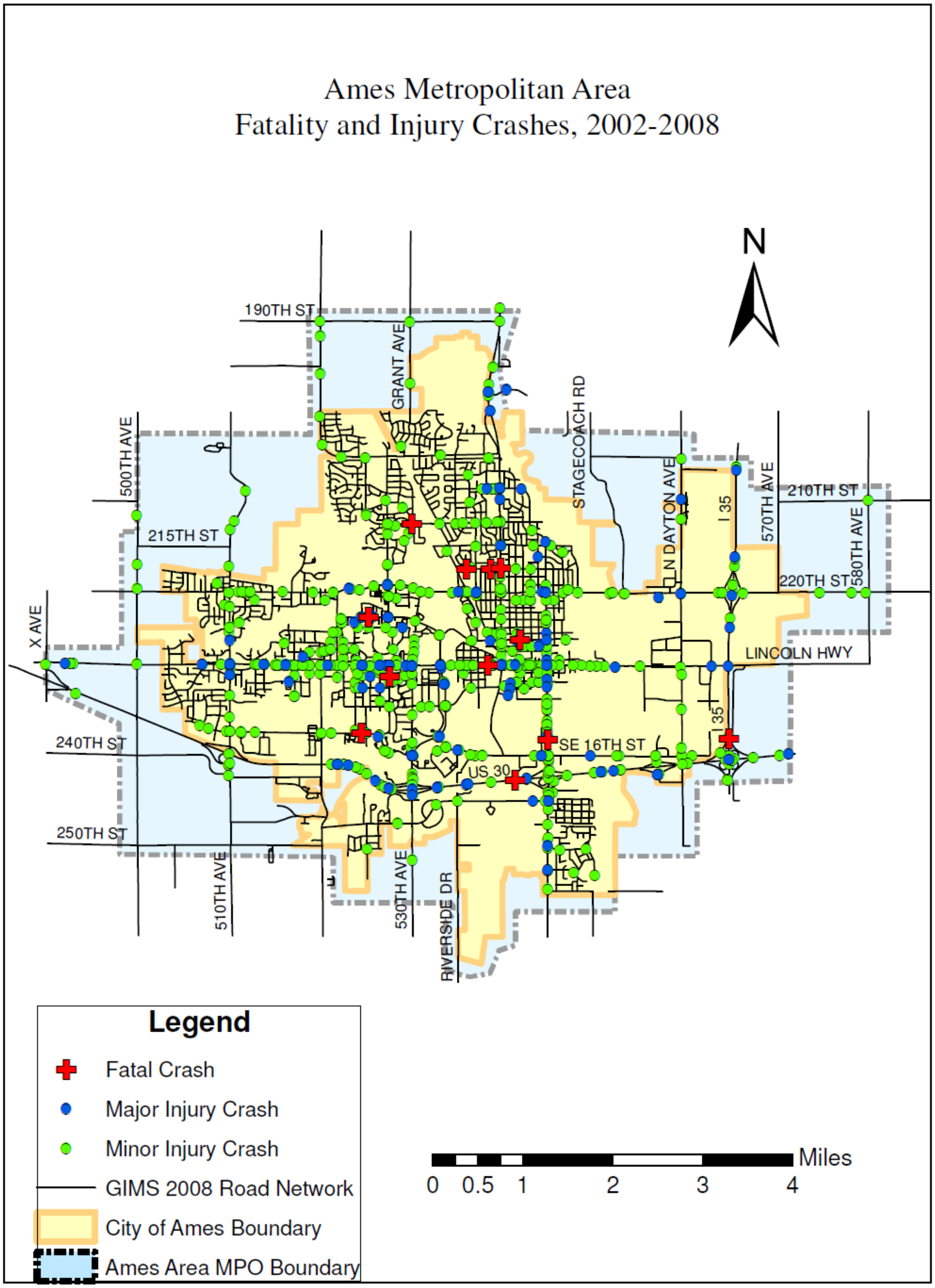

Figure 3.3. Fatality and Injury Crash map of the Ames Metropolitan Area, 2002 to 2008.

CHAPTER 4. PLANSAFE

4.1 PLANSAFE-like models calibration

As discussed in Chapter 2, PLANSAFE models use crash data, road network data, and census data as inputs to develop Safety Performance Functions (SPFs). In order to develop similar SPFs for the city of Ames, I carried out the following steps:

i) performed a geographic information system (GIS) spatial analysis to assign crashes (which are points in GIS) to the road network (which are lines in GIS) and then assign road network to TAZs (which are polygons in GIS);

ii) aggregated the crash data and road network data to the TAZ-level;

iii) aggregated the census data from the block level or block group level to the TAZ-level; and

iv) estimated log-linear regression crash frequency models based on the data collected for a total of 80 TAZs for the City of Ames.

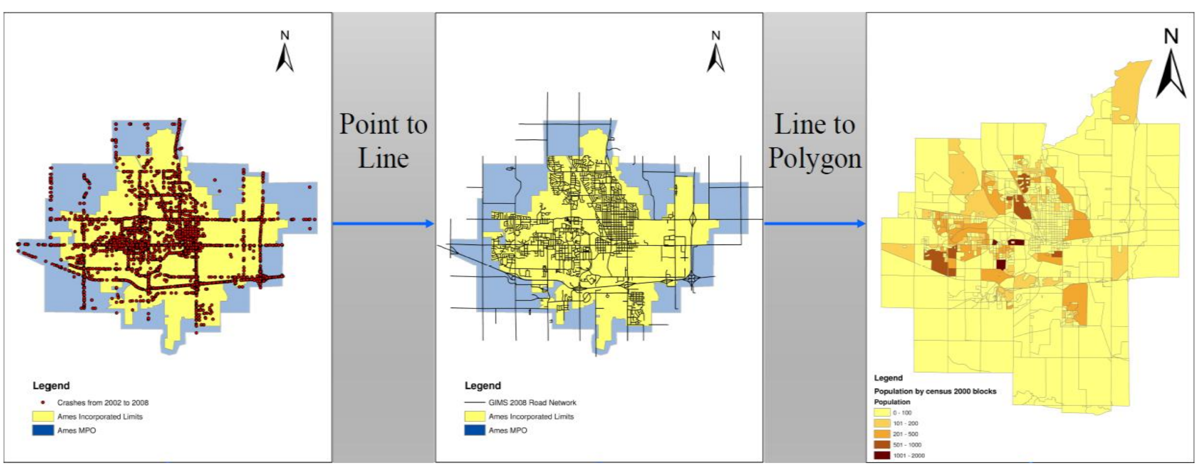

Figure 4.1. GIS spatial analysis process of PLANSAFE models

As it was shown in Table 3.1 in Chapter 3, during the seven-year analysis period, there were 12 fatalities and 124 major injury crashes. Due to the small sample size of fatal crashes, a crash frequency model was not estimated. In addition, calibrating a major injury crash frequency model did not yield any statistically significant results. As such, only two crash frequency models (a total crash frequency and a minor injury crash frequency model) were estimated and calibrated for the City of Ames.

A summary of the socio-economic and demographic data from the 2000 US Census was presented in Table 3.5 in Chapter 3. These data were used to calibrate the PLANSAFE models.

Table 4.1. Statistical data summary of variables used in the Ames PLANSAFE models

Variable and Definition of Variable	**Mean**	**Std.Dev**
POPTOT:Total population per TAZ	660.99	645.60
ACRE:TAZ area in acres	531.18	1142.68
POP_PAC:Population density in persons per acre	6.55	7.32
URB_POP:Urban population per TAZ	638.69	651.82
PPOPURB:Urban population as a portion of the total population in %	2.59	2.77
TOT_MILE:Total road mileage per TAZ	4.23	5.63
UH: Number of urban housing units	235.53	230.72
HU: Number of housing units	245.45	231.48
PH_URB: Number of urban housing units as portion of all housing units in	0.82	0.38
VMT: Vehicle miles traveled per TAZ (in thousands)	519.3	10382.1
PNF_0111: Total mileage of urban and rural interstates as a portion of the total mileage in %	0.02	0.08
PNF_0214: Total mileage of urban and rural principal arterials as a portion of the total mileage in %	0.21	0.51
POPMIN: Total number of minorities	72.44	108.42
PPOPMIN: Total number of minorities as a portion of the total in %	0.09	0.11
WORKERS: Total number of workers 16 years and over	326.38	457.43
WORK_PAC: Total number of workers 16 years and over per acre	2.51	2.80
INT: Number of intersections per TAZ	23.46	21.89

Table 4.1 (continued) INT_PMI: Number of intersections per mile	9.15	6.90
POP00_15: Total population of ages 0 to 15	23.90	22.45
POP16_64: Total population of ages 16 to 64	527.61	580.93
HH_INC: Median household income in 1999 US dollars (in thousands)	41.67	20.19
PWTPRV: Proportion of workers 16 years and older that use a car, truck, or a van as a means of transportation to work in %	0.71	0.29
MI_PACRE: Total mileage of the TAZ per acre of the TAZ	0.02	0.02

Table 4.2 Variable correlation table

Variables	POP_PAC	PNF_0214	POP_16_64	HH_INC	TOT_MILE	HU	POPTOT	INT	ACRE
POP_PAC	1.000	-0.155	0.441	-0.308	-0.352	0.120	0.380	-0.312	-0.341
PNF_0214	-0.155	1.000	0.180	0.084	0.758	0.282	0.216	0.516	0.653
POP_16_64	0.441	0.180	1.000	-0.114	0.180	0.587	0.980	0.439	0.028
HH_INC	-0.308	0.084	-0.114	1.000	0.379	-0.038	-0.041	0.287	0.362
TOT_MILE	-0.352	0.758	0.180	0.379	1.000	0.291	0.245	0.726	0.930
HU	0.120	0.282	0.587	-0.038	0.291	1.000	0.699	0.581	0.119
POPTOT	0.380	0.216	0.980	-0.041	0.245	0.699	1.000	0.535	0.073
INT	-0.312	0.516	0.439	0.287	0.726	0.581	0.535	1.000	0.512
ACRE	-0.341	0.653	0.028	0.362	0.930	0.119	0.073	0.512	1.000

4.1.1 Total Crash Frequency Model

Table 4.3 and Table 4.4 below show the log-linear regression estimation results for the total crash frequency in Ames.

Table 4.3 Likelihood Ratio Test for Goodness of Fit (total crash frequency model)

Model	**LogLikelihood**	**L-R ChiSquare**	**DF**	**Prob>ChiSq**
Difference	200.69143	0.0000	4	1.0000
Full	-67.3627959			
Reduced	-120.460413			

ρ^2 = 1- LL(Full)/LL(Reduced) = 0.441

Table 4.4 Model Parameter Estimates (total crash frequency model)

Variable	Estimate	Std Error	Prob>ChiSq	Lower CL	Upper CL
Intercept	3.1815884	0.1660721	<.0001	2.8479896	3.4994254
POP_PAC	-0.02763	0.010067	0.0042	-0.048032	-0.008462
PNF_0214	0.5814724	0.0914128	<.0001	0.3977179	0.7571393
POP16_64	0.0003754	0.0001014	0.0003	0.0001731	0.0005713
HH_INC	-1.948e-5	3.6282e-6	<.0001	-2.668e-5	-1.244e-5

The prediction equation for the Annual Total Crash Frequency Model (crashes per year per TAZ) is:

Eq 4-1: Total crash frequency = exp(3.1815884 - 0.02763(POP_PAC) + 0.5814724(PNF_0214) + 0.0003754(POP16_64) -1.948e-5(HH_INC)) – 1

Equation 1 shows that if the total mileage of urban and rural principal arterials as a portion of the total mileage in % (PNF_0214) increases, the predicted total crash frequency will also increase, as expected. Interestingly, an increase in the median household income (in 1999 US dollars) (HH_INC) would decrease total crash frequency.

4.1.2 Minor Injury Crash Frequency Model

Table 4.5 and Table 4.6 below show the log-linear regression estimation results for the minor injury crash frequency in Ames.

Table 4.5 Likelihood Ratio Test for Goodness of Fit (minor injury crash frequency model)

Model	LogLikelihood	L-R ChiSquare	DF	Prob>ChiSq
Difference	-253.795118	507.5902	4	<.0001
Full	-243.559939			
Reduced	-368.975422			

ρ^2 = 1- LL(Full)/LL(Reduced) = 0.3399

Table 4.6 Model Parameter Estimates (minor injury crash frequency model)

Variable	Estimate	Std Error	Prob>ChiSq	Lower CL	Upper CL
Intercept	0.894607	0.114067	<.0001	0.666884	1.115986
PNF_0214	0.325518	0.085142	0.0003	0.152046	0.488777
POP16_64	0.000175	7.6e-05	0.0256	2.18e-05	0.000322
INT	0.004303	0.002259	0.0611	-0.000203	0.008734
HH_INC	-1.03e-05	2.52e-06	<.0001	-1.53e-05	-5.34e-06

The prediction equation for the Annual Minor Injury Crash Frequency Model (crashes per year per TAZ) is:

Eq 4-2: Minor injury crash frequency = exp(0.894607 + 0.325518 (PNF_0214) + 0.000175 (POP16_64) + 0.004303 (INT) – 1.03e-05 (HH_INC)) – 1

Equation 4-2 shows that if the total mileage of urban and rural principal arterials as a portion of the total mileage in % (PNF_0214), the total population of ages 16 to 64 (POP16_64) and the number of intersections per TAZ (INT) increase, the predicted minor injury crash frequency will also increase, as expected. However, an increase in the median household income (in 1999 US dollars) (HH_INC) would decrease minor injury crash frequency.

4.2 PLANSAFE Software Analysis

The PLANSAFE software program *PLANSAFE: Forecasting the Safety Impacts of Socio-Demographic Changes and Safety Countermeasures* was published as a result of NCHRP 8-44-2 in February 2010. As claimed in the user manual, the PLANSAFE program should be used at the planning-level and not the project-level safety planning project. This is because project-level projects, such as an intersection or a road segment, require more detailed information, which is not supported by PLANSAFE.

The process of using PLANSAFE software and the final outputs are listed as follows:

1. Selected Analysis Area and Units

This step asked the user to select state, county and jurisdiction. The default analysis was Traffic Analysis Zone (TAZ).

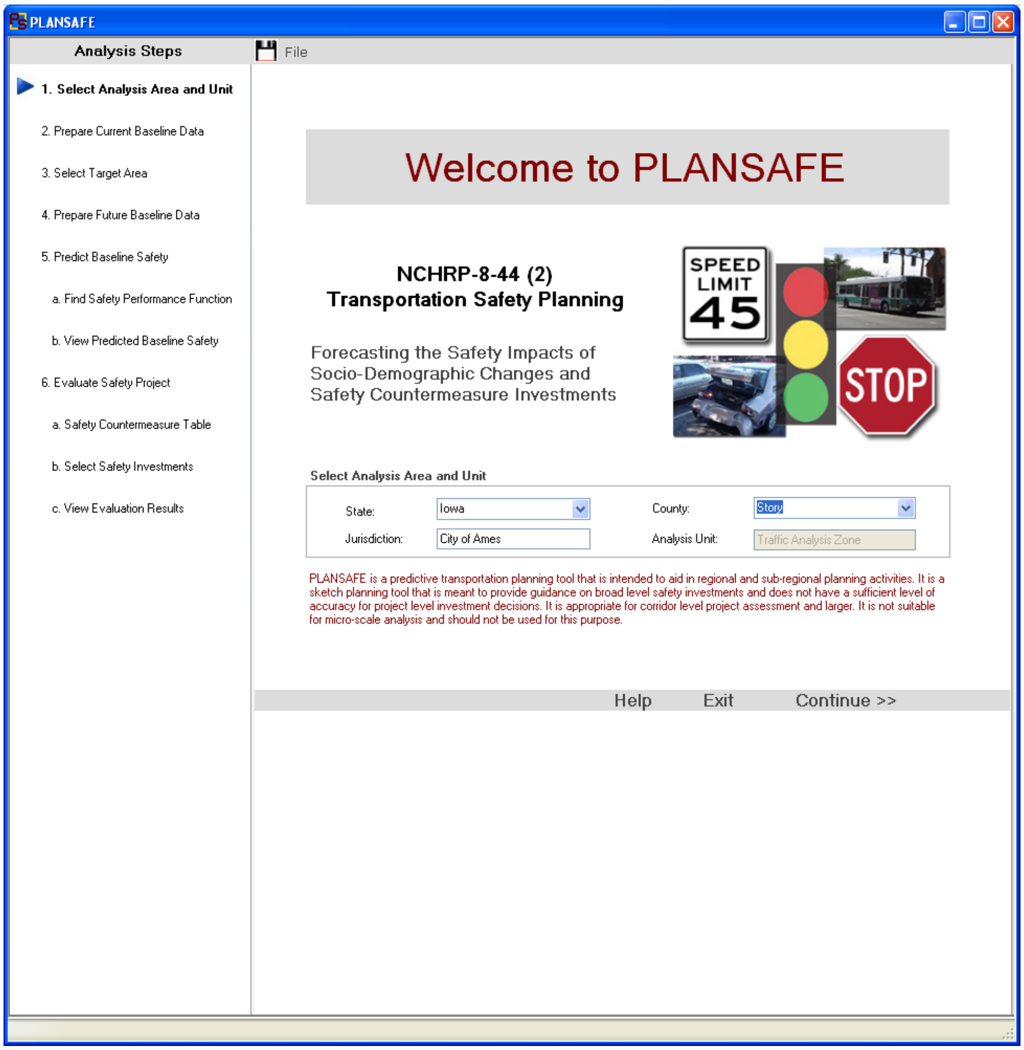

Figure 4.2 PLANSAFE select analysis area and units

2. Prepare Current Baseline Data

This step asked the user to import current baseline polygon data (TAZ data) which included variables like the total crashes per TAZ, VMT per TAZ, housing units per acres etc. Beside the TAZ data mentioned above, crash data included crash ID, crash polygon ID and point-in-polygon portion were also required to be imported.

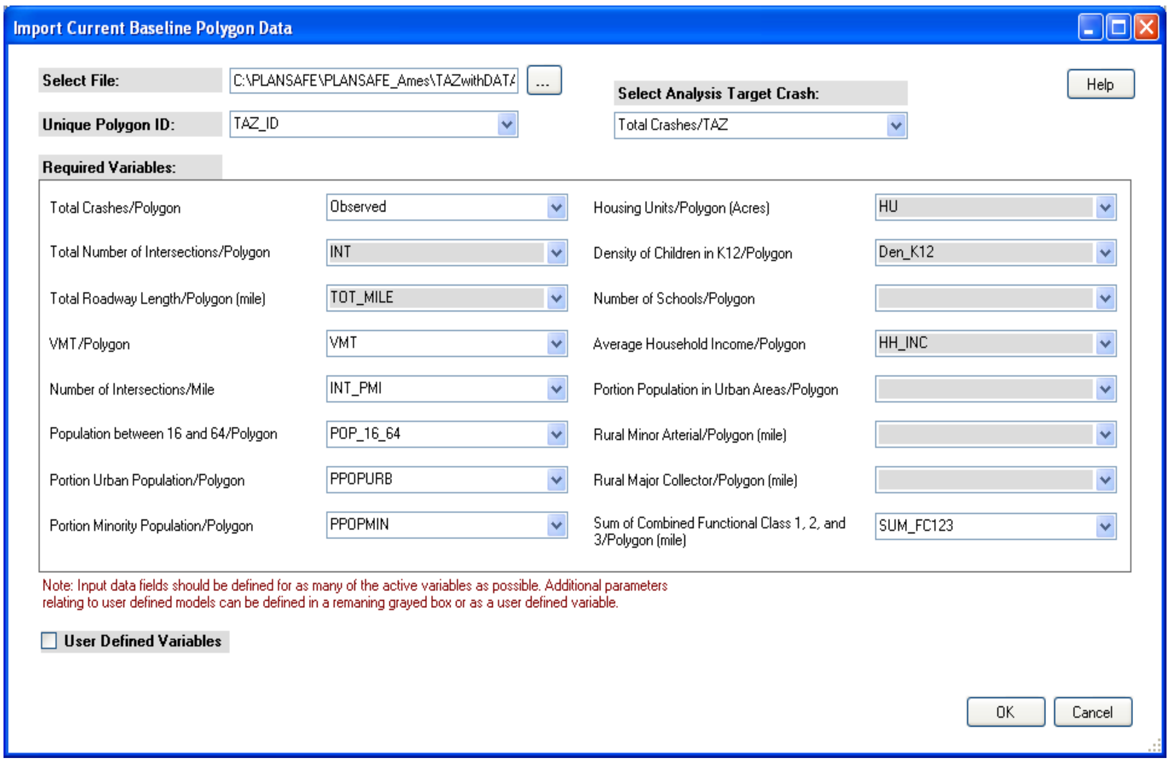

Figure 4.3 PLANSAFE import current baseline polygon data

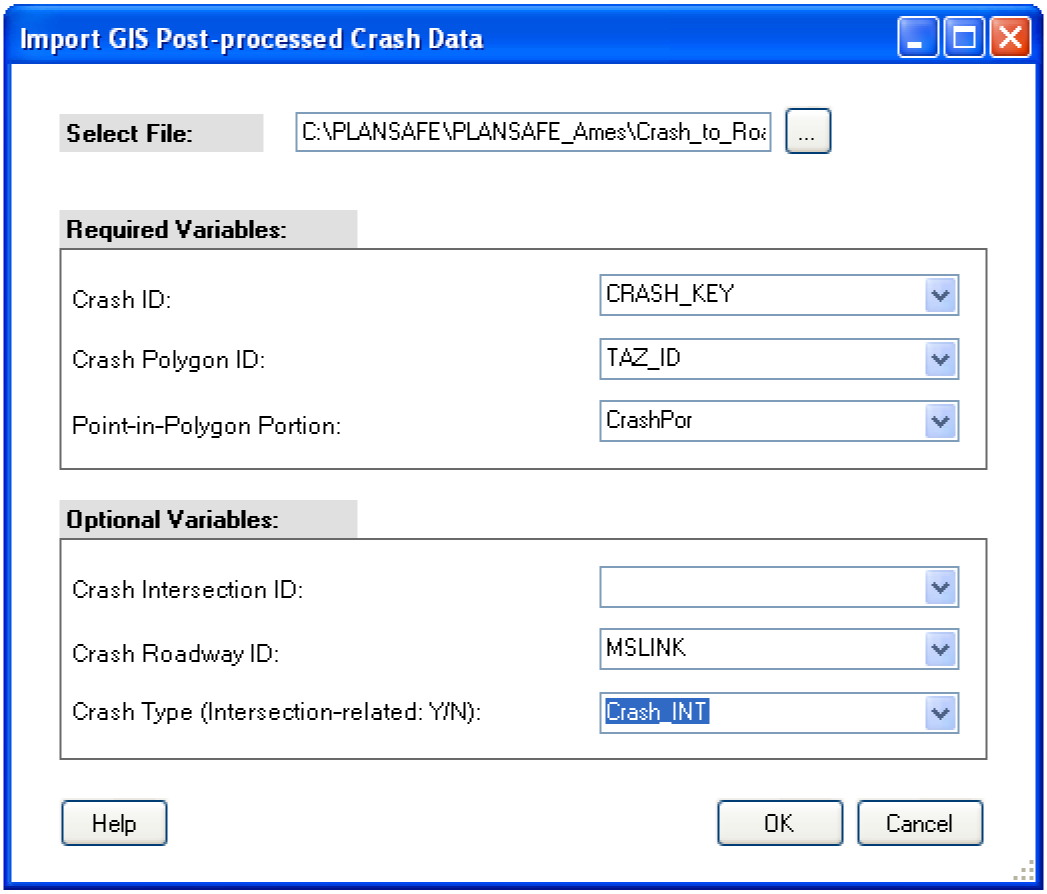

Figure 4.4 PLANSAFE import GIS post-processed crash data.

3. Select Target Area

In this step, the user could select the target area to apply the grow factor for the variables such as population, road mileage, etc. In this case, I selected 3 TAZs located at the west Ames area.

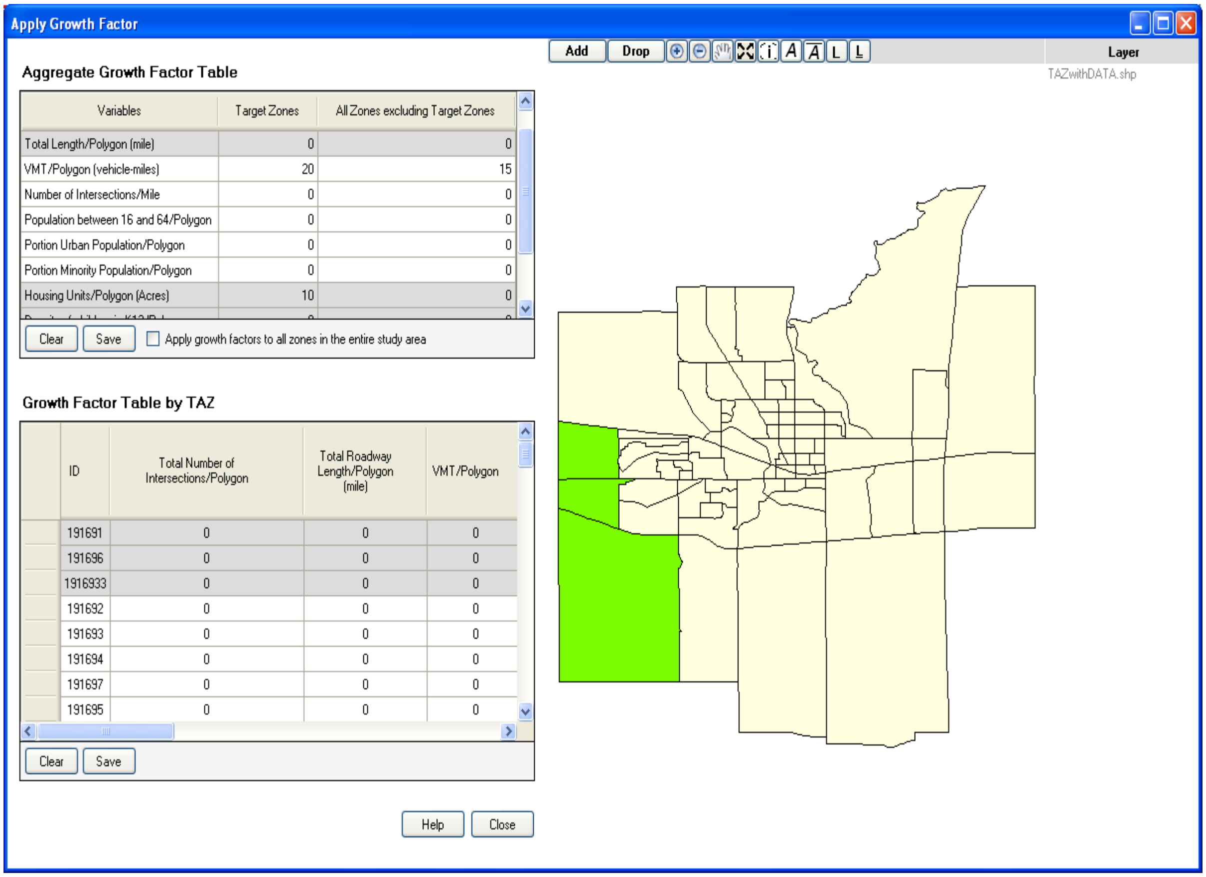

Figure 4.5 PLANSAFE apply growth factor.

4. Prepare Future Baseline Data

This process is similar to step 2, user can either upload the new TAZ and road network data as planned in future or assume they will keep the same as current.

5. Predict Baseline Safety

The user selects safety performance functions (SPFs), which are estimated and calibrated by different predictor variables with *R-Squared* goodness of fit provided.

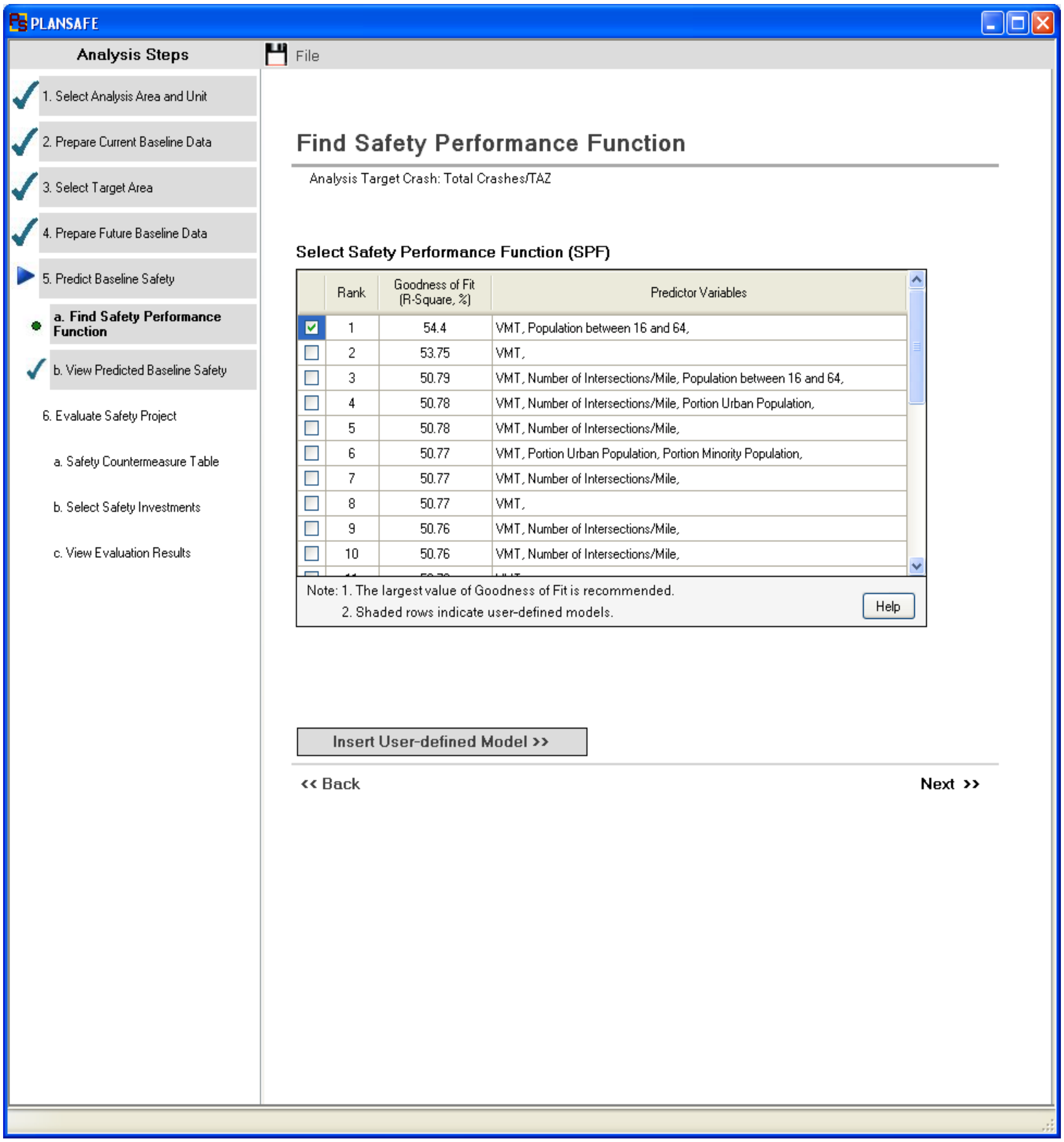

Figure 4.6 PLANSAFE find safety performance function

Figure 4.7 shows the predicted baseline safety performance as the result of the SPFs.

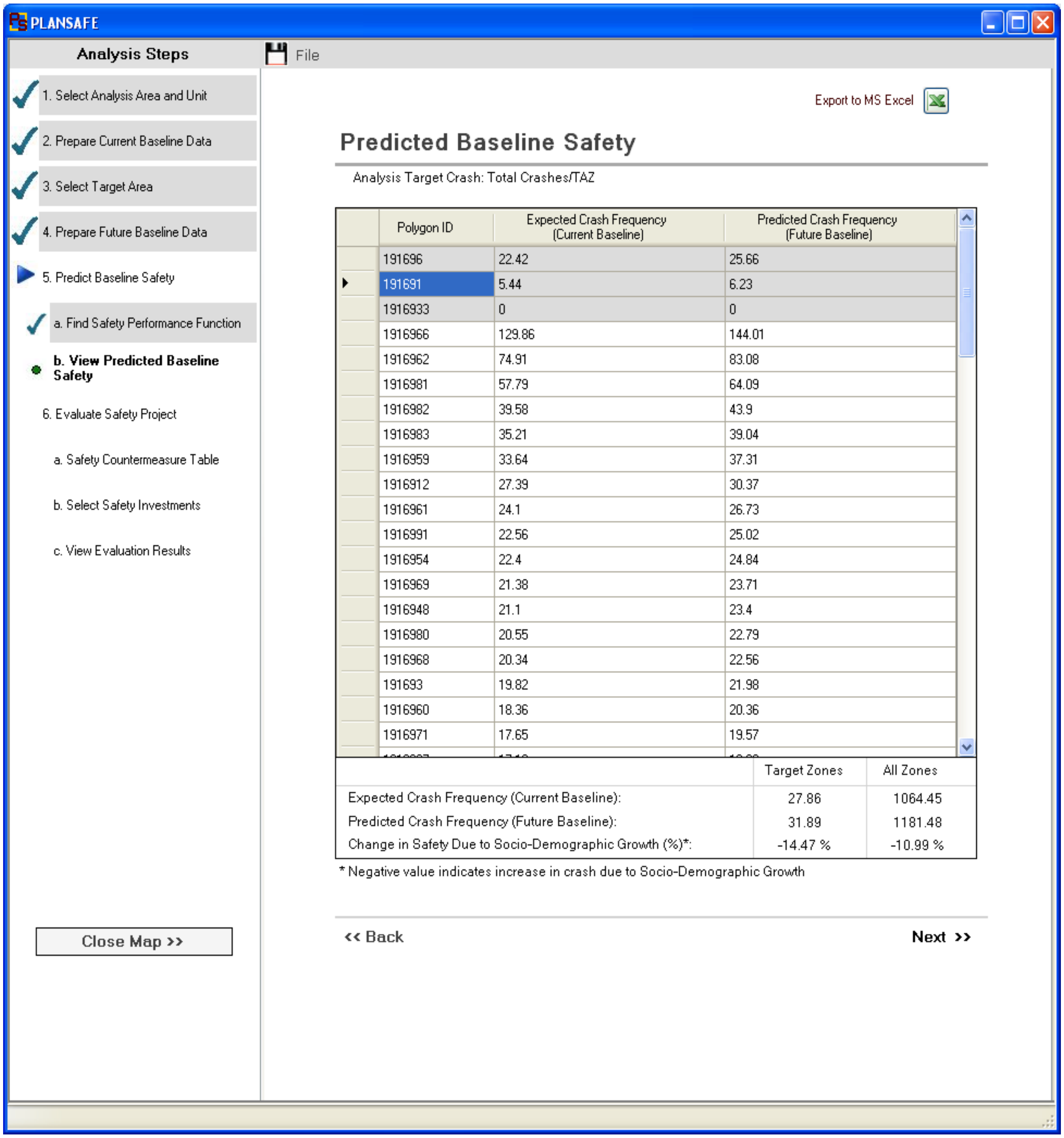

Figure 4.7 PLANSAFE predicted baseline safety

6. Evaluate Safety Projects

First, the software provided a database of different countermeasures with different crash reduction factors (CRF). The users are allowed to update the existing countermeasure table or upload their own countermeasure table as shown below

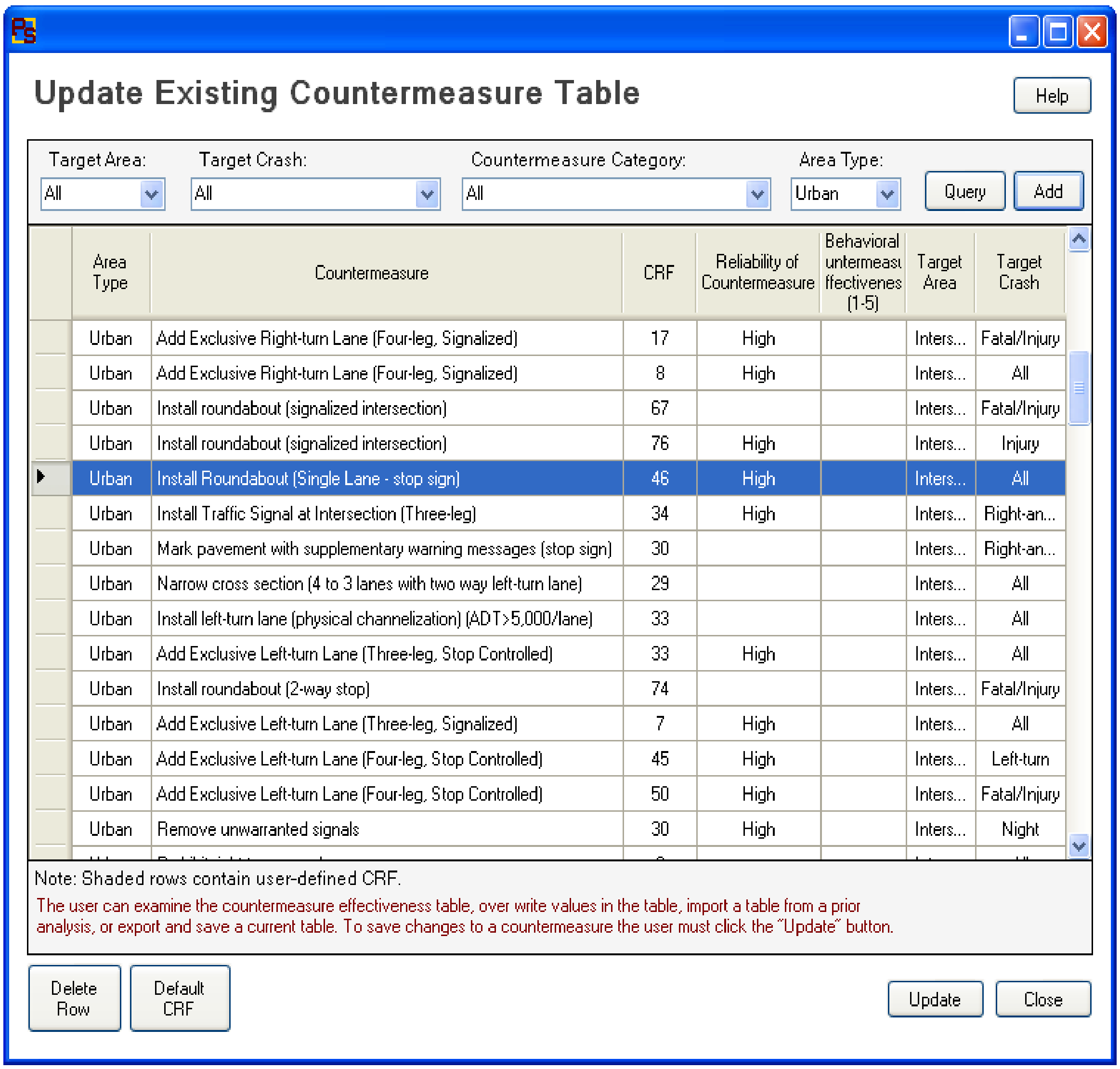

Figure 4.8 PLANSAFE update existing countermeasure table

Next, the user can select safety investments/countermeasures for any TAZs or the specific intersections and/or road segments.

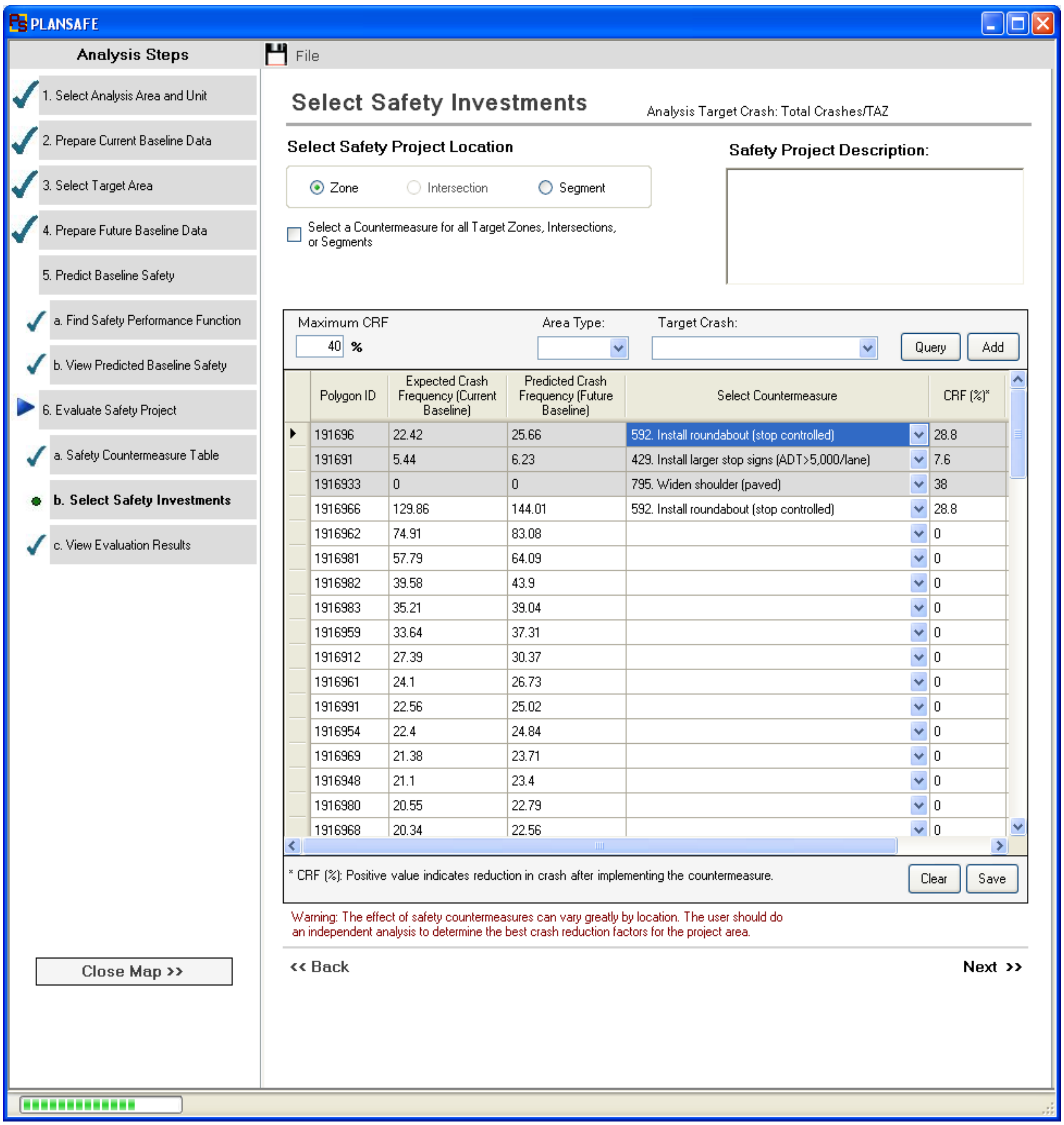

Figure 4.9 PLANSAFE select safety investments

Finally, the safety project evaluation results report was generated.

View Safety Project Evaluation Results

Analysis Area and Unit:

State	Iowa	County	Story
Jurisdiction	City of Ames	Analysis Unit	Traffic Analysis Zone

Analysis Target Crash: Total Crashes/TAZ

Target Area Description: West Ames Area

Safety Project Description: Install roundabout the the target area

Safety Impacts of Socio-Demographic Changes and Safety Countermeasure Investments

The assumed maximum effectiveness is 40%.	Target Zones	All Zones
A. Expected Crash Frequency (Current Baseline):	27.86	1064.45
B. Predicted Crash Frequency (Without Countermeasure):	31.89	1181.48
C. Predicted Crash Frequency (With Countermeasure):	19.77	1127.89
D. Change in Safety Due to Socio-Demographic Growth (%)*:	-14.47 %	-10.99 %
E. Project Effectiveness (%)**:	38 %	4.54 %

* Negative value indicates increase in crash due to Socio-Demographic Growth
** Positive value indicates reduction in crash after implementing the selected countermeasure in the future.

Expected Crash Frequency Plot

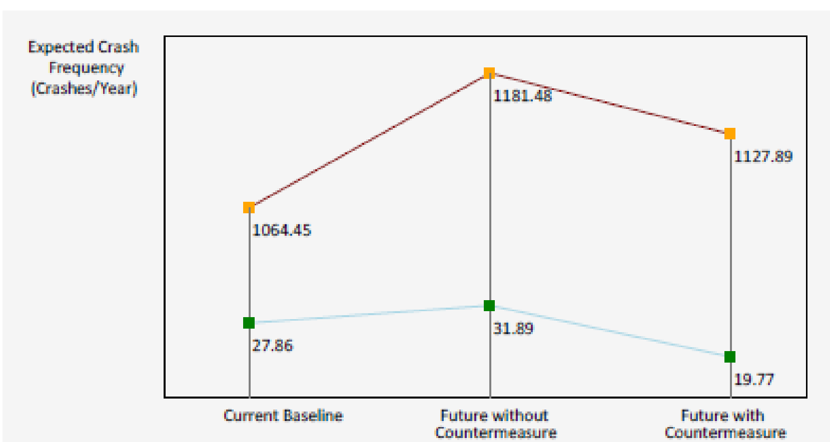

Figure 4.10 PLANSAFE safety project evaluation results

Figure 4.10 shows the change of safety performance of the target zones and all zones due to the socio-demographic changes in future. It also shows the safety performance of the TAZs before and after applying these countermeasures. For example, as shown in the expected crash frequency plot in Figure 4.10, the total crash frequency for all TAZs is 1,064 at current baseline, and it will reach 1,181 in the future due to population growth and land development without any countermeasures being applied. However, upon applying some countermeasures such as installing roundabout in the target area, the future crash frequency will drop to 1,127 which is higher than the current baseline but still better than the future without the countermeasure looks like.

4.3 Summary/Conclusions

Both the PLANSAFE like models and the software could be applicable for safety planning analysis at planning-level. Both of them require a lot of data such as road network data, crash data and socio-demographic data as input to conduct the analysis at the smallest analysis unit of a TAZ. In addition, both methods require a lot of GIS based spatial analysis to obtain the GIS post-processed data as inputs to perform future safety planning analysis.

The PLANSAFE software is more user friendly for the planner without the statistical background. However, there are some limitations to using the software; for example, the models in the software were hard to calibrate by using some particular variables and some of the countermeasures were applicable only at the transportation corridor level not at the planning TAZ level (for example, we can install a roundabout at a certain intersection but not at every intersection located in a TAZ). As such, the models in the PLANSAFE software were not applicable to the City of Ames and I had to develop my own models which give more flexibility for the user to estimate and calibrate the models by using specific variables and allow planners to estimates changes in safety as a result of changes in population, network density, number of housing units and other.

CHAPTER 5. EMPIRICAL BAYES

5.1 Overview

One of the problems encountered when planning for safety in a small/medium-sized community like the City of Ames is the small sample size of variables of interest (for example, crashes).In specific, about 1,000 crashes in total occurred in Ames per year during the period of 2002-2008. As such, the average number of crashes by road type (for example, arterial, collector or local roads) is considered a small number from the aspect of statistic. Table 1 shows the average number of crashes by road type. As it can be observed, there is high variance of crash frequency from year to year for each road type. By using the crash data of City of Ames to screen the high risk locations and predict future crash, different statistical methods were discussed in the next paragraph.

Typically, engineers use the crash data and road attributes for the similar sites to develop Safety Performance Functions (SPFs). SPFs are statistical functions, which present the relationship between crash frequency and road attributes, such as the relationship between crash frequency and annual average daily traffic (AADT) for a two lane rural road. SPFs are used to predict the crash frequency in the future with the change of road attributes or the crash frequency of a similar road. For example, SPFs can predict how the change of AADT in the next two years can change the crash frequency of the two lane rural road, or predict the crash frequency of a similar two lane rural road with a different AADT. Another method to screen the high risk locations and predict future crash is the crash count/frequency method, which involves using historical data on the number of crashes of a similar site over several years and using the average number of crashes for predicting crashes in the future. But if we only use one method either SPF estimation or the crash count/frequency method, the predicted results would be inaccurate and subject to the “regression-to-mean” bias. To increase the precision of estimation in the SPFs and correct for the “regression-to-mean” bias by using the crash count/frequency method only, one statistical approach, known as Empirical Bayes (EB) has been adopted in this thesis.

The EB method uses both datasets from the observed road segments (i.e., Ames road network) and similar sites, which have similar crash frequency and road characteristics to the observed road segments. Hence, the EB method is preferred in this study as it combines both the information contained in the SPFs model estimation from similar sites and the information contained in the crash counts of the observed site (Hauer et al. 2002).

5.2 Statistical Data Analysis

5.2.1 Negative Binomial Regression

As stated in Chapter 2.3, some regression models such as Poisson regression model or Negative Binomial regression model are used to build SPFs. It is required that the count data has a mean equals its variance when the Poisson regression model can be applied. If the variance is significantly larger than the mean, the Negative Binomial regression model is preferred because of the overdispersion. Also noticed in Table 5.2 all the means of crashes are all smaller than the variance of the crashes, so the negative binomial model was used instead of the Poisson model (Washington et al. 2011).

The general expression for the Negative Binomial regression model for each observation is

Eq.5-1 $$yi{\sim}Poisson\ (\lambda i),\ \lambda i = EXP(\beta * Xi + \varepsilon i)$$

where EXP (εi) is a Gamma distribution with mean 1 and variance α. The Negative Binomial regression model has an additional overdispersion parameter Phi (φ).

The variance of yi is given by

Eq. 5-2 $$VAR[y_i] = E[y_i]*[1+ \alpha* E[y_i]]$$

Which shows under this model, $VAR[y_i] > E[y_i]$ for $\alpha > 0$. The Goodness-of-Fit measure for the Negative Binomial regression model can be assessed using the -2 x log-likelihood ratio test as shown below

Eq. 5-3 $$x^2 = -2[LL(\beta r) - LL(\beta u)]$$

Where x^2 follows a Chi-square distribution, $LL(\beta r)$ *i*s the log-likelihood at convergence of the "restricted" model and $LL(\beta u)$ is the log-likelihood at convergence of the "unrestricted" model. The degree of freedom of the x^2 statistic equal the difference in number of parameters of the two models (Washington et al. 2011).

5.2.2 Model Specification

In this study, I first developed SPFs for the City of Ames road segments by different types of road and average crashes over different years. As shown in Table 1, all road segments in the City of Ames are assigned into seven road types, 2 lane arterial (2LArterial), 2 lane collector (2LCollect), 2 lane local (2LLCOAL), 4 lane divided (4LD), 4 lane undivided (4LU), freeway and ramp. The negative binomial regression model based SPFs were developed using the statistic software "R" for each type of road. For each type of road, SPFs were built and calibrated by using one year 2008 crash only, two years average crashes from 2007 to 2008, three years average crashes from 2006 to 2008, etc, until seven years average crashes from 2002 to 2008. As you can find in Table 5.1 because of the number of observations for freeway and ramp are small and no statistical significant SPFs could be built because of the small sample size.

Table 5.1 Average crashes for each type of road to build SPFs.

No. of Ave. Crashes	2LArterial	2LCollect	2LLCOAL	4LD	4LU	Freeway	RAMP	Total
SPF08	78	124	301	233	360	104	30	1230
SPF07-08	86	103	234	216	331	92	28	1090
SPF06-08	81	87	230	200	316	87	27	1028
SPF05-08	79	82	200	198	311	79	25	974
SPF04-08	82	80	214	203	315	78	24	996
SPF03-08	80	76	185	207	310	76	20	954
SPF02-08	76	75	188	204	307	76	20	946
# of obs.	41	66	790	44	55	3	33	
Total Length	17.22	35.76	167.35	12.7	18.1	12.46	8.52	

Table 5.1 (continued)							
% of Length	6.33	13.14	61.49	4.67	6.66	4.58	3.13

To build SPFs, we use μ, the average crashes/year of one road segment as the dependent variable and AADT as independent variable as shown in Table 2.

Table 5.2 Summary statistic

Model(SPFs)	Crash Mean(Variance)	Crash Max./Min.	AADT Mean(Std Dev.)	AADT Max./Min.	# of Obs.
2LArterial(SPF02-08)	1.9024(4.8686)	12/0	7188.05(3103.19)	15100/1500	41
2LCollect(SPF08)	1.8788(10.7427)	22/0	3221.67(2265.35)	8700/50	66
2LLCOAL(SPF07-08)	0.2962(1.0918)	12/0	684.52(1029.29)	15600/6	790
4LD(SPF05-08)	4.5(57.3867)	39/0	10071.98(4507.82)	22717/386	44
4LU(SPF07-08)	6.0182(90.4915)	47/0	9564.05(4804.76)	24200/1100	55

When the SPFs are developed, the overdispersion parameter Phi (φ) of each SPFs in Table 3 are obtained from the model outputs at the same time.

The final estimated SPFs are in the format as Eq. 5-4 below.

Eq. 5-4 $$\mu = L * e^{\theta} * AADT^{\beta}$$

Where μ = number of crashes/year predicted from model

L = Length of the road segment in mile

e = mathematical constant, 2.7182818284

AADT = Annual Average Daily Traffic of the road segment

θ = Intercept

β = parameter for AADT

Table 5.3 Overdispersion parameter Phi (φ) for all each SPFs estimated and calibrated on different years of crashes

Phi (φ)	2LArterial	2LCollect	2LLCOAL	4LD	4LU	Freeway	RAMP
SPF08	0.1832	**0.6173**	2.1022	0.9588	0.5882	N/A	N/A
SPF07-08	0.0079	0.5928	**3.0779**	1.1765	**0.7037**	N/A	N/A
SPF06-08	0.0013	0.4892	1.1494	1.1038	0.4307	N/A	N/A
SPF05-08	0.0002	0.5269	1.4881	**1.2346**	0.3876	N/A	N/A
SPF04-08	0.0175	0.3831	0.6540	1.2019	0.3497	N/A	N/A
SPF03-08	0.0213	0.4808	1.1173	1.2255	0.3509	N/A	N/A
SPF02-08	**0.1192**	0.5308	0.5737	0.8889	0.3597	N/A	N/A
# of obs.	41	66	790	44	55	3	33
Total Length	17.22	35.76	167.35	12.7	18.13	12.46	8.52
% of Length	6.33	13.14	61.49	4.67	6.66	4.58	3.13

These Phi values in bold are the largest Phi values among SPFs in each type of road (Note: for 2 lane arterial (2LArterial), the largest Phi value is from the SPF08, but the variables in the SPF08 model are not significant, so I used the second largest Phi value from SPF02-08 instead).

The final SPFs model specifications in Table 5.4 and Table 5.5 as shown below

Table 5.4 Negative binomial estimated equations by road type

ROADTYPE	SPFs
2LArterial(SPF02-08)	crash in one year = LENGTH*2.71828183^(-8.3553)*AADT^1.1155
2LCollec(SPF08)	crash in one year = LENGTH*2.71828183^(-6.2014)*AADT^0.9667
2LLOCAL(SPF07-08)	crash in one year = LENGTH*2.71828183^(-5.3953)*AADT^0.8845
4LD(SPF05-08)	crash in one year = LENGTH*2.71828183^(-6.669)*AADT^1.038
4LU(SPF07-08)	crash in one year = LENGTH*2.71828183^(-6.4516)*AADT^1.0095

Table 5.5 Negative binomial model specification by road type

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-8.3553	-2.707	0.00679 ***
logAADT	1.1155	3.216	0.00130 ***
Phi φ	0.119		
-2 x log-likelihood	125.425	p-value	<0.0001***
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-6.2014	-3.922	8.79e-05 ***
logAADT	0.9667	4.903	9.43e-07 ***
Phi φ	0.617		
-2 x log-likelihood	197.437	p-value	<0.0001***
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-5.3953	-7.51	5.92e-14 ***
logAADT	0.8845	8.115	4.85e-16 ***
Phi φ	3.078		
-2 x log-likelihood	802.814	p-value	<0.0001***
4LD			
Variable	Estimate	t-statistic	p-value

Table 5.5 (continued)			
Intercept	-6.669	-1.758	0.0788 *
logAADT	1.038	2.519	0.0118 **
Phi φ	1.235		
-2 x log-likelihood	206.803	p-value	<0.0001***
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-6.4516	-2.426	0.015260 **
logAADT	1.0095	3.488	0.000487 ***
Phi φ	0.704		
-2 x log-likelihood	267.016	p-value	<0.0001***

Note: ***, **, *==> Significance at 1%, 5%, 10%

5.2.3 Empirical Bayes Methodology

After the SPFs are built, EB uses both the crash data from the SPFs model estimation and observed site crash counts to compute the estimate, which is a weighted average of both. This process can be explained as below (Hauer et al., 2002).

Eq. 5-5 *EB Estimate of the Expected Crashes for an entity = Weight * Crashes expected on similar entities + (1 – Weight) * Count of crashes on this entity, where 0 ≤ Weight ≤ 1*

The weight in the equation above plays an important role in the EB estimate. The weight that is assigned on between the SPF model estimate and the site observation should depend on both the results of the SPFs (μ and φ) and on how many years of site crash data are available. The weight can be calculated as follows (Hauer et al., 2002).

Eq. 5-6
$$W = \frac{1}{1+(\mu * Y)/\varphi} = \frac{\varphi}{\varphi+\mu * Y}$$

Where W = weight applied to model estimate

μ = mean number of crashes/year from model

φ = overdispersion parameter

Y = the number of years during which the crash count was taken

As $\varphi \rightarrow 0$ (i.e.; the average crash rate at our site is a good estimate of the long-run average crash rate), then $W \rightarrow 0$ and the EB estimate depends only on the crash information at the site.

Although I built all the SPFs by using average crash data over different years for each type of road as shown in Table 5.3, I only selected the SPFs with the largest overdispersion parameter (Phi values) in each type of road to calculate the EB estimate. From Eq. 5-6, it's easy to understand that the larger the overdispersion parameter, the larger the weight. By selecting the SPFs with the largest overdispersion parameter, a heavier weight is assigned to the SPF model estimate, as shown in Eq. 5-5.

5.3 EB Analysis Results

After I got the SPFs by different types of road as shown in Table 4, I calculated the EB estimates using these SPFs combined with different years site observed crash data. To keep using the same SPFs results as "*Crashes expected on similar entities*" and changing "*Count of crashes on this entity*" in Eq. 5-5 from one year 2008 crash only, two years average crashes from 2007 to 2008, three years average crashes from 2006 to 2008, etc, to seven years average crashes from 2002 to 2008, finally, I got total 7 different EB estimations as EB 08, EB 07-08, EB 06-08, etc, to EB 02-08.

Then I calculated the corresponding root mean square error (RMSEs) using equation 5-7 below that compared the EB estimated crash frequency in 2009 with the actual crash frequency in 2009. I also calculated the corresponding RMSEs that compared the average crashes over different years with the actual crash frequency in 2009. All results are shown in Table 5.6.

Eq. 5-7 $\theta 1 = \begin{bmatrix} x1,1 \\ x1,2 \\ \vdots \\ x1,n \end{bmatrix}$ and $\theta 2 = \begin{bmatrix} x2,1 \\ x2,2 \\ \vdots \\ x2,n \end{bmatrix}$

$$RMSE(\theta 1, \theta 2) = \sqrt{E((\theta 1 - \theta 2)^\wedge 2)} = \sqrt{\frac{\sum_{i=1}^{n}(x1,i - x2,i)^\wedge 2}{n}}$$

θ1 and θ2 are the datasets the analyst wishes to compare.

Table 5.6 EB estimate vs Crash 2009 and Average Crashes vs crash 2009 by RMSEs

(EB estimates are calculated by using the largest Phi values SPFs)

Years of crash used		$RMSE_{AVE}$		$RMSE_{EB}$
1	Crash 2008 vs 2009	1.7345	EB 08 vs 2009	1.6546
2	Ave. 07-08 vs 2009	1.5754	EB 07-08 vs 2009	1.5211
3	Ave. 06-08 vs 2009	1.5064	EB 06-08 vs 2009	1.4743
4	Ave. 05-08 vs 2009	1.5022	EB 05-08 vs 2009	1.4784
5	Ave. 04-08 vs 2009	1.4898	EB 04-08 vs 2009	1.4690
6	Ave. 03-08 vs 2009	1.5036	EB 03-08 vs 2009	1.5015
7	Ave. 02-08 vs 2009	1.5136	EB 02-08 vs 2009	1.5119

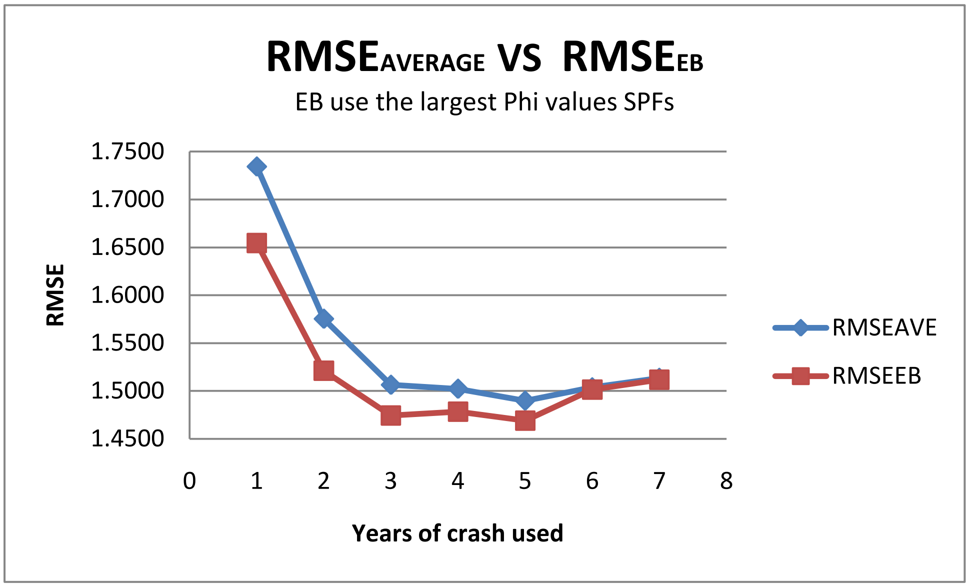

Figure 5.1 RMSE$_{\text{AVERAGE}}$ vs RMSE$_{\text{EB}}$, EB use the largest Phi values SPFs.

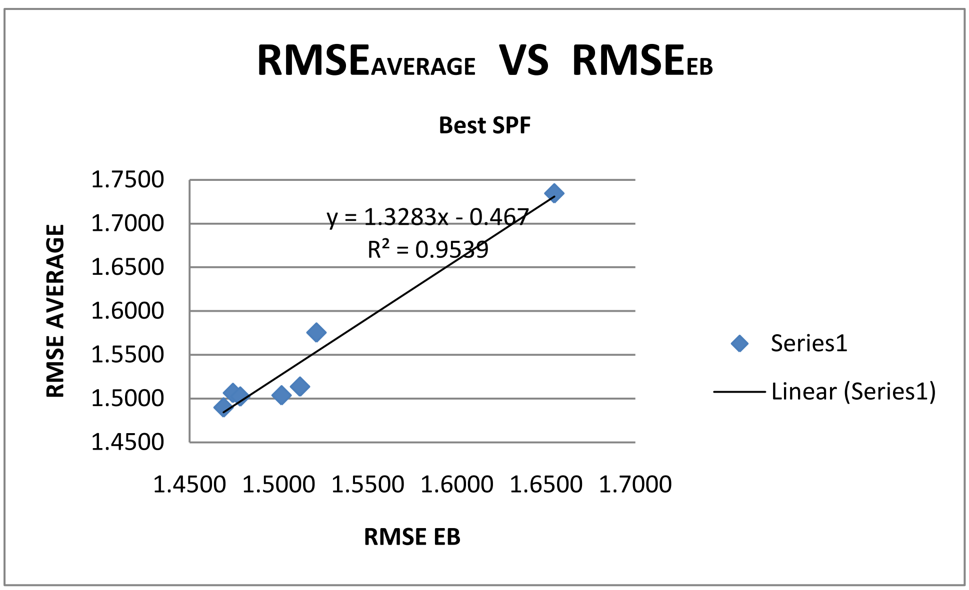

Figure 5.2 RMSE$_{\text{AVERAGE}}$ vs RMSE$_{\text{EB}}$, EB use the largest Phi values SPFs (R^2).

There are two research questions to be addressed here. First, whether the EB method is better than the average crash method for prediction purposes. Second, whether the multiple year crashes used in the EB method or the average crash method over different years are better than using less years or one year crash data.

It can be observed from Table 5.6 and Figure 5.1, first, that in all cases, the EB method is better than the average crash method for predicting crashes, as indicated by the smaller RMSEs. Second, the RMSEs become smaller when more years of crash data are used, which suggests a higher confidence in the predictions with more years of crashes available. However, this trend only holds up to 5 years of crash data being used. The prediction accuracy does not improve (actually, it is worse) when more than 5 years of crash data are used. This is probably attributed to the fact that crash data over 5 years old cannot accurately represent the current safety situation for the site.

I also conducted another EB analysis similar as the one above; the only differences are using the seven years average crash of 2002-2007 to build SPFs for all types of road and calculate the EB estimates using all year's combination. The results are shown below.

Table 5.7 EB estimate vs Crash 2009 and Average Crashes vs crash 2009 by RMSEs

(EB estimates are calculated by using the most comprehensive crash data from 02-08 to build SPFs)

Years of crash used		$RMSE_{AVE}$		$RMSE_{EB}$
1	Crash 2008 vs 2009	1.7345	EB 08 vs 2009	1.6709
2	Ave. 07-08 vs 2009	1.5754	EB 07-08 vs 2009	1.5438
3	Ave. 06-08 vs 2009	1.5064	EB 06-08 vs 2009	1.4900
4	Ave. 05-08 vs 2009	1.5022	EB 05-08 vs 2009	1.4904
5	Ave. 04-08 vs 2009	1.4898	EB 04-08 vs 2009	1.4801
6	Ave. 03-08 vs 2009	1.5036	EB 03-08 vs 2009	1.4957
7	Ave. 02-08 vs 2009	1.5136	EB 02-08 vs 2009	1.5071

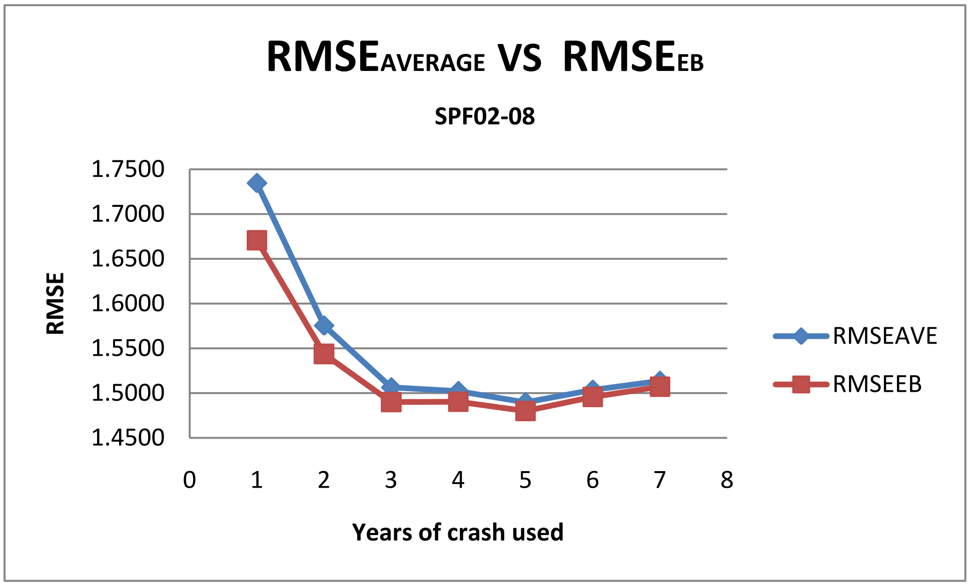

Figure 5.3 RMSEAVERAGE vs RMSEEB, EB use the SPF02-08.

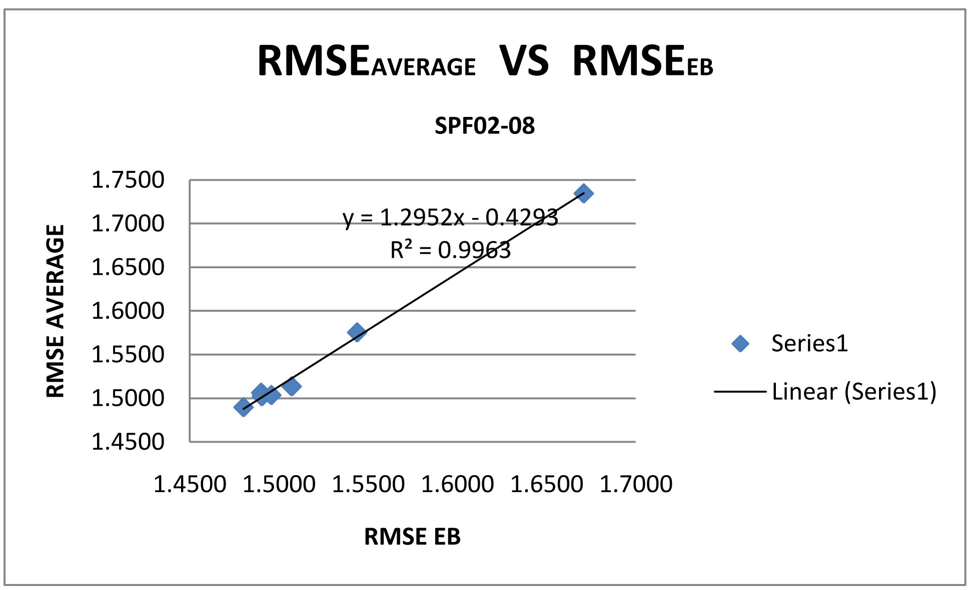

Figure 5.4 RMSEAVERAGE vs RMSEEB, EB use the SPF02-08 (R^2).

The results are similar to what was presented above. First, in all cases, the EB method is better than the average crash method for predicting crashes. Second, the RMSEs become smaller when more years of crash data are used, which suggests a higher confidence in the predictions with more years of crashes available. However, this trend only holds up to 5 years of crash data being used. The only difference is that the RMSE average is closer to RMSE EB, which makes sense because I used more comprehensive crash data from 02-08 to build SPFs and develop EB, hence the EB prediction will be as effective as the average crash prediction.

5.4 Summary/Conclusions

If a long period of site crash data is not available (for at least four years) for predicting the crash frequency for a certain site, the EB methodology can produce estimates that are more accurate than those obtained from the average crash method. If more than four years of site crash data are available, using the EB methodology is not preferred to just using the average number of crashes on that site over that time period. This analysis also showed that there is no benefit, in terms of improving the accuracy of the predictions, of collecting crash data over a time period longer than 4 years.

All SPFs model outputs and EB calculations can be found in the Appendix.

CHAPTER 6. USRAP STYLE RISK MAPPING

6.1 Overview

The consideration of safety in metropolitan planning is a requirement of federal highway legislation (SAFETEA-LU). However, no specific guidance has yet been provided to metropolitan planning organizations (MPOs) on how safety should be considered (qualitatively or quantitatively), nor where or at what level it should be considered (project, corridor or region wide). The lack of guidance is particularly challenging to small planning agencies. In recent years, several safety analysis techniques have been developed that may be applicable to explicitly incorporate safety objectives in the planning process.

This chapter investigates road assessment program (RAP) and risk mapping strategies that may be applicable to small area metropolitan safety planning. These methodologies were originally developed by EuroRAP and have subsequently been adapted for use in the US Road Assessment Program (usRAP), sponsored by the AAA Foundation for Traffic Safety (AAAFTS). usRAP risk mapping and road assessment methods have previously been applied to state highways by the Midwest Research Institute (MRI) and the Center for Transportation Research and Education (CTRE) at Iowa State University. usRAP has three safety assessment protocols that are potentially applicable to regional planning: risk mapping, star ratings and countermeasure programs selection (known as Safer Roads Investment Programs). The objective of this chapter is to report on the investigation of applicability of usRAP risk mapping method to small and medium sized urban area safety planning.

Previous usRAP efforts have concentrated on serious crashes, as those crashes have the most profound effect on society. However, for small metropolitan areas with many lower speed roads, serious crashes are (thankfully) rare events. In order to have a reasonable number of crashes to analyze and display, total crashes are used in the risk mapping section of this chapter. Risk maps are based on crash data and can provide various views of roadway safety to support safety investment.

The principal objective of the research reported in this chapter is to demonstrate the applicability of the usRAP risk mapping protocol to small area urban safety planning.

To accomplish this objective, the following tasks were conducted:

1. Invite and assemble an advisory team (see below for specific composition). Outcome: advisory committee formation.
2. Assemble data for risk mapping. Outcome: GIS crash database in usRAP risk mapping format for Ames roads.
3. Develop 4 basic risk maps for the City of Ames (crash density, crash rate, crash rate ratio and potential crash savings). Outcome: series of usRAP style risk maps for Ames.
4. Test risk mapping for low volume local urban roads (residential streets). Outcome: summary of results and implications
5. Prepare final report.

6.2 usRAP style risk mapping

6.2.1 Methodology

As discussed in section 6.1, the application of usRAP risk mapping to small and medium-sized communities was evaluated for the first time in this research. Due to the unique characteristics of small and medium-sized communities, there are some limitations to this proposed application. First, number of fatal and major injury crashes is too small to develop meaningful maps for these categories of crashes. Second, the road network in the city has shorter segments, a more complex environment, more types of roads and more intersections and traffic control devices as compared to rural roads. Therefore, all severities of crashes were used for this analysis.

The road segmentation in GIS was completed by using the street name, AADT category (0-100-400-1000-5000-10000-max), speed category (0-25mph, 30-35mph, 40-45mph, 50-55mph and >55mph) and road type (2 lane local, 2 lane collector, 2 lane arterial, 4 lane undivided, 4 lane divided and freeway) and each segment had a unique ID. Next the new road network and crash data were used to create the usRAP style crash density map, crash rate map, crash rate ratio map and potential crash savings map.

For the usRAP style crash map 1 and 2, the crash density map and crash rate map, first, calculate the crash density (in crashes per mile) and crash rate (in crashes per 100M VMT), The resulting risk of a road segment from high to low is presented with five categories. High, means the crash density or crash rate of a certain segment is ranked in the highest top 5% of all segments by total mileage, medium-high is between top 5%-15%, medium is between top 15%-35%, low-medium is between 35%-60% and low is between 60%-100%.

For the usRAP style crash map 3, crash rate ratio map, first, calculate the average crash rates of each road types (2 lane local, 2 lane collector, 2 lane arterial, 4 lane undivided, 4 lane divided and freeway); second, calculate the crash rate ratio of each road segment compare to average crash rates for the same or similar roads. The resulting risk of a road segment from high to low is presented with five categories. High, means the crash rate ratio of a certain segment is ranked in the highest top 5% of all segments by total mileage, medium-high is between top 5%-15%, medium is between top 15%-35%, low-medium is between 35%-60% and low is between 60%-100%.

For the usRAP style crash map 4, potential crash savings map, calculate the number of total crashes saved per mile in seven years of each road segment if crash rate were reduced to the average crash rate for similar roads. The resulting potential crash savings of a road segment from high to low is presented with five categories. High, means the potential crash savings of a certain segment is ranked in the highest top 5% of all segments by total mileage, medium-high is between top 5%-15%, medium is between top 15%-35%, low-medium is between 35%-60% and low is between 60%-100%.

6.2.2 Results

The four usRAP style risk maps are shown below.

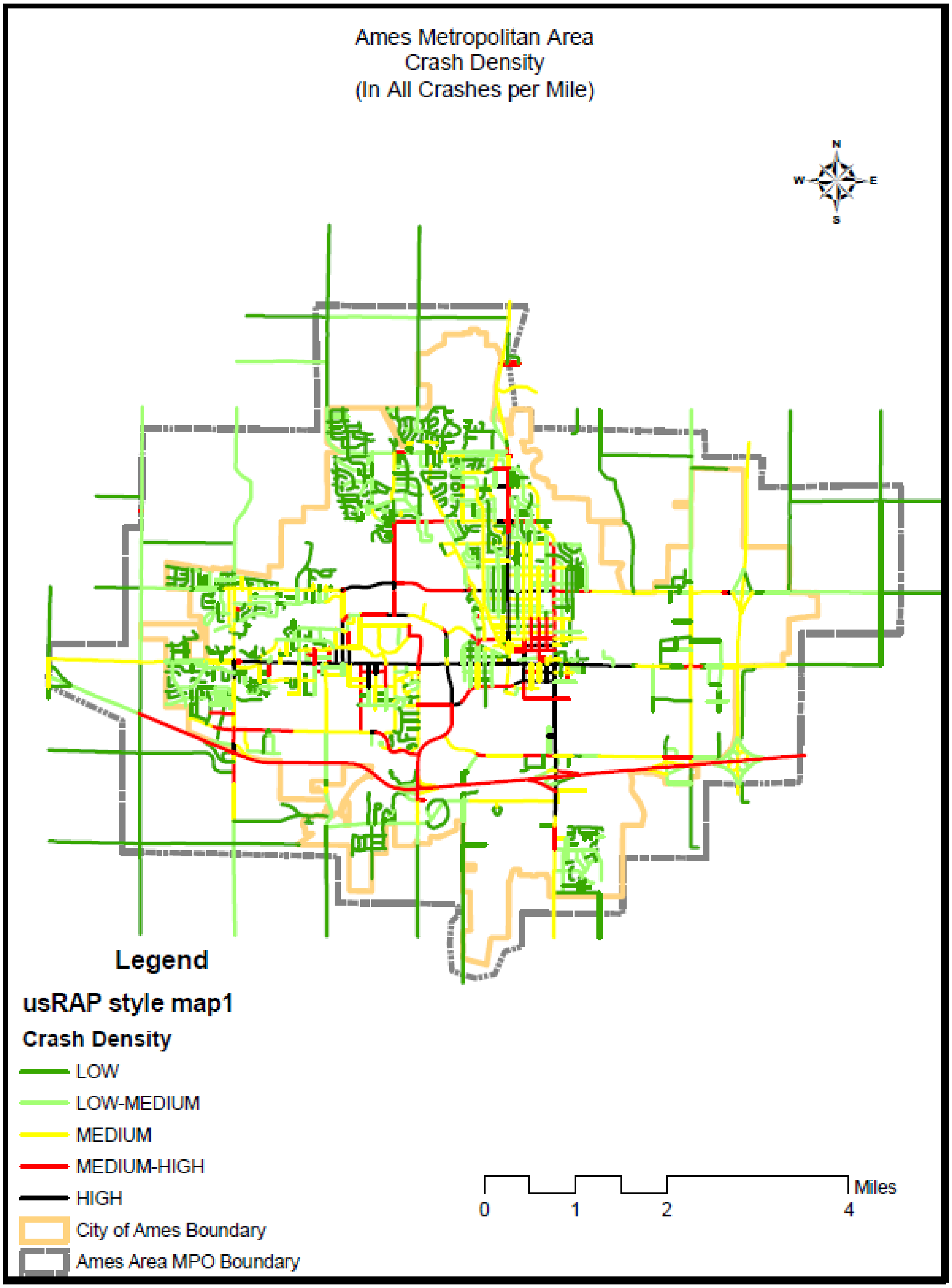

Figure 6.1 usRAP style map1 Crash Density

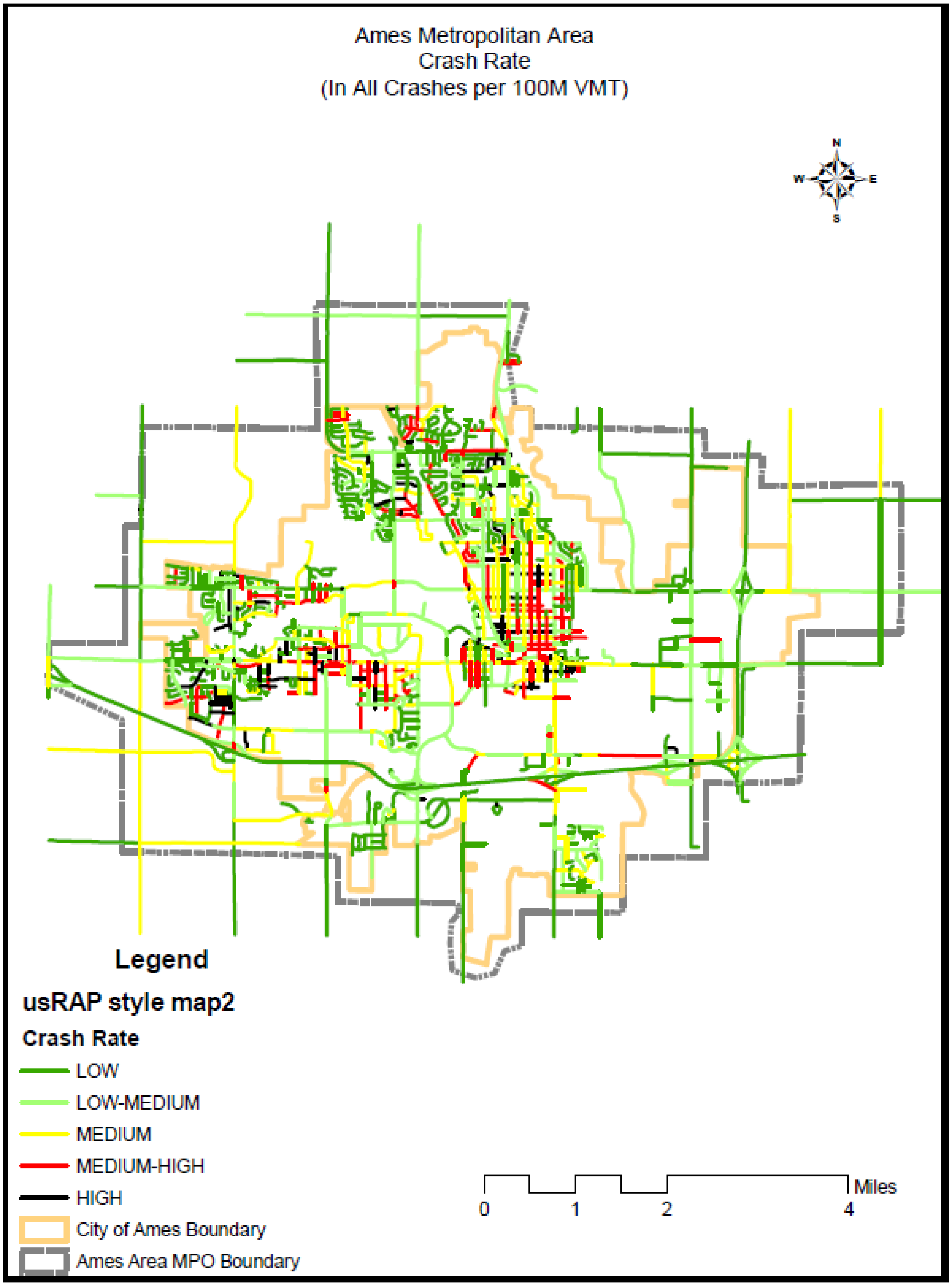

Figure 6.2 usRAP style map2 Crash Rate

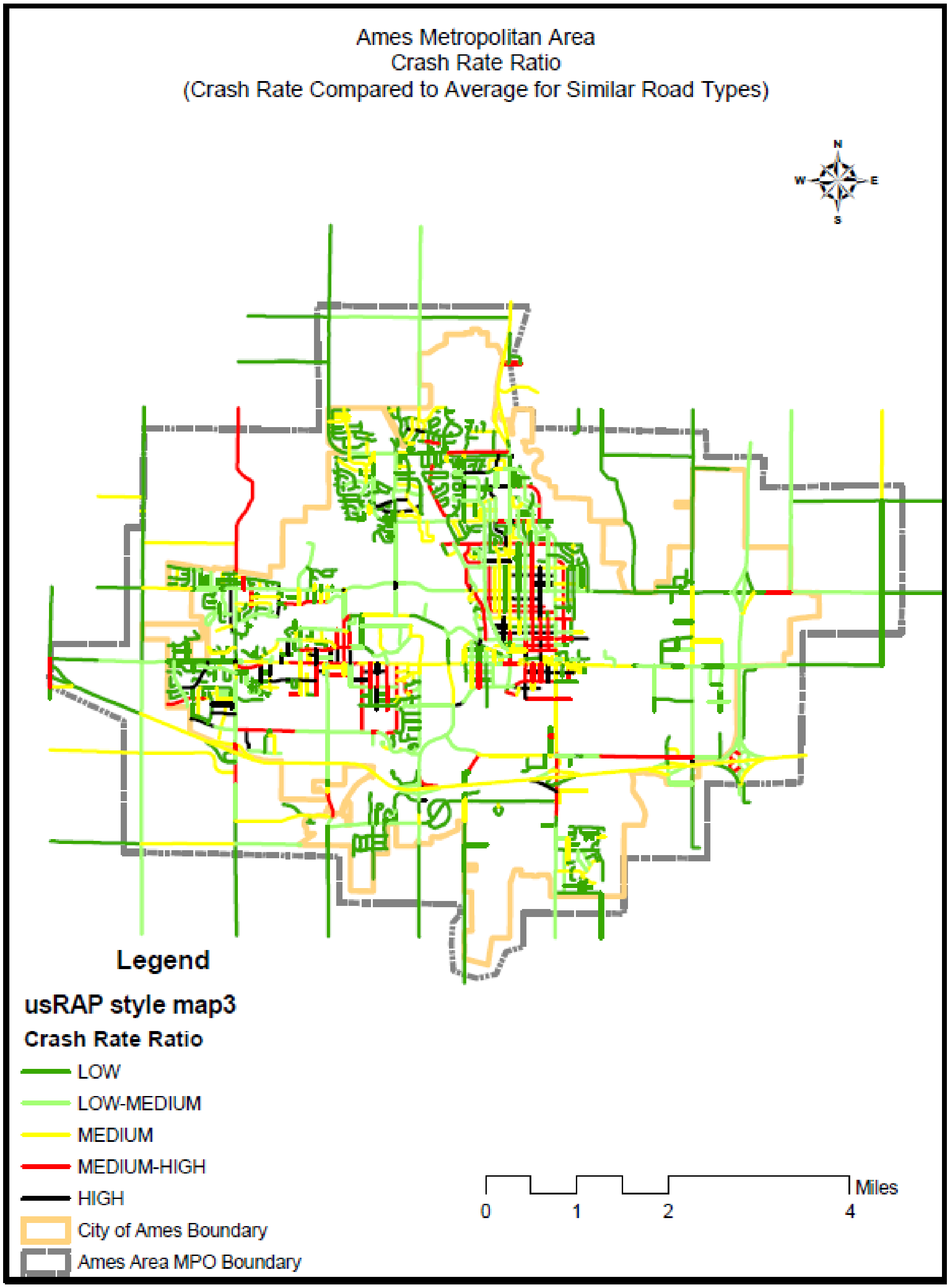

Figure 6.3 usRAP style map3 Crash Rate Ratio

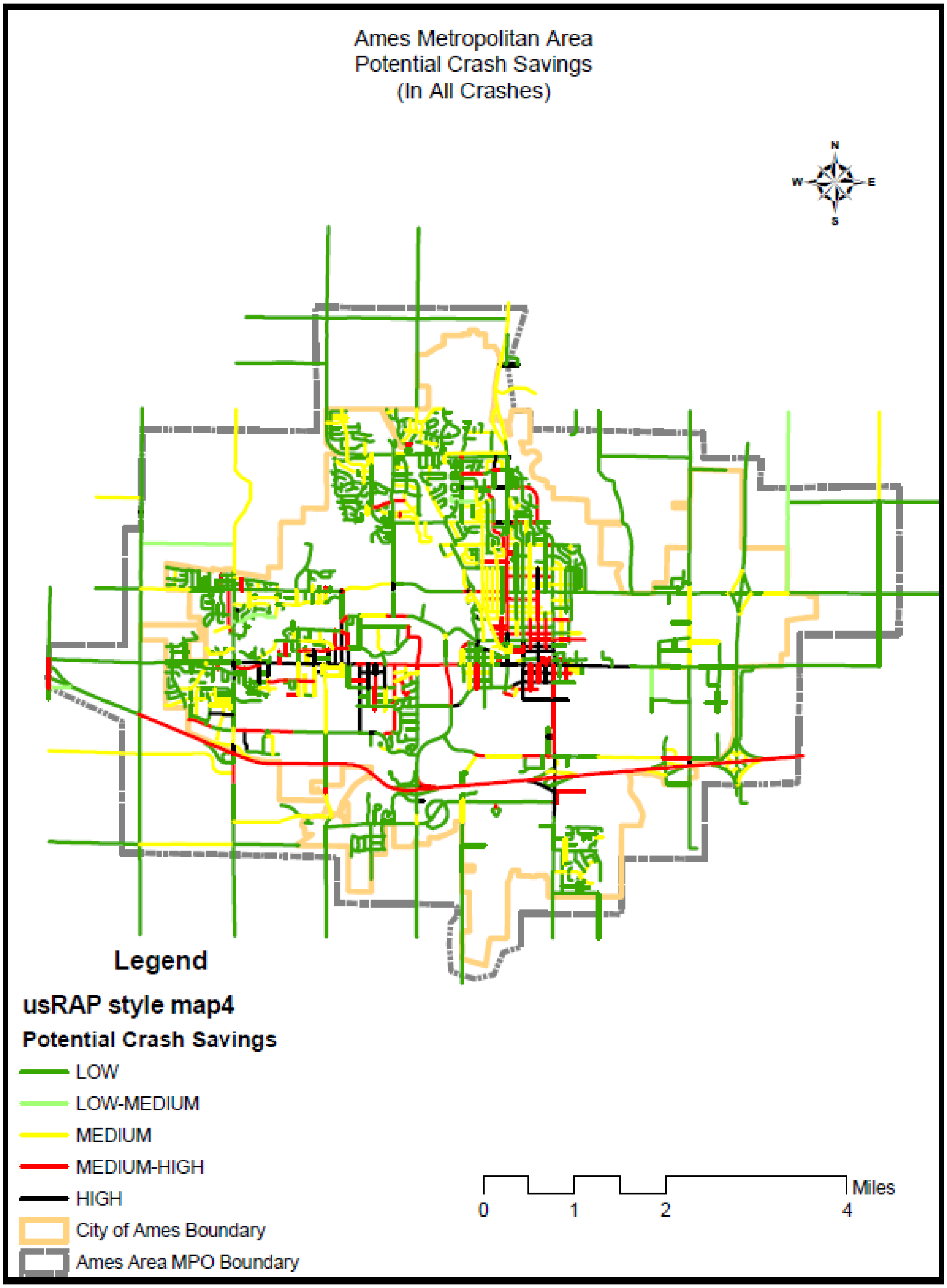

Figure 6.4 usRAP style map4 Potential Crash Savings

The summary risk mapping data is listed below in table 6.1

Table 6.1 Risk Mapping Data Summary (Ames Metropolitan Area 2002-2008)

Road Type	Sections	Road Miles	Average Length (mi)	Average AADT (vel/day)	Annual VMT (Million)	Total Crashes				Fatal Crashes	Major Injury Crashes
						Total Frequency	Annual Frequency	Annual Density	Annual Rate per M VMT		
Two-lane Local	790	167.4	0.212	683	41.7	1691	242	1.44	5.79	2	21
Two-lane Collector	66	35.8	0.542	3217	42	631	90	2.52	2.15	2	5
Two-lane Arterial	41	17.2	0.420	7189	45.1	607	87	5.04	1.92	0	9
Four-lane Undivided	55	18.1	0.329	9557	63.1	2236	319	17.65	5.06	6	28
Four-lane Divided	44	12.7	0.289	10064	46.7	1508	215	16.96	4.61	0	25
Freeway	3	12.5	4.167	19080	87.1	569	81	6.50	0.93	2	19
Ramp	33	8.5	0.258	2908	0.9	168	24	2.82	26.67	0	3
Total	1032	272.2	0.264	2102	326.6	7410	1059	3.89	3.24	12	110

6.3 Summary/Conclusions

The usRAP style maps 1 and 2, the crash density (in crashes per mile) map and crash rate (in crashes per 100M VMT) map can be used to identify top high-risk locations.

The usRAP style map 3, the crash rate ratio map, is based on the relative total crash rate per100 million vehicle-miles traveled for road segments in comparison to the average crash rate for similar segments. This map can be used to identify road segments that may not be performing as well as similar roads.

The usRAP style map 4, the potential crash savings map, is based on the number of total crashes saved per mile in seven years of each road segment if the crash rate were reduced to the average crash rate for similar segments. This map can be used to identify road segments that may have the potential opportunity for safety improvements by applying the countermeasures like infrastructure modifications or enforcement programs.

All of these four usRAP style risk maps can help people in local transportation office and planning agencies to indentify the high-risk locations and improve the safety features of roads with limited funds and achieve the highest cost-benefit ratio for both motorists and general public.

CHAPTER 7. CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

7.1 Conclusions and Limitations

Although the three safety techniques studied in this work have potential for application in planning, all have limitations.

The calibrated PLANSAFE-like SPF models provide predicted crash frequency based on historical crash data, road network data, and socio-demographics data at the planning-level. The PLANSAFE software uses the same theory as the models but provides a more user friendly interface for the planner without statistical background. Both approaches can be policy sensitive, by including variables within the control of decision makers, such as planning and zoning restrictions, utility provisions or road plans. However, for cities the size of Ames, small crash datasets and short road segments limit the calibration of policy sensitive models. In fact, only two, limited variable PLANSAFE-like SPFs could be developed for Ames. In addition, the PLANSAFE software was not applicable given the available data, necessitating the development of customized models.

The Empirical Bayes crash analysis methodology is useful for problem site identification. EB is useful for small, lower crash density locations as it combines the limited information available from site-specific crash histories with information from similar locations (SPFs). The EB method gives more precise and less biased crash prediction than traditional count (frequency), rate, critical rate, cost or combined methods. The method is particularly useful when long crash histories (more than, say, four years) are not available.

usRAP-style risk mapping can be used to incorporate risk into decision making. Each of the four usRAP-style maps clearly present area-wide crash risk information of interest to various user groups (road authorities, drivers), demonstrating that no single map can provide all the information needed to make effective safety planning decisions. The maps can be used to identify higher-risk roads that could be useful as agencies comply with Federal SAFETEA-LU requirements. However, while the risk mapping protocols of usRAP were demonstrated, it was not possible in the scope of this work to investigate the potential of the usRAP Road Protection Score/Star Rating or Safer Roads Investment Program protocols, which would seem to hold additional promise for application in small urban areas.

Lastly, all of the studied methodologies require significant amounts of detailed data, including located crash data and road attribute data. For planning agencies with limited access to such data, approximations may be possible using appropriate statewide databases.

7.2 Recommendations

Following on the state of the practice review presented herein, as well as the demonstrations of the three safety planning tools, it is recommended that small and medium-sized metropolitan areas consider the following:

1. As set forth in legislation, safety should be an integral part of the agency's planning objectives and goals and emphasized throughout the life cycle of transportation planning.
2. Data-driven safety planning requires the collection and maintenance of quality data including geocoded crash and road network data.
3. Due to the clarity and effective graphical presentation of usRAP style risk maps, they may be more useful in early stages of the transportation planning and public involvement process.
4. More detailed evaluation of high risk locations should be conducted with the EB methodology.
5. The PLANSAFE models or software are most useful in "big picture" planning and policy analysis. Even if models cannot be developed to be sensitive to policies within the control of metro planners, the models can be used to forecast the impacts of changes in socioeconomics and demographics so that cities may be more prepared for long-run changes in safety.

6. Following this process, quantitative safety may be incorporated into the planning process, through effective visualization and increased awareness of safety issues (usRAP), the identification of high risk locations with potential for improvement, (usRAP maps and EB), countermeasures for high risk locations (EB before and after study and PLANSAFE), and socio-economic and demographic induced changes at the planning-level (PLANSAFE).

Overall, while the applicability of these tools was examined for the City of Ames, it is recommended that additional case studies be performed as the tools may be more or less applicable in other locations. It is also recommended that the additional protocols of usRAP be examined for applicability to the small urbanized area.

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APPENDIX: EB MODEL SPECIFICATION

SPF based on 2008 crash data

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-0.6991	-0.266	0.790
logAADT	0.2551	0.852	0.394
Phi φ	0.18315		
-2 x log-likelihood	132.809		
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-6.2014	-3.922	8.79e-05 ***
logAADT	0.9667	4.903	9.43e-07 ***
Phi φ	0.617		
-2 x log-likelihood	197.437		
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-3.64502	-6.698	2.11e-11 ***
logAADT	0.67114	7.996	1.29e-15 ***
Phi φ	2.1022		
-2 x log-likelihood	1029.0390		
4LD			
Variable	Estimate	t-statistic	p-value
Intercept	-11.0765	-2.824	0.004743 ***
logAADT	1.5196	3.582	0.000341***
Phi φ	0.9588		
-2 x log-likelihood	205.333		
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-8.117	-2.426	0.00192***
logAADT	1.193	4.200	2.67e-05 ***
Phi φ	0.5882		
-2 x log-likelihood	267.617		

Note: ***, **, *==> Significance at 1%, 5%, 10%

SPF based on 2007-2008 crash data

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-2.2318	-0.981	0.3264**
logAADT	0.4382	1.698	0.0895***
Phi φ	0.00787		
-2 x log-likelihood	124.864		
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-7.8229	-4.273	1.93e-05 ***
logAADT	1.1494	5.073	3.92e-07 ***
Phi φ	0.592768		
-2 x log-likelihood	186.714		
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-5.3953	-7.51	5.92e-14 ***
logAADT	0.8845	8.115	4.85e-16 ***
Phi φ	3.078		
-2 x log-likelihood	802.814		
4LD			
Variable	Estimate	t-statistic	p-value
Intercept	-7.091	-1.906	0.05667*
logAADT	1.098	2.719	0.00655 ***
Phi φ	1.17647		
-2 x log-likelihood	214.914		
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-6.4516	-2.426	0.015260 **
logAADT	1.0095	3.488	0.000487 ***
Phi φ	0.704		
-2 x log-likelihood	267.016		

Note: ***, **, *==> Significance at 1%, 5%, 10%

SPF based on 2006-2008 crash data

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-1.7366	-0.759	0.448
logAADT	0.3751	1.443	0.149
Phi φ	0.001305		
-2 x log-likelihood	122.532		
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-8.4645	-4.409	1.04e-05 ***
logAADT	1.2077	5.098	3.43e-07 ***
Phi φ	0.4892		
-2 x log-likelihood	171.756		
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-5.03677	-8.693	<2e-16 ***
logAADT	0.8845	8.115	<2e-16 ***
Phi φ	1.1494		
-2 x log-likelihood	841.070		
4LD			
Variable	Estimate	t-statistic	p-value
Intercept	-6.927	-1.884	0.05953 *
logAADT	1.069	2.680	0.00735 ***
Phi φ	1.10375		
-2 x log-likelihood	210.566		
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-6.4765	-2.748	0.00599 ***
logAADT	1.0011	3.919	8.91e-05 ***
Phi φ	0.43066		
-2 x log-likelihood	253.910		

Note: ***, **, *==> Significance at 1%, 5%, 10%

SPF based on 2005-2008 crash data

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-5.4538	-2.128	0.03334 **
logAADT	0.7933	2.746	0.00603***
Phi φ	0.000234		
-2 x log-likelihood	119.854		
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-10.2421	-4.781	1.75e-06 ***
logAADT	1.4195	5.403	6.56e-08 ***
Phi φ	0.52687		
-2 x log-likelihood	167.467		
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-5.27116	-8.193	2.55e-16 ***
logAADT	0.84120	8.758	< 2e-16 ***
Phi φ	1.4881		
-2 x log-likelihood	750.735		
4LD			
Variable	Estimate	t-statistic	p-value
Intercept	-6.669	-1.758	0.0788 *
logAADT	1.038	2.519	0.0118 **
Phi φ	1.235		
-2 x log-likelihood	206.803		
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-7.067	-3.012	0.0026***
logAADT	1.060	4.173	3.01e-05 ***
Phi φ	0.3876		
-2 x log-likelihood	246.341		

Note: ***, **, *==> Significance at 1%, 5%, 10%

SPF based on 2004-2008 crash data

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-6.0553	-2.327	0.01998 **
logAADT	0.8654	2.952	0.00315 ***
Phi φ	0.017544		
-2 x log-likelihood	128.637		
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-9.9789	-4.951	7.40e-07 ***
logAADT	1.3845	5.602	2.12e-08 ***
Phi φ	0.38314		
-2 x log-likelihood	165.274		
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-5.44226	-9.685	<2e-16 ***
logAADT	0.87914	10.676	<2e-16 ***
Phi φ	0.654		
-2 x log-likelihood	780.887		
4LD			
Variable	Estimate	t-statistic	p-value
Intercept	-5.7783	-1.605	0.1086
logAADT	0.9478	2.421	0.0155 **
Phi φ	1.2019		
-2 x log-likelihood	212.621		
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-7.094	-3.107	0.00189 ***
logAADT	1.063	4.306	1.66e-05 ***
Phi φ	0.34965		
-2 x log-likelihood	245.002		

Note: ***, **, *==> Significance at 1%, 5%, 10%

SPF based on 2003-2008 crash data

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-7.8320	-2.832	0.004625 ***
logAADT	1.0622	3.420	0.000625 ***
Phi φ	0.021277		
-2 x log-likelihood	123.395		
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-10.5066	-4.843	1.28e-06 ***
logAADT	1.4433	5.431	5.61e-08 ***
Phi φ	0.480769		
-2 x log-likelihood	160.869		
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-5.37975	-8.497	<2e-16 ***
logAADT	0.84565	9.018	<2e-16 ***
Phi φ	1.117318		
-2 x log-likelihood	707.995		
4LD			
Variable	Estimate	t-statistic	p-value
Intercept	-7.2010	-1.863	0.0624**
logAADT	1.0943	2.609	0.0091***
Phi φ	1.22549		
-2 x log-likelihood	206.044		
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-7.3950	-3.184	0.00145***
logAADT	1.0916	4.348	1.37e-05 ***
Phi φ	0.350877		
-2 x log-likelihood	240.345		

Note: ***, **, *==> Significance at 1%, 5%, 10%

SPF based on 2002-2008 crash data

2LArterial			
Variable	Estimate	t-statistic	p-value
Intercept	-8.3553	-2.707	0.00679 ***
logAADT	1.1155	3.216	0.00130 ***
Phi φ	0.11919		
-2 x log-likelihood	125.425		
2LCollec			
Variable	Estimate	t-statistic	p-value
Intercept	-10.6527	-4.800	1.59e-06 ***
logAADT	1.4617	5.377	7.56e-08 ***
Phi φ	0.530786		
-2 x log-likelihood	161.678		
2LLOCAL			
Variable	Estimate	t-statistic	p-value
Intercept	-5.59933	-9.632	<2e-16 ***
logAADT	0.88365	10.426	<2e-16 ***
Phi φ	0.573723		
-2 x log-likelihood	716.995		
4LD			
Variable	Estimate	t-statistic	p-value
Intercept	-9.1246	-2.445	0.01448**
logAADT	1.2935	3.203	0.00136 ***
Phi φ	0.8889		
-2 x log-likelihood	202.718		
4LU			
Variable	Estimate	t-statistic	p-value
Intercept	-6.0298	-2.676	0.007448 ***
logAADT	0.9457	3.876	0.000106 ***
Phi φ	0.359712		
-2 x log-likelihood	246.376		

Note: ***, **, *==> Significance at 1%, 5%, 10%