A Transportation Safety Planning Tool for the City of Ames

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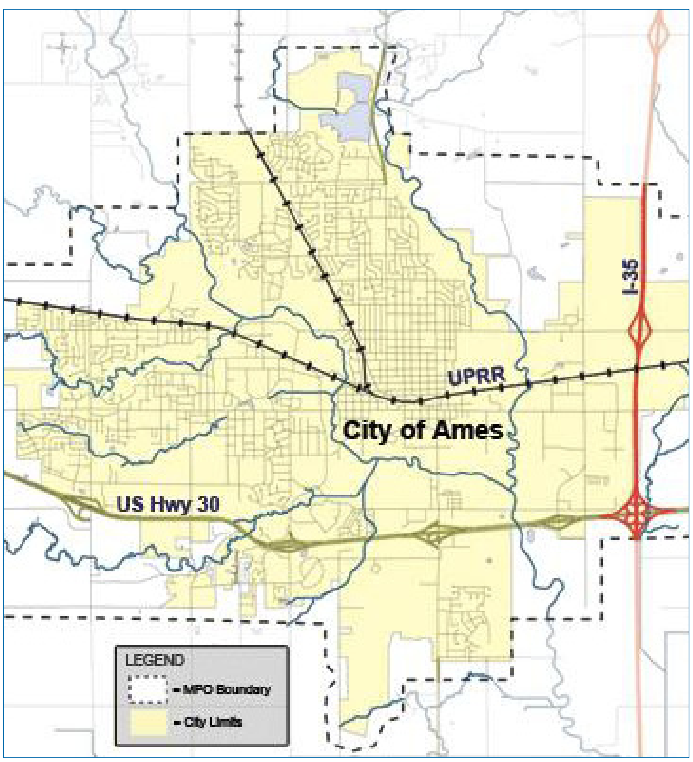
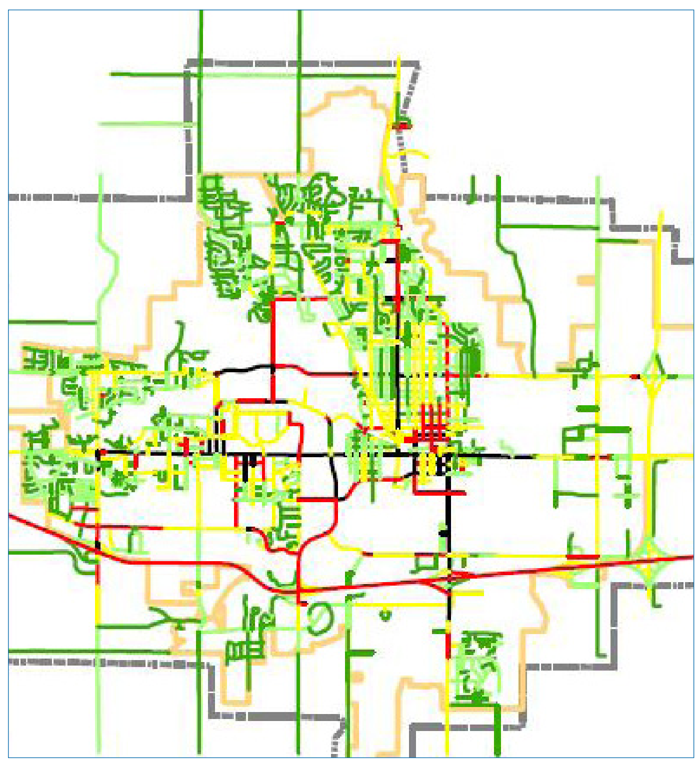
Center for Transportation Research and Education

Final Report
August 2011





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IOWA STATE UNIVERSITY
Institute for Transportation

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16. Abstract

The historically-reactive approach to identifying safety problems and mitigating them involves selecting black spots or hot spots by ranking locations based on crash frequency and severity. The approach focuses mainly on the corridor level without taking the exposure rate (vehicle miles traveled) and socio-demographics information of the study area, which are very important in the transportation planning process, into 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 the long-range transportation planning process.

In this study, existing planning tools (such as the PLANSAFE models presented in NCHRP Report 546) were evaluated 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 research also evaluated the applicability of the Empirical Bayes (EB) method to network-level analysis. In addition, application of the United States Road Assessment Program (usRAP) protocols at the local urban road network level was investigated.

This research evaluated the applicability of these three methods for the City of Ames, Iowa. The outcome of this research is a systematic process and framework for considering road safety issues explicitly in the small and medium-sized community transportation planning process and for quantifying the safety impacts of new developments and policy programs. More specifically, 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).

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A TRANSPORTATION SAFETY PLANNING TOOL FOR THE CITY OF AMES

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EXECUTIVE SUMMARY

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 from 2002 through 2008, on average, 1,000 traffic crashes (with property damage more than $1,000) occurred. To meet the requirement of future development and solve the transportation problem faced today, city planners and engineers are seeking additional ways to consider safety explicitly 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 the 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 the long-range transportation planning process.

This research examines how existing planning models (such as the PLANSAFE models presented in NCHRP Report 546) can be used to forecast safety in the future, in small and medium-sized communities, given the changes in socio-demographics, traffic demand, road network, and countermeasures.

The research also evaluates the applicability of the Empirical Bayes (EB) method to network-level analysis for small planning areas. Finally, application of the United States 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 toward transportation safety goals.

CHAPTER 1. INTRODUCTION

1.1 Problem Statement and Background Summary

According to the National Highway Traffic Safety Administration (NHTSA), more than 40,000 crash fatalities occurred in the US every year during the period from 2002 through 2007. In 2009, the number of crash fatalities dropped to 33,808. Still, the Federal Highway Administration (FHWA) emphasizes that, "Safety should be considered first, every time, and at every stage of a project. Make safety your first consideration in every investment decision" (FHWA).

Safety-related legislation (e.g., the Safe, Accountable, Flexible, Efficient Transportation Equity Act/SAFETEA-LU) mandates planning by state departments of transportation (DOTs) that "considers the results of state, regional, or local transportation and highway safety planning processes" (FHWA). Although there is an increasing interest in developing safety performance measures and incorporating safety into the transportation planning process, few tools are available that planning agencies can use.

Moreover, there is no national guidance on how to measure and incorporate safety into the transportation planning process for small and medium-sized communities. This research 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 (City of Ames). In 2003, the Ames Area Metropolitan Planning Organization (AAMPO) was designated with a planning area of 36 square miles (City of Ames). Ames hosts Iowa State University with an enrollment of 27,945 as of Fall Semester 2009 (Iowa State University).

During the period from 2002 through 2008, on average, 1,000 traffic crashes (of property damage more than $1,000) occurred per year (AAMPO). City planners and engineers are seeking additional ways to consider safety explicitly in the transportation planning process.

Ames is representative of hundreds of small and medium-sized communities across the US. 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 crash frequency and severity. The approach focuses mainly on the corridor level without taking the exposure rate (vehicle miles traveled) and socio-demographics information of the study area, which are very important in the transportation planning process, into 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 community development in the future and incorporate safety into the long-range transportation planning process.

In this study, existing planning tools (such as 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-demographic characteristics, traffic demand, road network, and countermeasures.

The research 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, and Persaud and Lyon 2007). In addition, application of US Road Assessment Program (usRAP) protocols at the local urban road network level is investigated.

This research 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 toward transportation safety goals.

1.2 Research Objective and Tasks

The main objective of this research was to examine the applicability of existing models/tools for forecasting in small and medium-sized communities, given the changes in socio-demographics, traffic demand, road network, and countermeasures. The plan for this research included the following tasks.

Task 1: Literature Review

Synthesize the state-of-the practice at the state and regional levels, 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 (seven 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 (ITSDS) at Iowa State University (ISU) 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 through 2008 geocoded crash data for the City of Ames from the Iowa DOT statewide crash database, as well as the Geographic Information Management System (GIMS) 2008 road network data from the Iowa DOT.

In addition, socio-demographic data, such as 2000 population of a census block and median household income were acquired from the US Census Bureau. 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 graphic information system (GIS)-based tools. GIS tools 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 EB method was tested for network-level analysis. The EB method uses both datasets from observed road segments and similar sites, which have the same typical crash frequency and road characteristics as the observed road segments, to predict a more sensible and precise estimation (Hauer et al. 2002).

Task 5: usRAP Protocols Application

The 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

Finally, recommendations were offered to the City of Ames and the Iowa DOT regarding the use of the three tools studied for identifying candidate locations to enhance safety and incorporate safety into planning.

The outcome of this research is a systematic process and framework for considering road safety issues explicitly in the small and medium-sized community transportation planning process and for quantifying the safety impacts of new developments and policy programs.

CHAPTER 2. LITERATURE REVIEW

2.1 Overview

For this task, first we 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, we examined some of the existing safety forecasting tools, such as the PLANSAFE models presented in the NCHRP report, and other safety analysis tools like Empirical Bayes (EB) and the United States Road Assessment Program (usRAP). These tools can be used to forecast safety given changes in socio-demographics, traffic demand, road network, and countermeasures in small and medium-sized communities.

Fourteen analytical safety forecasting models were introduced in NCHRP Report 546. These 14 models ranged in coverage from corridor-level to project-level. For planning-level safety analysis, the coverage by the tools ranged from road segments to intersections and from motor vehicle crashes only to crashes involving bicyclists and pedestrians.

The PLANSAFE models are used to forecast safety in the future and inform safety-related decision making at the planning level (TAZ 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 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 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 SPFs and correct for the regression-to-the-mean bias that can arise when using the crash count/frequency method, one statistical approach, EB was adopted in this study.

The EB method uses both datasets from the observed road segments (i.e., Ames road network) and similar sites, which have crash frequency and road characteristics similar to the observed road segments. Typically, engineers use the crash data and road attributes for the similar sites to develop 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 usRAP and, specifically, the risk-mapping tool and star ratings were reviewed. The 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 in this study.

After examining each of the three proposed safety tools, we 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 EB.
- GIS software is helpful in incorporating safety into the transportation planning process. A significant amount of spatial analysis is necessary during this analysis process, for creating usRAP protocol risk maps, for example.

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

Finally, we studied other Metropolitan Planning Organizations (MPOs), which have characteristics similar to the City of Ames, 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 (TAZ level) transportation planning project.

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

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

In February 2010, the *PLANSAFE: Forecasting the Safety Impacts of Socio-Demographic Changes and Safety Countermeasures* software program was 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 the planning-level, apply different scenarios, and generate project reports. The detailed application of this software for the 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 and 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 and Cafiso et al. 2007).

To apply EB, the safety prediction models 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 SPF prediction results derive from the number of fatal to fatal 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 AADT, length of 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 (Lord and Persaud 2004), the Poisson regression model or negative binomial regression model is used to build 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 study.

The EB method uses both datasets from the observed road segments and similar sites, which have similar crash frequency and road characteristics to the observed road segments. The EB method could increase the precision of estimation in the SPFs calibrated. 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 the tutorial, Hauer first introduced the EB theory and how to build the SPFs for segments and intersections. Then, he gave 10 numerical examples of how to apply the 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, to the full EB procedure, "accounting for changing ADTs" example.

2.4 usRAP

The usRAP, sponsored by the AAAFTS, was originally developed by the European Road Assessment Programme (EuroRAP). Both the usRAP and EuroRAP are under the umbrella of the International Road Assessment Programme (iRAP), which is “a not-for-profit organization dedicated to saving lives through safer roads” (iRAP).

According to the usRAP website, the usRAP pilot program had archived phases 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: Florida, Illinois, Iowa, Kentucky, Michigan, New Jersey, New Mexico, and Utah. The detailed information could be found in the final report of usRAP phase I, II, III. The investigation of applicability of the 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 (AAMPO)

Website: http://www.aampo.org
Area: 36 sq mi (Figure 2.1). Designation year: 2003. Population: 56,510 by July 1, 2008. (Iowa Data Center)

The *Ames Area MPO 2035 Long Range Transportation Plan* (AAMPO 2010) includes the following in section 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 includes the descriptive crash data analysis, such as the crash counts by severities, GIS-based crash map, crash density map, and safety candidate locations by using the Iowa DOT Safety Improvement Candidate Location Listing (SICL). Toward the end of the chapter, the plan discusses two “safety-related strategies to be considered throughout the Ames area,” roundabouts and access management, to help resolve safety problems for the City of Ames.

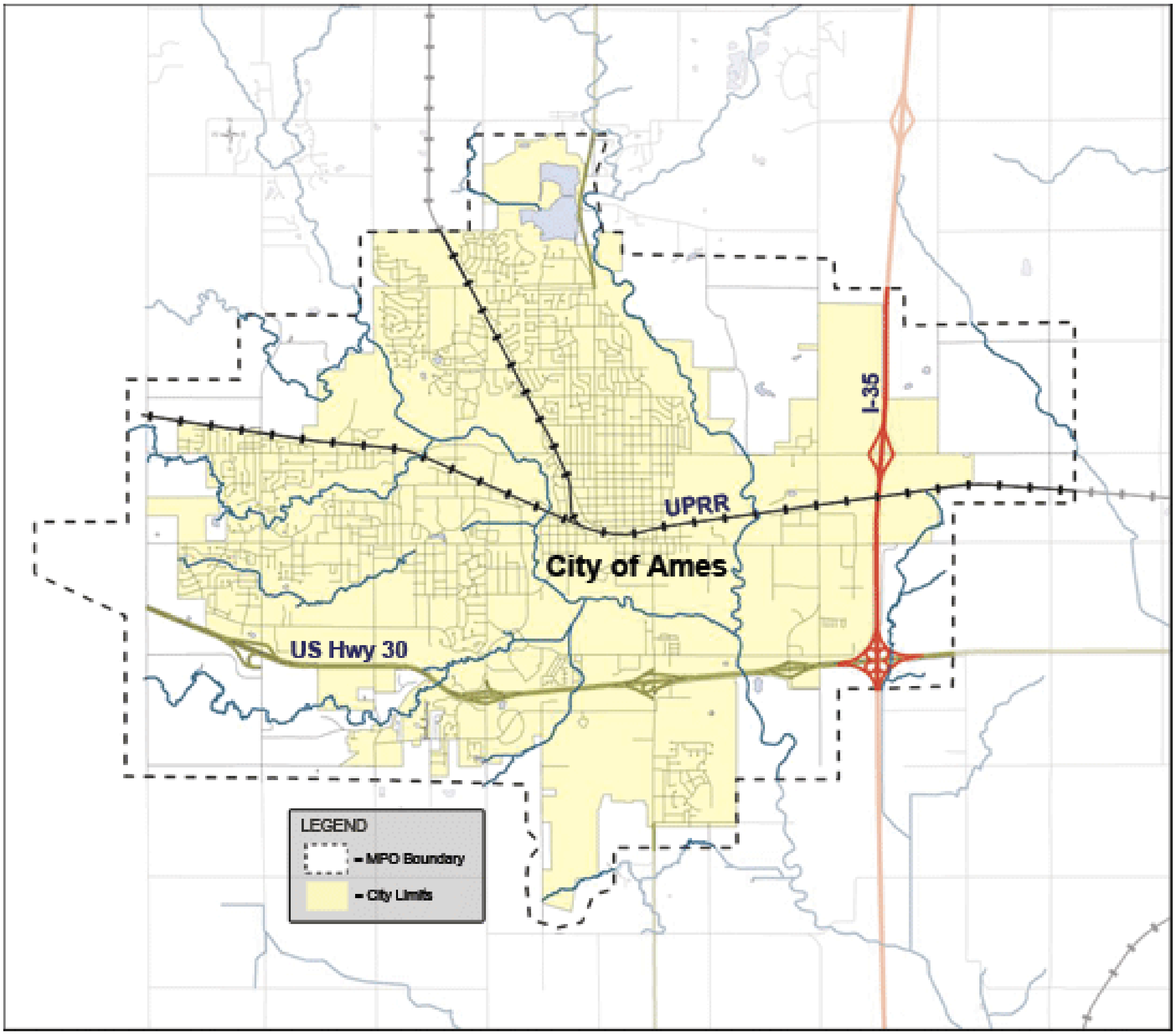

Figure 2.1. Ames area MPO study area

2.5.2 Other MPOs

Using the MPO Database from the FHWA (2010) and limiting the search to areas less than 1,000 sq mi and populations up to 140,000, we accessed 149 records. After reviewing these MPOs for those with a similar area and population as Ames and/or some other characteristics like a university town, we selected five MPOs to describe in more detail in this study:

1. Johnson County COG (JCCOG)
2. Corvallis Area MPO (CAMPO)
3. Wenatchee Valley Transportation Council (WVTC)
4. Lewis-Clark Valley MPO (LCVMPO)
5. Bend MPO

1. Johnson County COG (JCCOG)

Major city: Iowa City, Iowa. Area: 89 sq mi. Population: 88,980

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

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

They also created a map with top collision locations, which shows the 10 intersections and top mid-block collision locations for 2001-2004 (Figure 2.2). Many of these locations have had or undergoing construction projects to mitigate safety concerns.

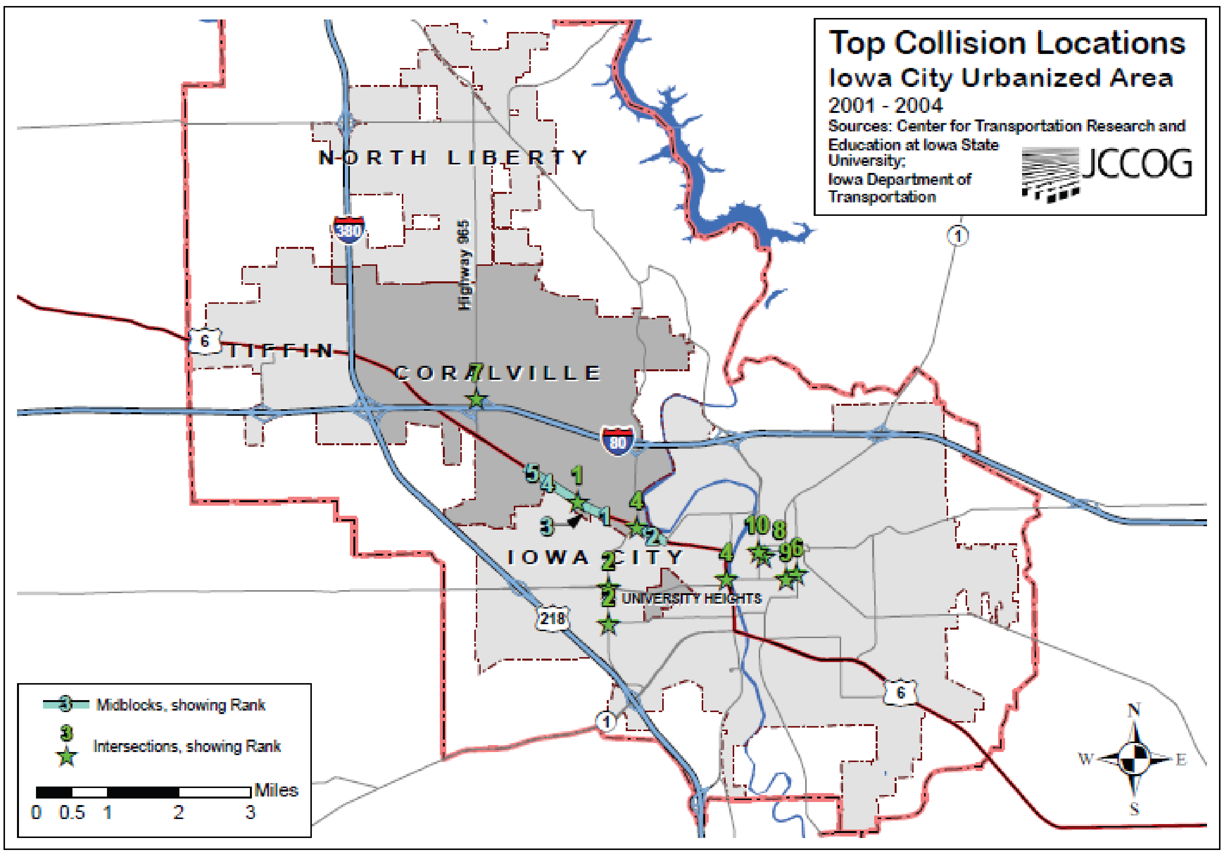

Figure 2.2. Top collision locations. from JCCOG

2. Corvallis Area MPO (CAMPO)

Major city: Corvallis, Oregon (Figure 2.3). Area: 38 sq. mi. Population: 59,277
Website: http://www.corvallisareampo.org/TransportationPlan.html

From the *Corvallis Area MPO Transportation Improvement Program (TIP) FY2008-2011*, CAMPO considered several methods for incorporating safety into the transportation improvement process, such as safety and educational activities for pedestrian and bicyclists and conducting 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." Besides that, they also used one section in the plan to evaluate safety and conducted crash analysis for the existing transportation system.

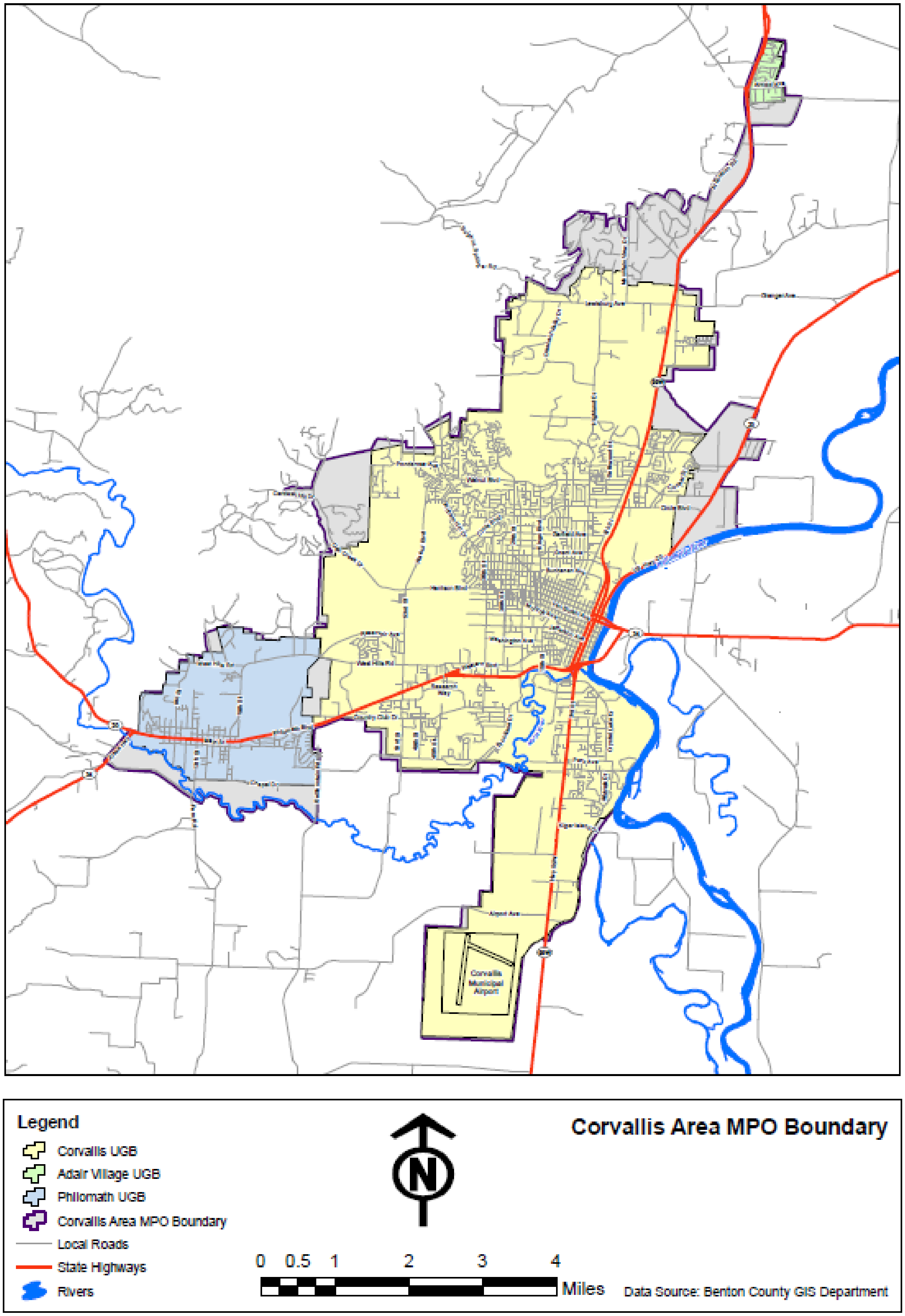

Figure 2.3. Corvallis area MPO boundary from CAMPO

3. Wenatchee Valley Transportation Council (WVTC)

Major city: Wenatchee, Washington. Area: 41 sq mi (Figure 2.4). Population: 56627
Website: http://www.wvtc.org/

In the *WVTC 2009 Regional Transportation Plan*, Part D, incorporating safety into the planning process is discussed in an entire chapter and includes the subjects of state highways (Figure 2.5), county roads (Figure 2.6), city streets, high accident corridor identification, public transit, and walking and bicycling.

Figure 2.4. Map of North Central Regional Transportation Planning Organization planning area from WVTC

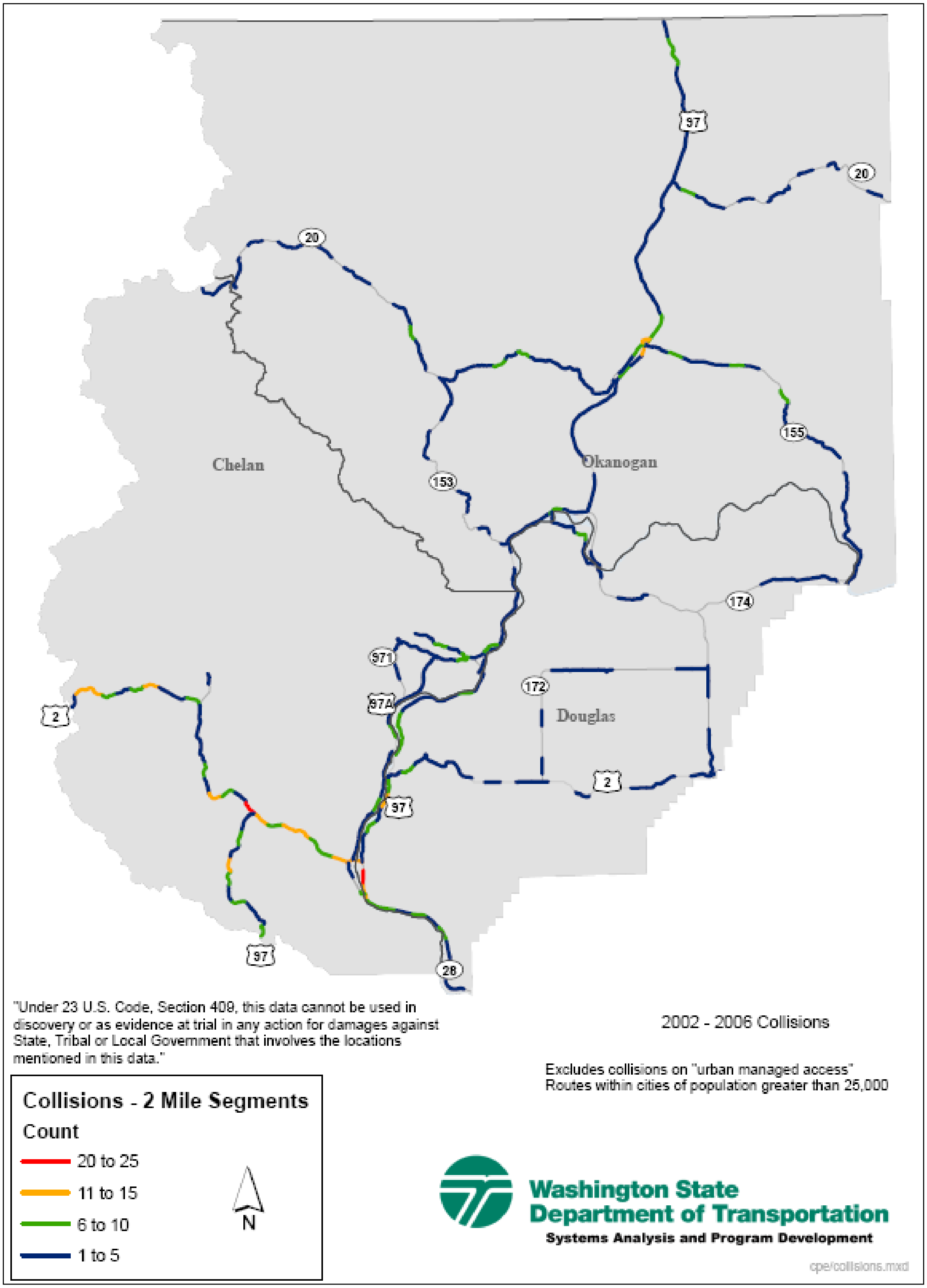

Figure 2.5. State highway accident corridors from WVTC

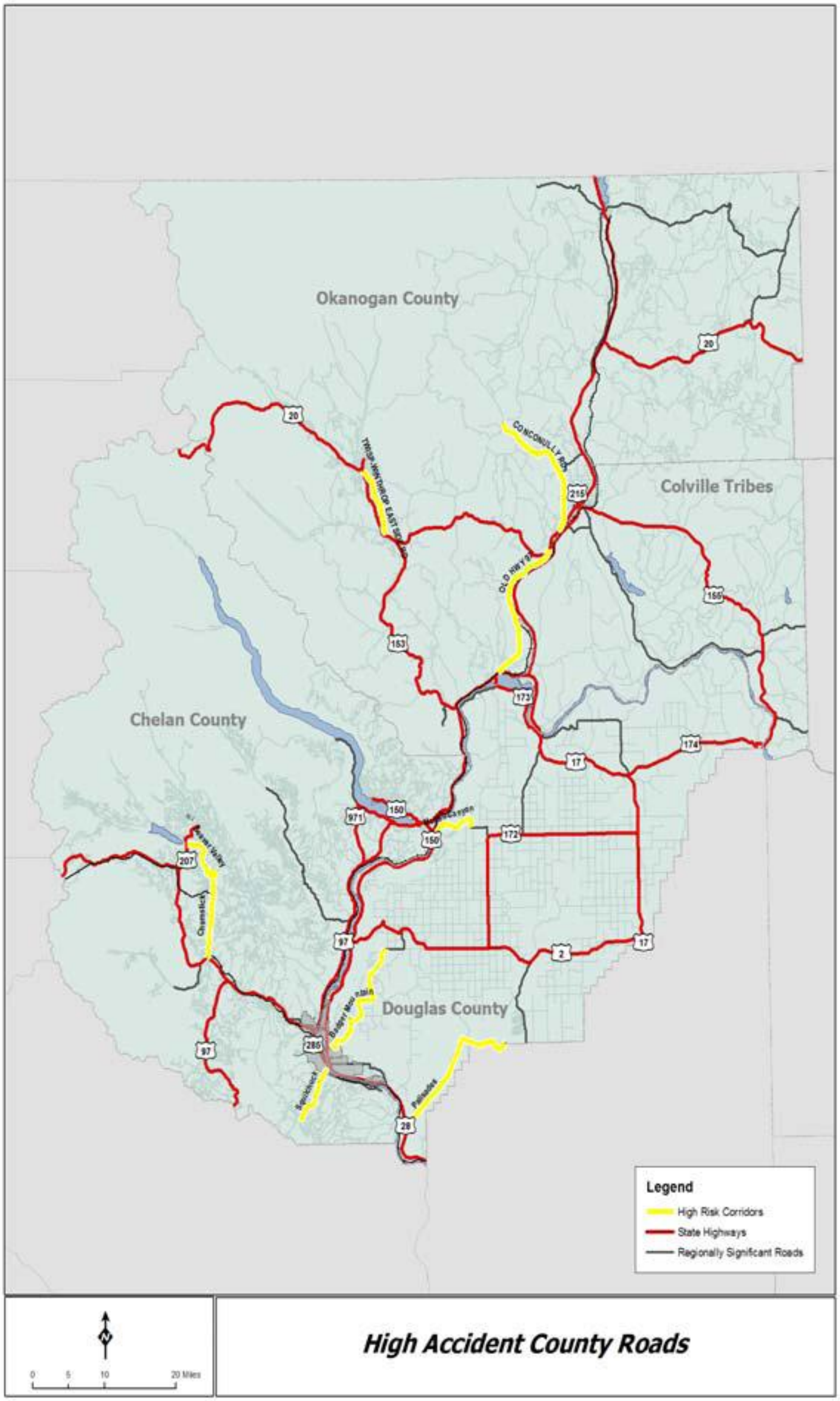

Figure 2.6. County road high accident corridors from WVTC

4. Lewis-Clark Valley MPO (LCVMPO)

Major city: Asotin, Washington. Area: 43 sq mi (Figure 2.7). Population: 50,856.
Website: http://lewisclarkmpo.org/

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 the Safe, Accountable, Flexible, Efficient Transportation Equity Act (SAFETEA-LU).

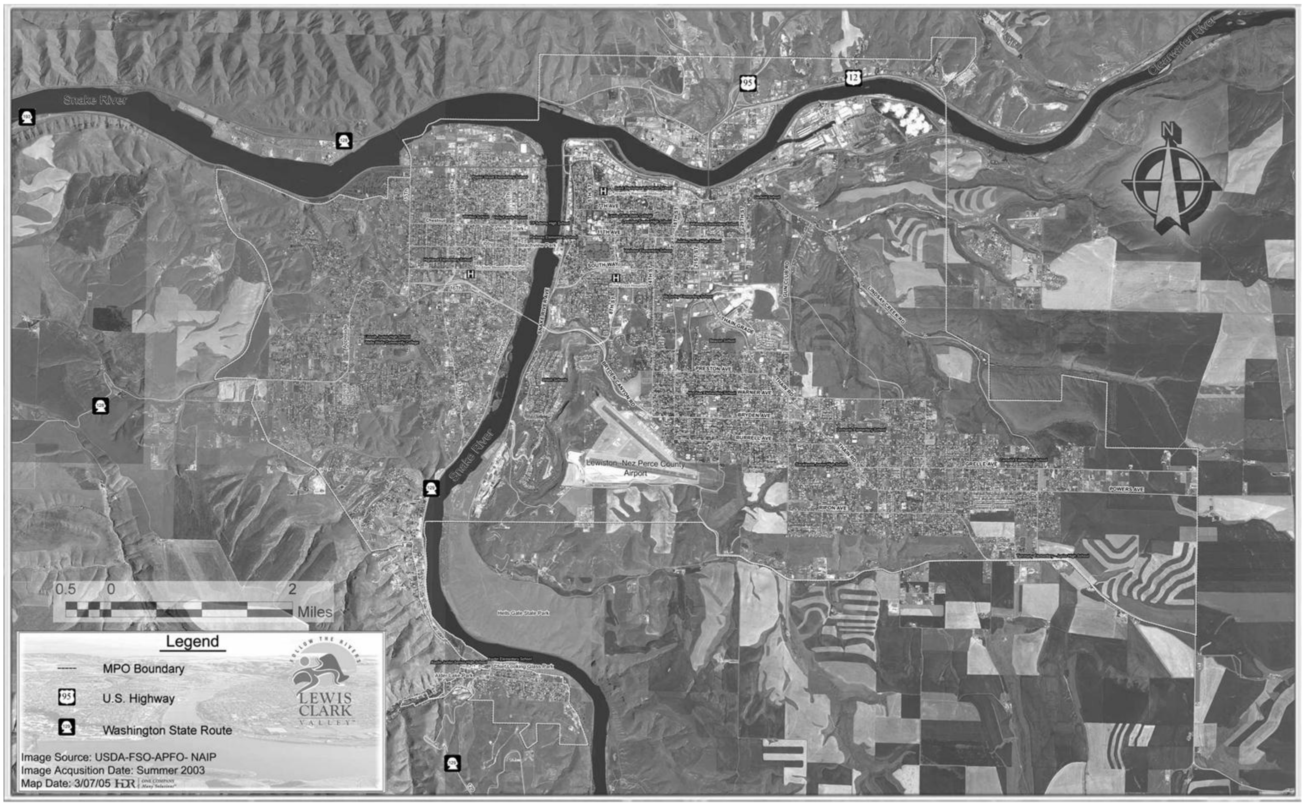

Figure 2.7. Lewis-Clark Valley MPO boundary

5. Bend MPO

Major city: Bend, Oregon. Area: 46 sq mi (Figure 2.8). Population: 59,027.
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 follows.

> 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.
>
> Objective
> In cases where improving safety will also improve efficiency, these projects should receive funding priority.

Chapter 12 addressed transportation safety. It includes federal, state, and regional area safety-related regulations. They also provided a crash analysis and suggest safety improvements and using ITS solutions to help in incorporating safety into the planning process.

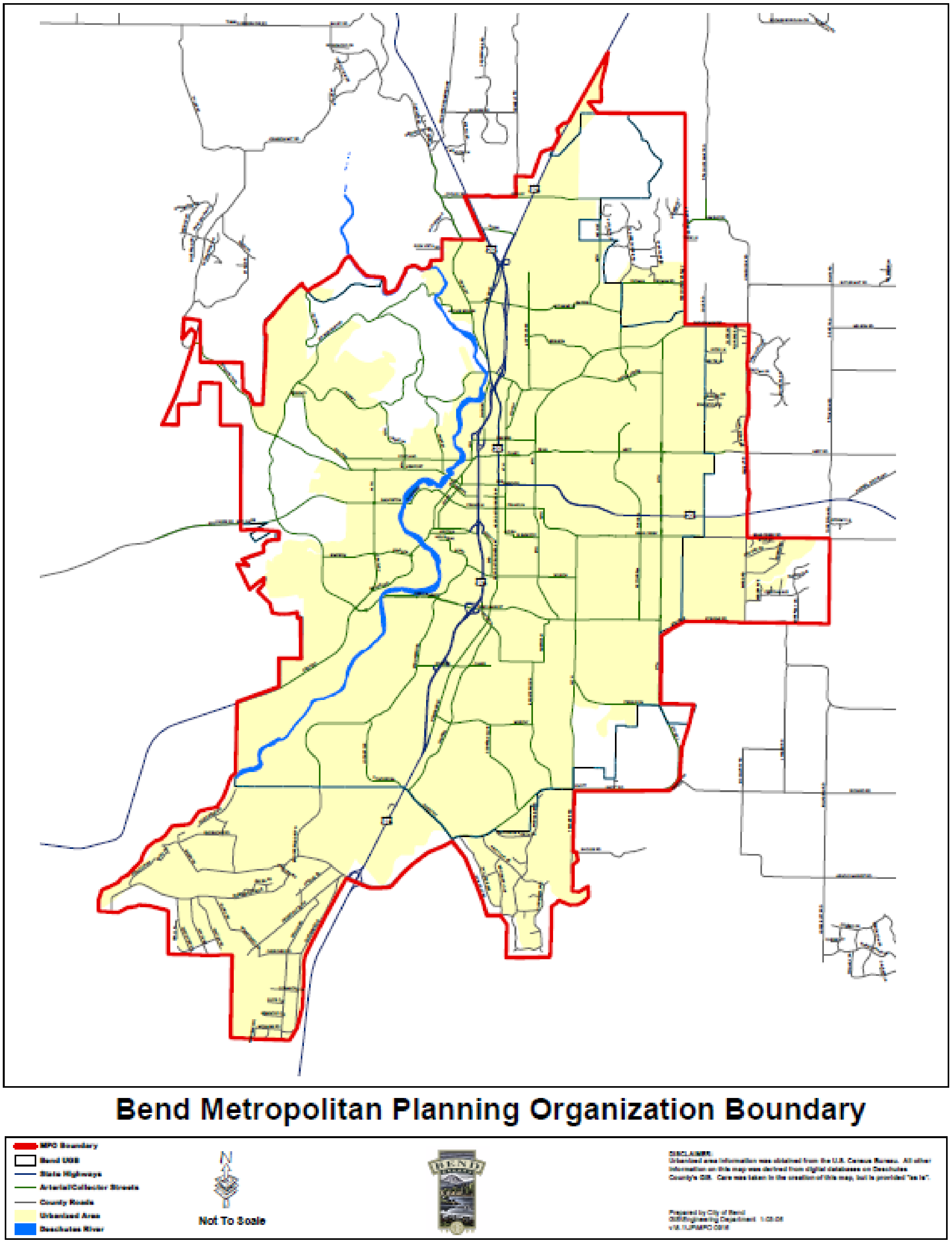

Figure 2.8. Bend MPO boundary (from Bend MPO)

2.5.3 MPO State-of-the-Practice Summary

A summary of the six MPO's safety planning performance based on their Transportation Improvement Plan (TIP) and/or Long Range Transportation Plan (LRTP) is shown in Table 2.1.

Table 2.1. Summary of MPO safety planning performance based on TIP and/or LRTP

	MPO					
Criteria	**AAMPO**	**JCCOG**	**CAMPO**	**WVTC**	**LCVMPO**	**Bend MPO**
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 NCHRP Report 546 and the TIPs and LRTPs of MPOs of similar size to Ames, we concluded that most MPOs emphasize safety in the transportation planning process. Safety is a solid part of the MPO planning objectives and goals. These objectives and goals are also incorporated into the planning process through the TIP, Metropolitan Transportation Plan (MTP) and LRTP.

However, specific guidance has not yet been provided to MPOs on how safety should be considered (qualitatively or quantitatively) or 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 follow in Chapters 4, 5, and 6.

CHAPTER 3. DATA COLLECTION AND DESCRIPTIVE ANALYSIS

3.1 Overview

This chapter describes the data used in this study.

- 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 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).
- GIS files of AAMPO 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 PDO 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 in Tables 3.1 through 3.3.

Table 3.1. City of Ames crash statistics for 2002 through 2008

Year	Total Crashes	Fatalities	Major Injuries	Minor/Possible Injuries
2002	1,000	0	21	292
2003	1,079	2	20	291
2004	1,114	1	11	310
2005	1,035	2	13	237
2006	963	4	19	296
2007	1,077	3	23	329
2008	1,248	0	17	343
Total	**7,516**	**12**	**124**	**2,098**

Source: Iowa DOT statewide geocoded crash database

Table 3.2. City of Ames total crashes by zone for 2002 through 2008

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	1,818	24.19
Highway-Oriented Commercial Zone	1,602	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	1,174	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	**7,516**	**100.00**

Highlighted records are the top three zones by crash number

Table 3.3. City of Ames crashes as a percentage of statewide crashes for 2002 through 2008

Year	2002	2003	2004	2005	2006	2007	2008	Total
Ames	1,000	1,079	1,114	1,035	963	1,077	1,248	7,516
Iowa	59,666	59,440	59,192	58,644	54,815	60,112	61,194	413,063
Percentage (%)	1.68	1.82	1.88	1.76	1.76	1.79	2.04	1.82

Source: Iowa DOT statewide geocoded crash database

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, AADT, segment length, and segment width. Figure 3.1 depicts the Ames road network and the city and MPO boundaries.

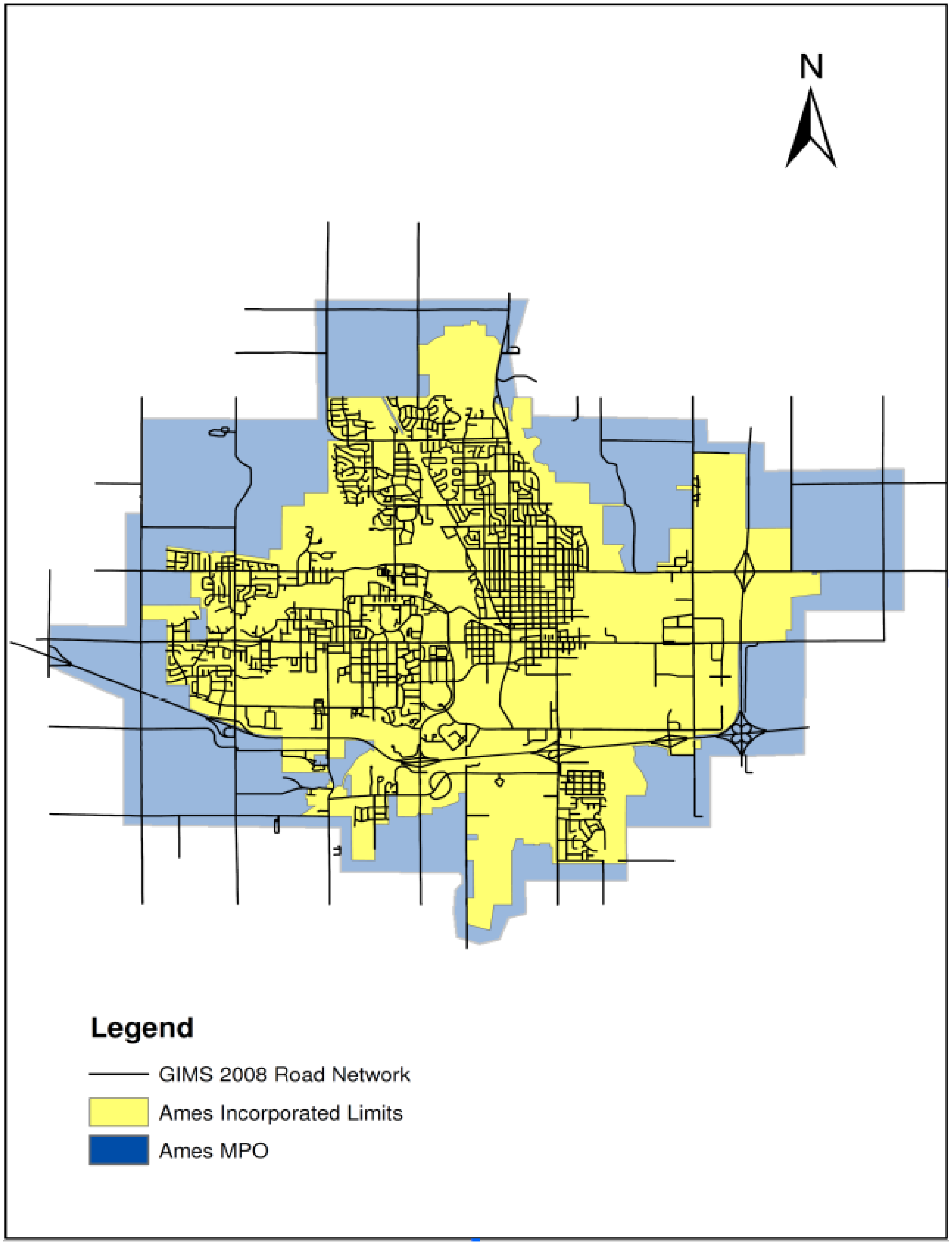

Figure 3.1. Ames road network and boundaries

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 for Ames metropolitan area for 2002 through 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 Avenue, and 220th Street (which is called 13th Street in Ames). More detailed and informative maps, such as crash density and rate maps, are present in Chapter 6.

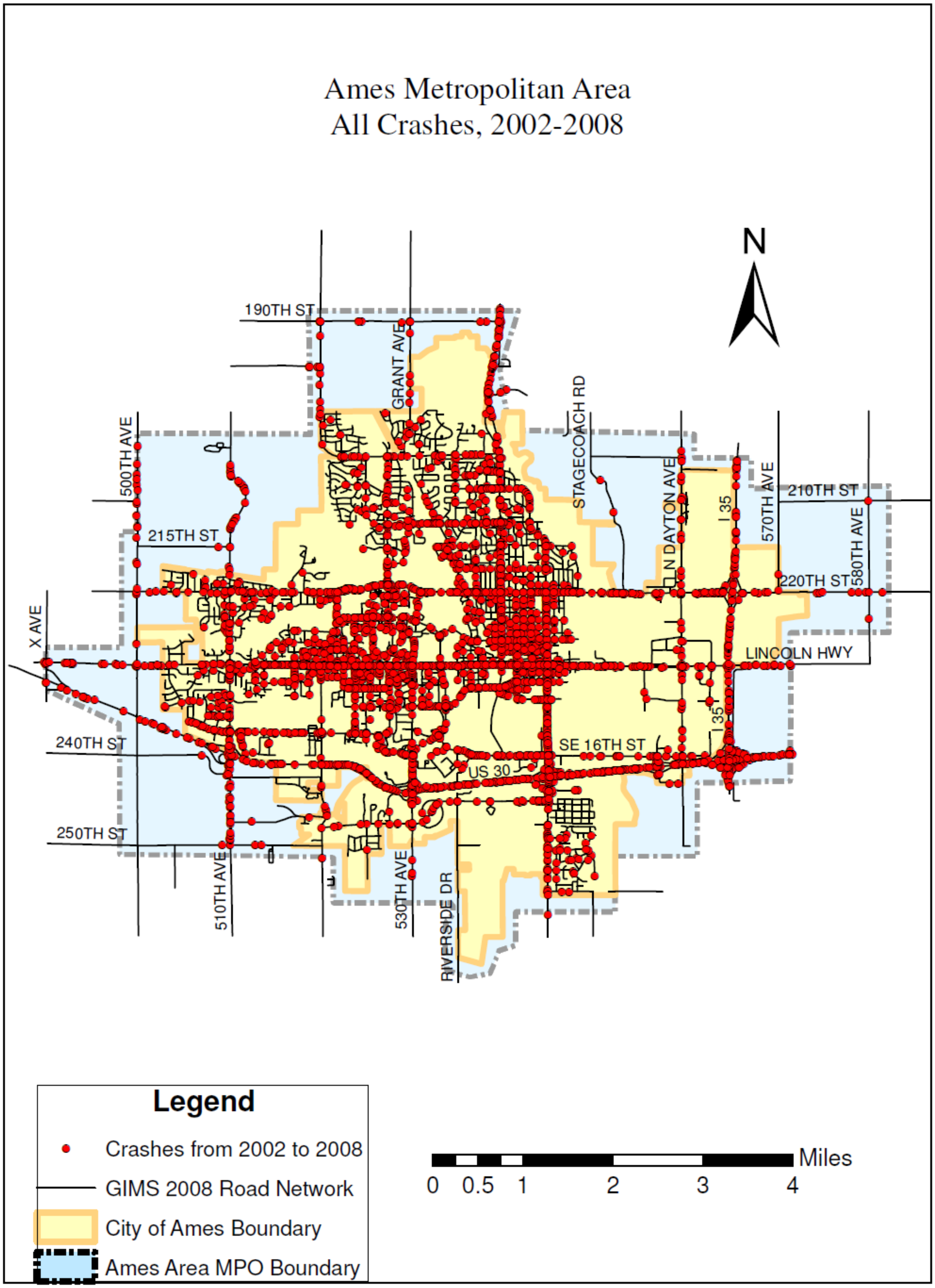

Figure 3.2. Ames metropolitan area total crash frequency map for 2002 through 2008

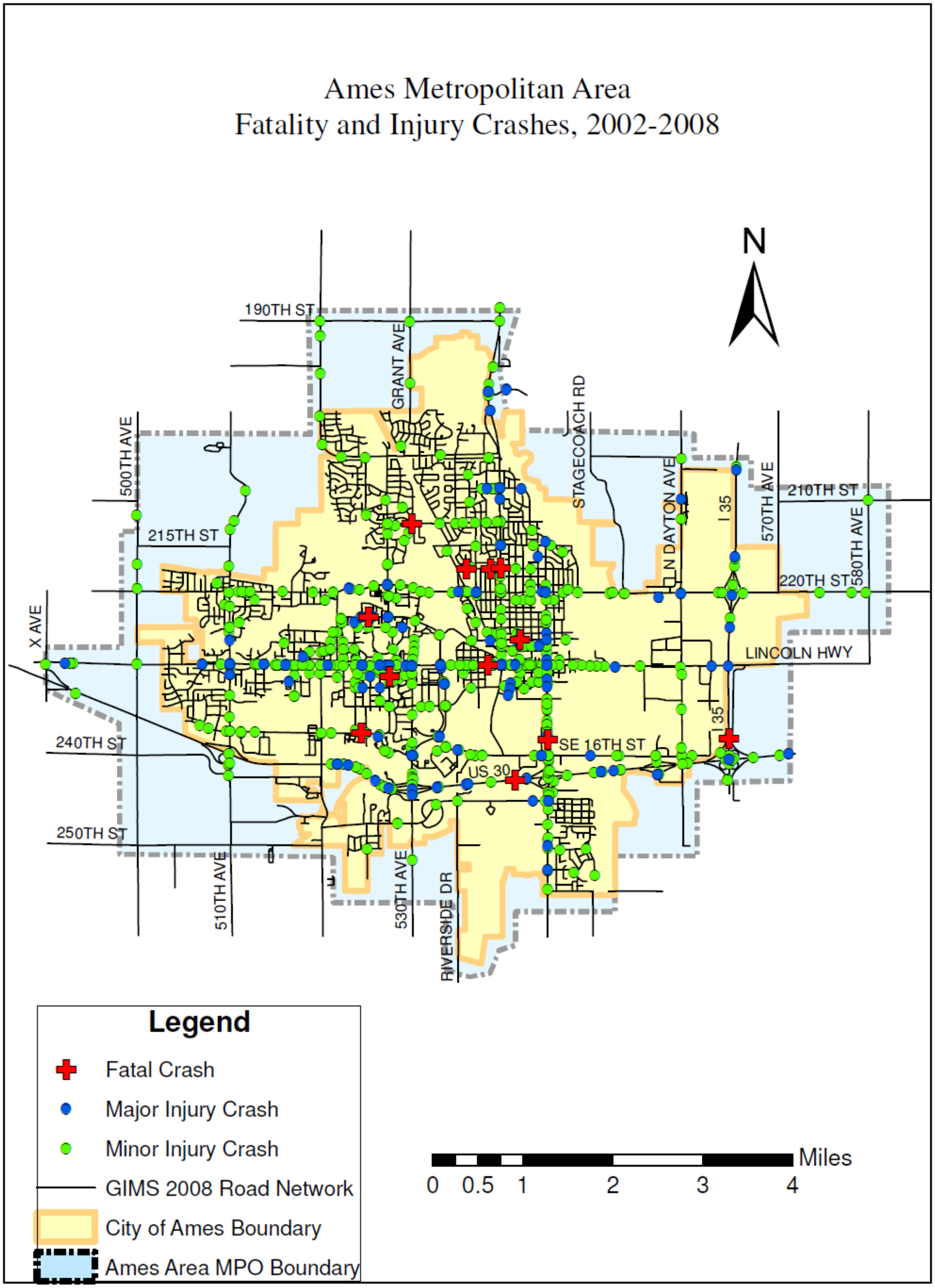

Figure 3.3. Ames metropolitan area fatality and injury crash map for 2002 through 2008

CHAPTER 4. PLANSAFE

4.1 PLANSAFE-Like Model Calibration

As discussed in Chapter 2, PLANSAFE models use crash data, road network data, and census data as inputs to develop SPFs. To develop similar SPFs for Ames, we carried out the following steps:

1. Performed a GIS spatial analysis to assign crashes (which are points in GIS) to the road network (which are lines in GIS) and, then, assigned road networks to TAZs (which are polygons in GIS) (Figure 4.1)
2. Aggregated the crash data and road network data to the TAZ-level
3. Aggregated the census data from the block level or block group level to the TAZ-level
4. Estimated log-linear regression crash frequency models based on the data collected for a total of 80 TAZs for the City of Ames

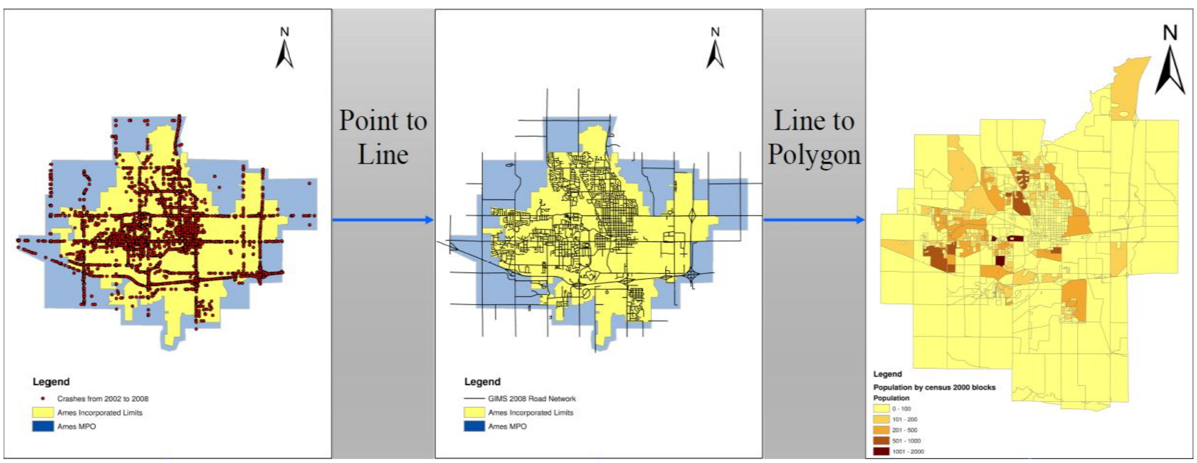

Figure 4.1. GIS spatial analysis process of PLANSAFE models

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 model 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	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
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

Highlighted values indicate high correlation between variables

4.1.1 Total Crash Frequency Model

Tables 4.3 and 4.4 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	Log Likelihood	L-R chi-square	DF	Prob> chi-square
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> chi-square	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:

$$\text{Total crash frequency} = \exp(3.1815884 - 0.02763(\text{POP\_PAC}) + 0.5814724(\text{PNF\_0214}) + 0.0003754(\text{POP16\_64}) - 1.948\text{e-}5(\text{HH\_INC})) - 1 \quad (4\text{-}1)$$

Equation 4-1 shows that if the total mileage of urban and rural principal arterials as a portion of the total mileage/as a percentage (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

Tables 4.5 and 4.6 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	Log Likelihood	L-R chi-square	DF	Prob> chi-square
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> chi-square	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:

$$\text{Minor injury crash frequency} = \exp(0.894607 + 0.325518\ (\text{PNF\_0214}) + 0.000175\ (\text{POP16\_64}) + 0.004303\ (\text{INT}) - 1.03\text{e-}05\ (\text{HH\_INC})) - 1 \quad (4\text{-}2)$$

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. This is because project-level planning, such as that for an intersection or a road segment, requires more detailed information, which is not supported by PLANSAFE.

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

1. Select Analysis Area and Units

This step asked the user to select state, county, and jurisdiction (Figure 4.2). The default analysis was Traffic Analysis Zone (TAZ).

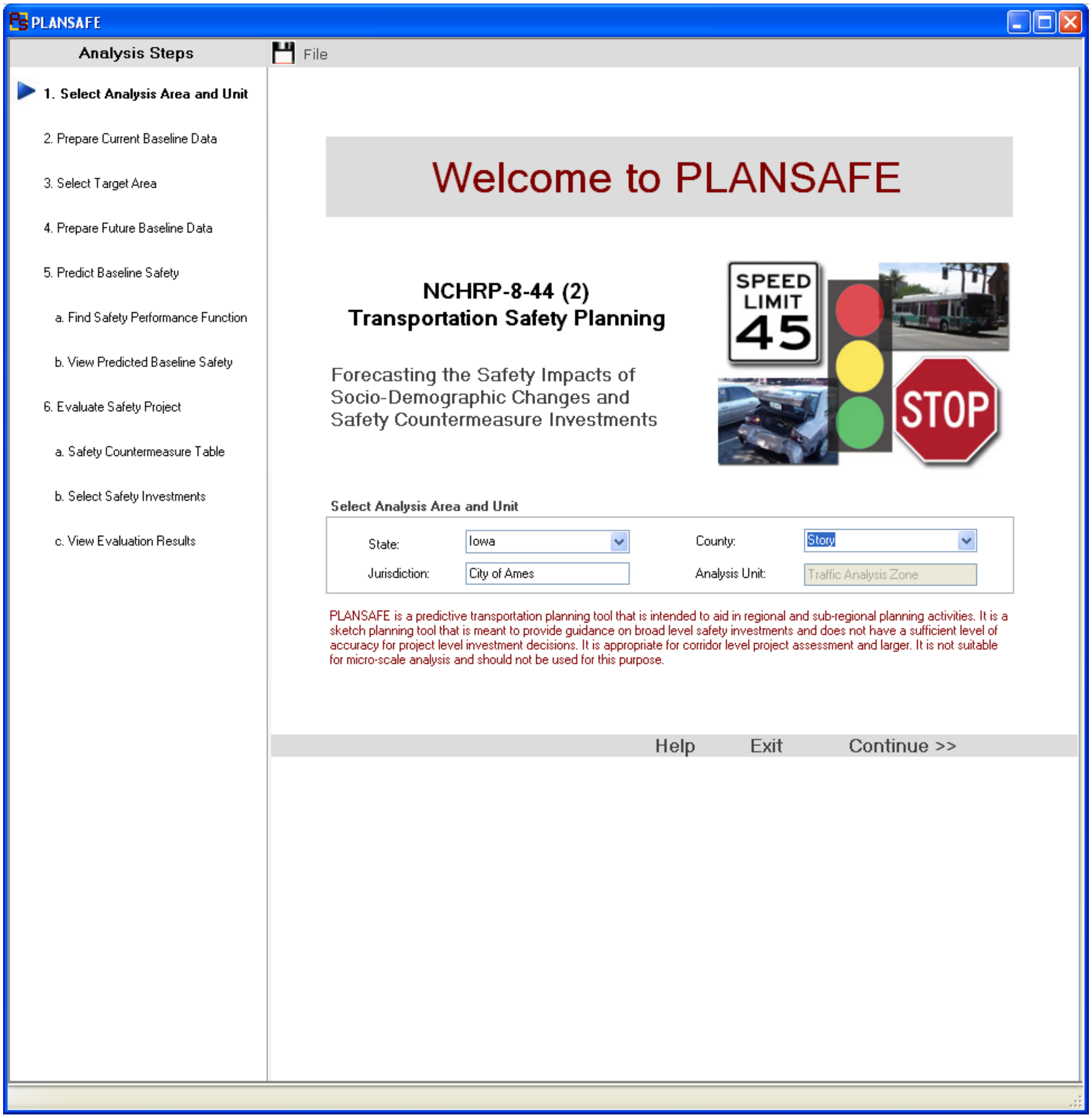

Figure 4.2. PLANSAFE select analysis area and units

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. (Figure 4.3). Besides the TAZ data just mentioned, crash data including crash ID, crash polygon ID, and point-in-polygon portion were required to be imported (Figure 4.4).

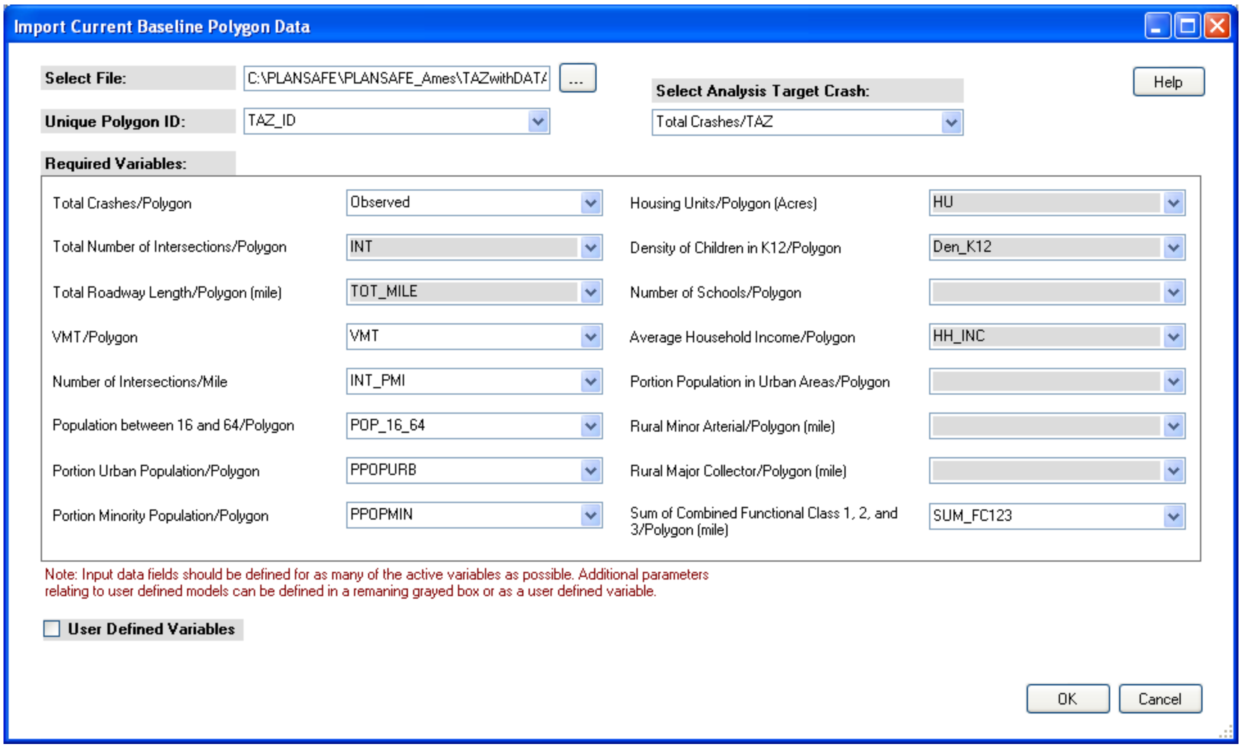

Figure 4.3. PLANSAFE import current baseline polygon data

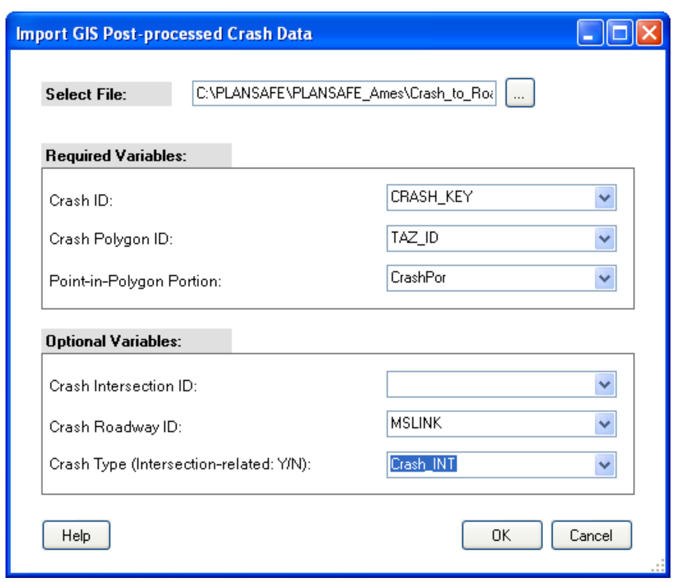

Figure 4.4. PLANSAFE import GIS post-processed crash data

3. Select Target Area

In this step, the user could select the target area to apply the growth factor to for variables such as population, road mileage, and so forth (Figure 4.5). In this case, we selected three TAZs located in the west Ames area.

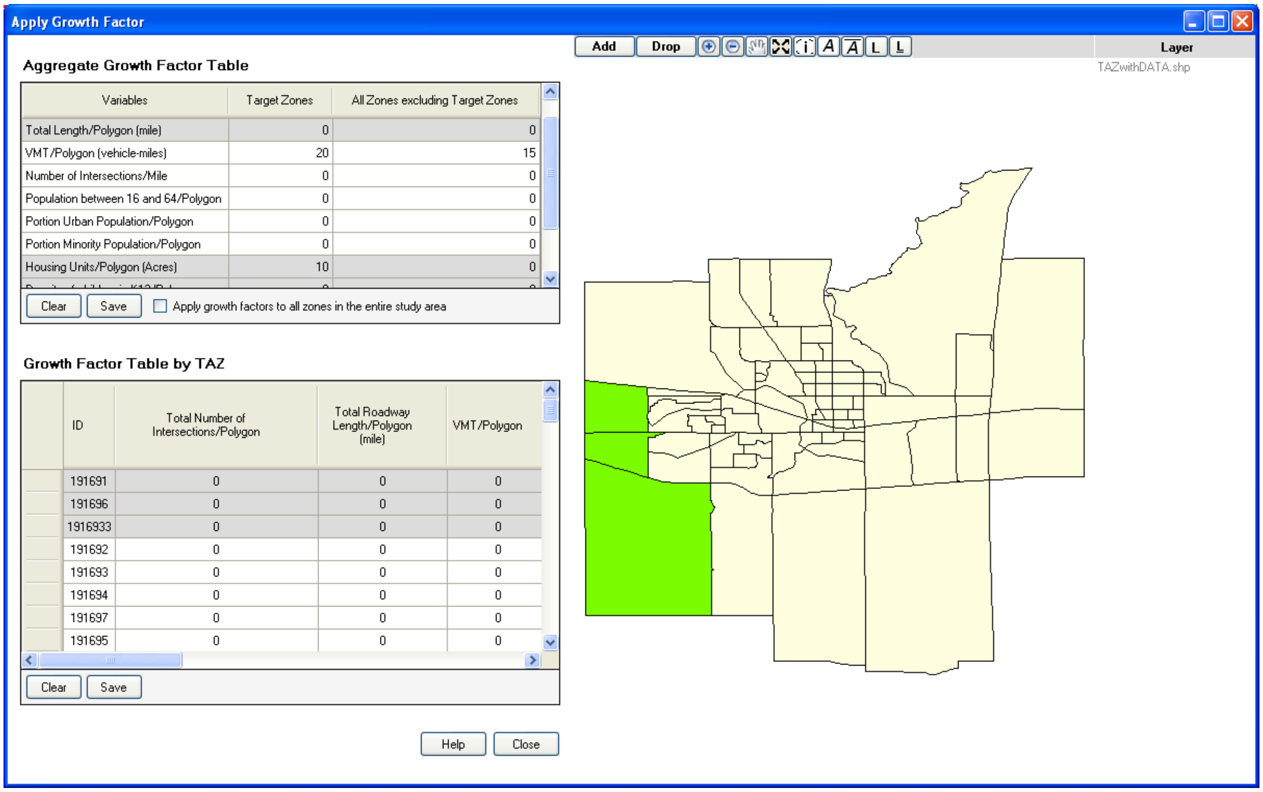

Figure 4.5. PLANSAFE apply growth factor

4. Prepare Future Baseline Data

This process is similar to step 2, where the 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).

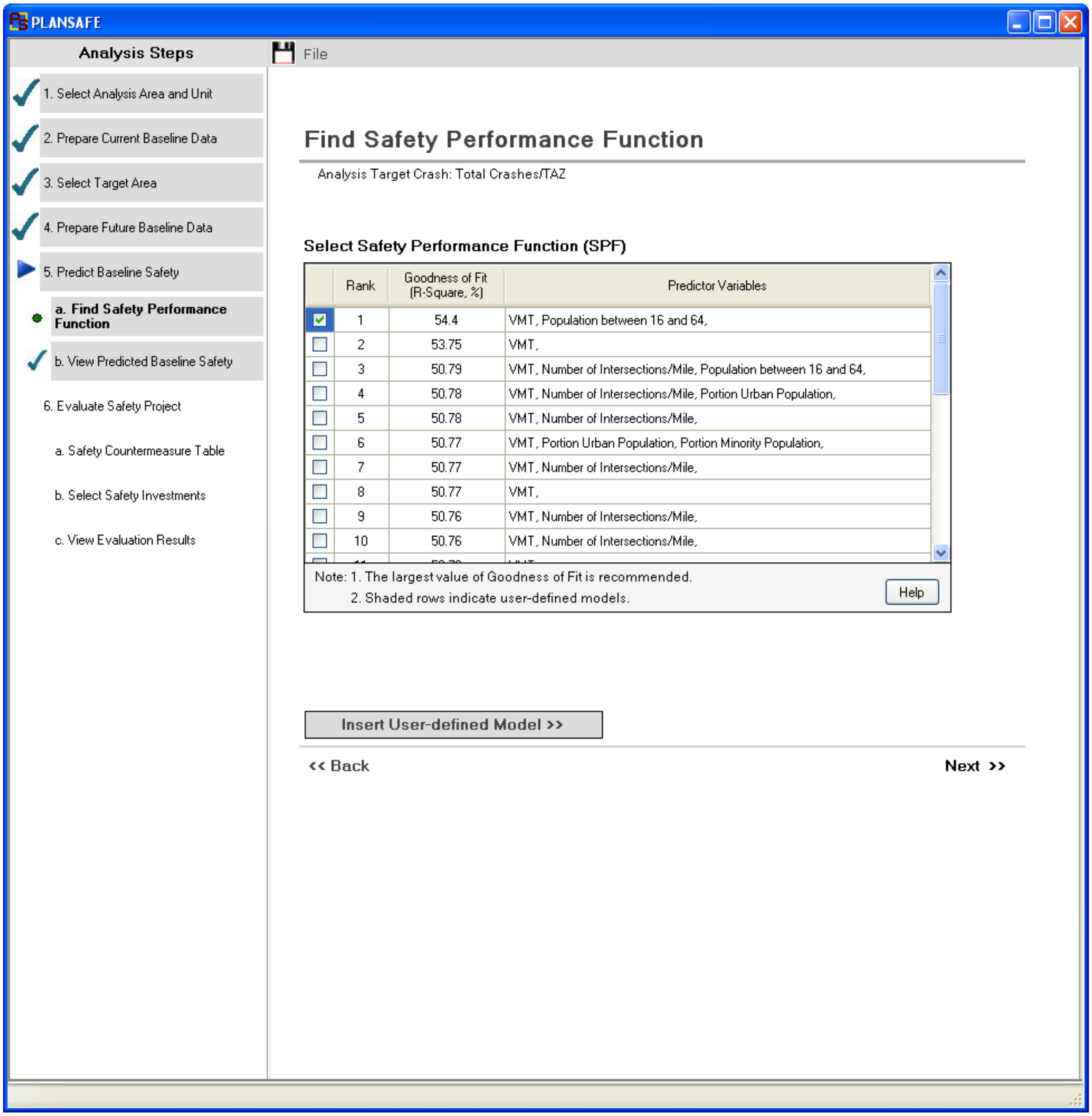

Figure 4.6. PLANSAFE find safety performance function

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

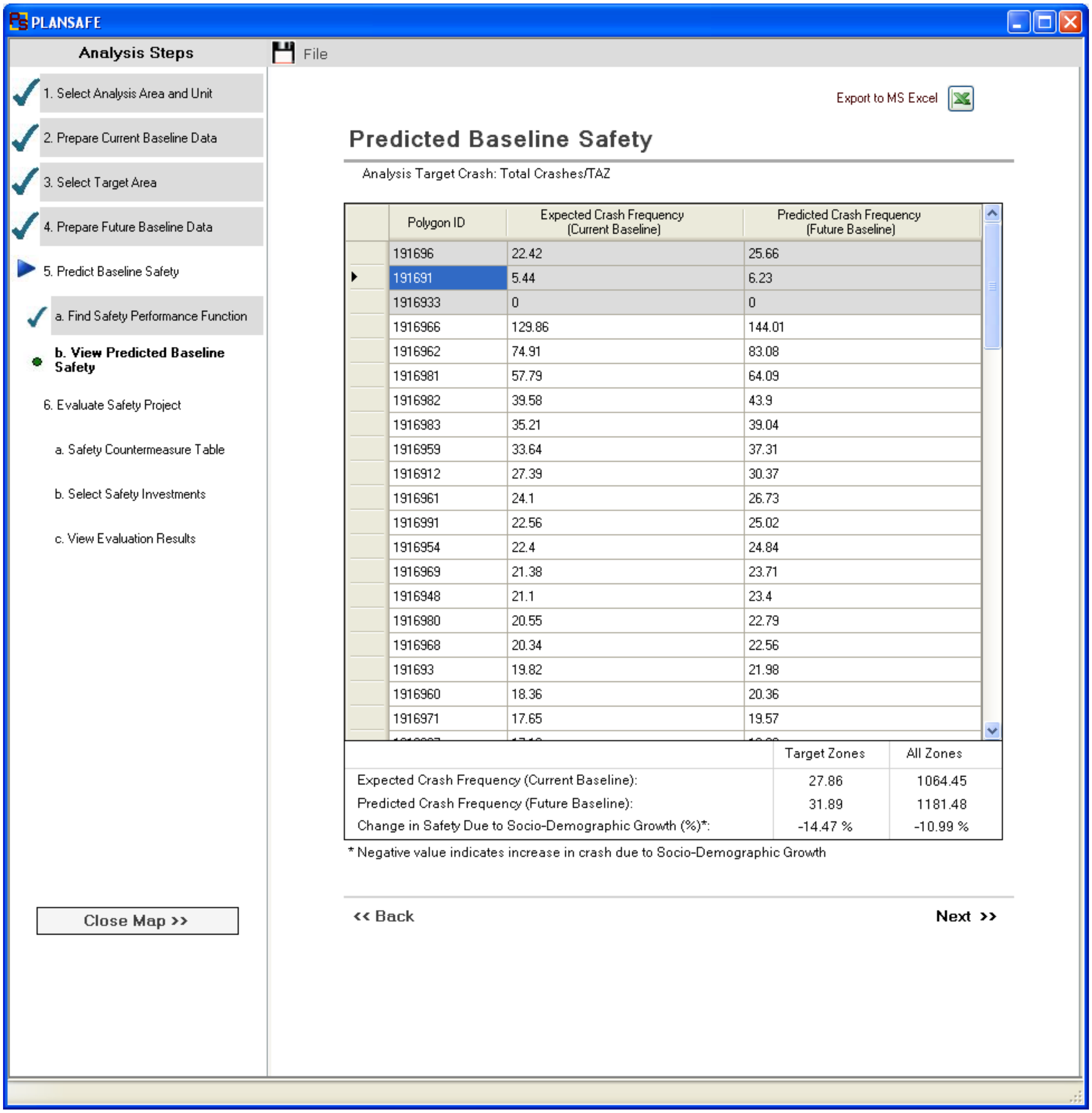

Figure 4.7. PLANSAFE predicted baseline safety

6. Evaluate Safety Projects

First, the software provided a database of different countermeasures with different crash reduction factors (CRFs). The users are allowed to update the existing countermeasure table or upload their own countermeasure table (Figure 4.8).

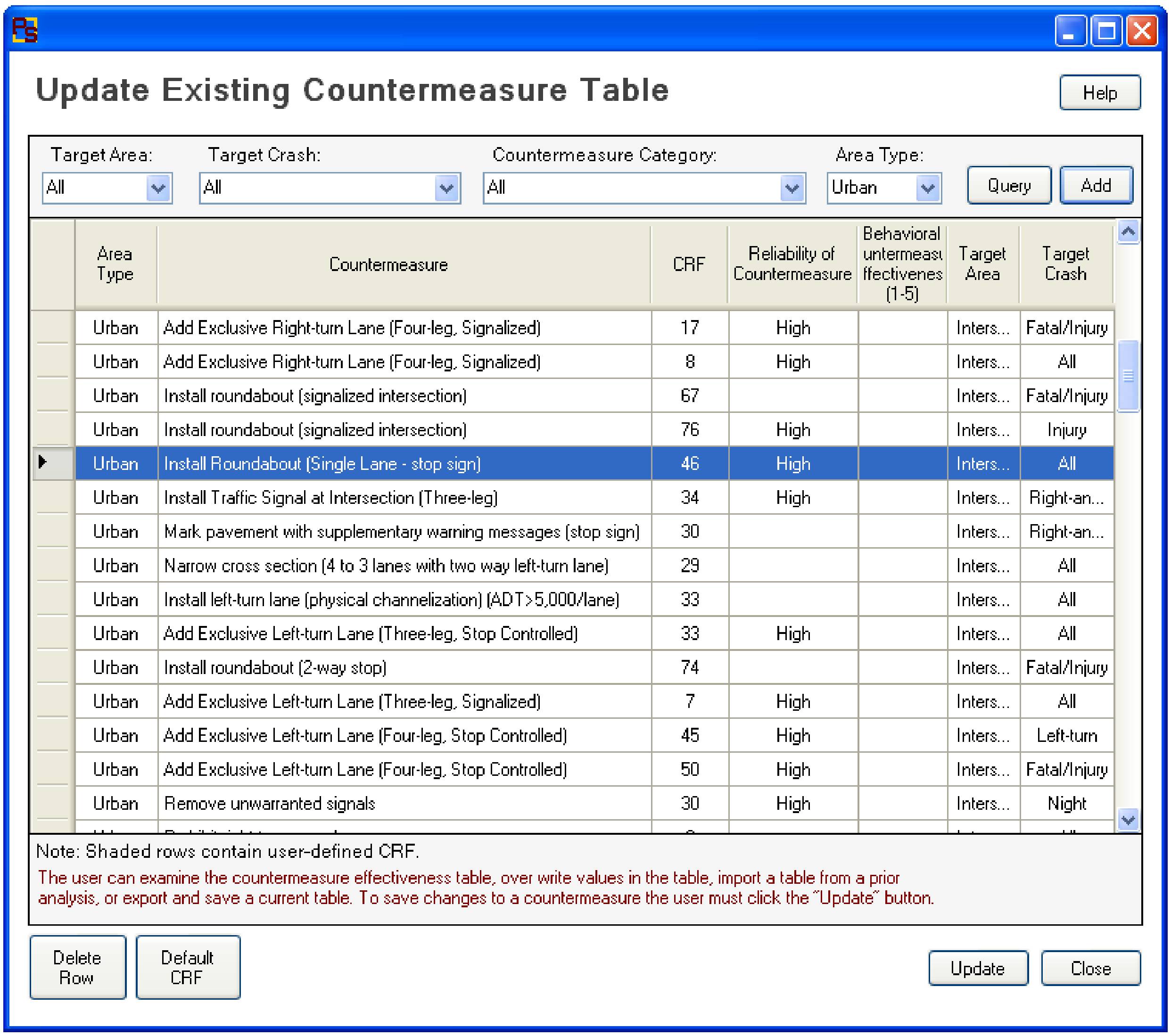

Figure 4.8. PLANSAFE update existing countermeasure table

Next, the user can select safety investments/countermeasures for any TAZs or the specific intersections and/or road segments (Figure 4.9).

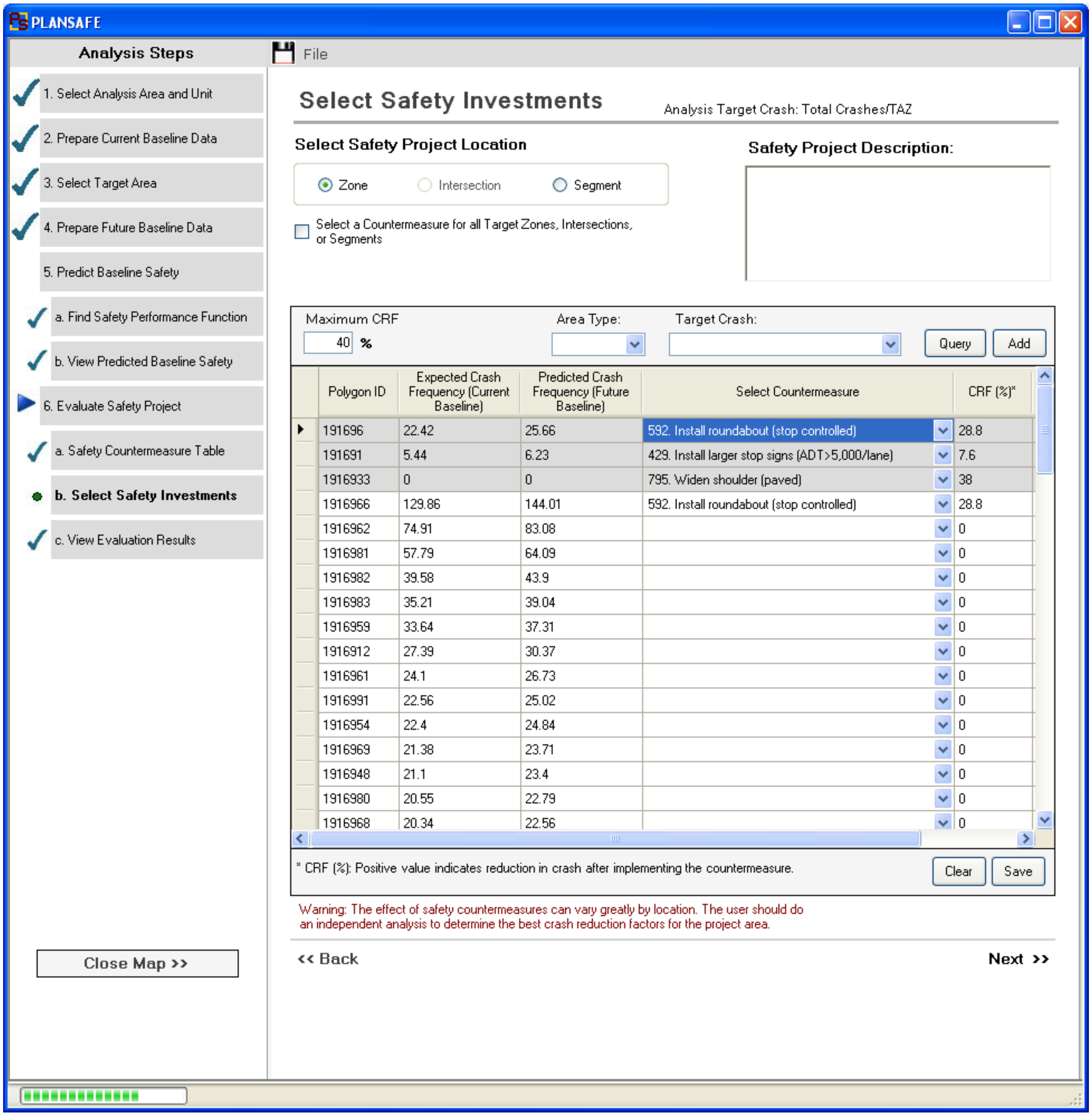

Figure 4.9. PLANSAFE select safety investments

Finally, the safety project evaluation results report was generated (Figure 4.10).

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

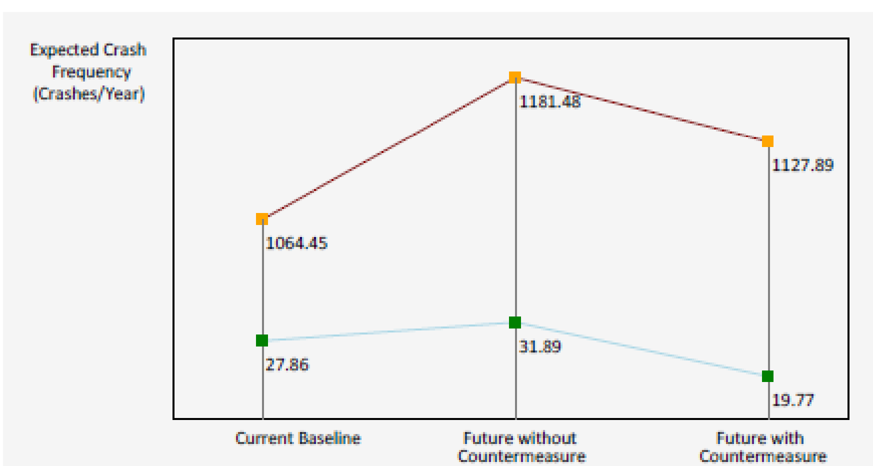

Figure 4.10. PLANSAFE safety project evaluation results

Figure 4.10 shows the change of safety performance of the target zones and all zones given the socio-demographic changes in the 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 the 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 a 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.

4.3 Summary/Conclusions

Both the PLANSAFE-like models and the software could be applicable for safety analysis at the 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 planners who do not have backgrounds in statistics. However, there are some limitations to using the software. For example, the models in the software were difficult to calibrate by using some particular variables and some of the countermeasures were applicable only at the transportation corridor level and 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 we had to develop our own models. These give more flexibility to the user in estimating and calibrating the models by using specific variables and allowing planners to estimate changes in safety as a result of changes in population, network density, number of housing units, and other factors.

CHAPTER 5. EMPIRICAL BAYES

5.1 Overview

One of the problems encountered when planning for safety in a small or medium-sized community like the City of Ames is the small sample size of variables of interest (for example, crashes). Specifically, about 1,000 crashes occurred in Ames per year during the period from 2002 through 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 statistics.

Table 5.1 shows the average number of crashes by road type.

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

	Road Type (no. of crashes)							
	2LArterial	**2LCollect**	**2LLCOAL**	**4LD**	**4LU**	**Freeway**	**RAMP**	**Total**
SPF08	78	124	301	233	360	104	30	1,230
SPF07-08	86	103	234	216	331	92	28	1,090
SPF06-08	81	87	230	200	316	87	27	1,028
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
Number of Observations	41	66	790	44	55	3	33	
Total Length	17.22	35.76	167.35	12.7	18.1	12.46	8.52	
% of Length	6.33	13.14	61.49	4.67	6.66	4.58	3.13	

2LArterial=two-lane arterial
2LCollect=two-lane collector
2LLCOAL two-lane local
4LD=four-lane divided
4LU=four-lane undivided

The researchers observed some variance of crash frequency from year to year for each road type. By using the City of Ames crash data to screen the high-risk locations and predict future crashes, different statistical methods were discussed, as follows.

Typically, engineers use the crash data and road attributes for similar sites to develop SPFs. SPFs are statistical functions, which present the relationship between crash frequency and road attributes, such as the relationship between crash frequency and 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 crashes 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.

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) was adopted in this study.

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 section 2.3, some regression models, such as the Poisson regression model or negative binomial regression model, are used to build SPFs. It is required that the count data has a mean equal to its variance for the Poisson regression model to be applied. If the variance is significantly larger than the mean, the negative binomial regression model is preferred, because of the over dispersion. As shown in Table 5.2, all of the means for crashes are smaller than the variance of the crashes, so the negative binomial model was used instead of the Poisson model (Washington et al. 2011).

Table 5.2. Summary statistics

Model (SPFs)	Crash Mean (variance)	Crash Max./Min.	AADT Mean (std deviation)	AADT Max./Min.	# of Observations
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

2LArterial=two-lane arterial
2LCollect=two-lane collector
2LLCOAL two-lane local
4LD=four-lane divided
4LU=four-lane undivided

The general expression for the negative binomial regression model for each observation is:

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

where EXP (εi) is a Gamma distribution with mean 1 and variance α. The negative binomial regression model has an additional over-dispersion parameter Phi (φ).

The variance of yi is given by:

$$\mathrm{VAR[yi] = E[yi]*[1+ \alpha* E[yi]]} \tag{5-2}$$

which shows under this model, VAR[yi] > E[yi] for α > 0. The goodness-of-fit measure for the negative binomial regression model can be assessed using the -2 x log-likelihood ratio test:

$$x^2 = -2[LL(\beta r) - LL(\beta u)] \tag{5-3}$$

where x^2 follows a Chi-square distribution, $LL(\beta r)$ is 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 equals the difference in number of parameters of the two models (Washington et al. 2011).

5.2.2 Model Specification

In this study, we 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 5.1, all road segments in the City of Ames were assigned into seven road types: two-lane arterial (2LArterial), two-lane collector (2LCollect), two-lane local (2LLCOAL), four-lane divided (4LD), four-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 (Crawley 2007). For each type of road, SPFs were built and calibrated by using one year (2008) crashes, two years average crashes (from 2007 through 2008), three years average crashes (from 2006 through 2008), etc., until seven years of average crashes (from 2002 through 2008) were built and calibrated.

As can be seen in Table 5.1, because the number of observations for freeway and ramp are small, no statistically-significant SPFs could be built.

To build SPFs, we use μ, the average crashes/year of one road segment as the dependent variable and AADT as the independent variable as shown in Table 5.2.

When the SPFs are developed, the over-dispersion parameter Phi (φ) of each SPF in Table 5.3 is obtained from the model outputs at the same time.

Table 5.3 Over-dispersion parameter Phi (φ) for each SPF estimated and calibrated

	Road Type (Phi parameter)						
	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 Observations	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

2LArterial=two-lane arterial
2LCollect=two-lane collector
2LLCOAL two-lane local
4LD=four-lane divided
4LU=four-lane undivided
Phi values in bold and highlighted are the largest Phi values among SPFs for each type of road
For 2LArterial, the largest Phi value is from the SPF08, but the variables in the SPF08 model are not significant, so the second-largest Phi value, from SPF02-08 was used

The final estimated SPFs are in the format of equation 5-4:

$$\mu = L * e^{\theta} * AADT\beta \quad (5\text{-}4)$$

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

The Phi values in bold and highlighted in Table 5.3 are the largest Phi values among SPFs in each type of road. Note: for two-lane arterial, the largest Phi value is from the SPF08, but the variables in the SPF08 model are not significant, so we used the second-largest Phi value from SPF02-08 instead.

The final SPF model specifications are shown in Tables 5.4 and 5.5.

Table 5.4. Negative binomial estimated equations by road type

ROADTYPE	**SPF (equation for number of crashes in one year)**
2LArterial(SPF02-08)	LENGTH*2.71828183^(-8.3553)*AADT^1.1155
2LCollec(SPF08)	LENGTH*2.71828183^(-6.2014)*AADT^0.9667
2LLOCAL(SPF07-08)	LENGTH*2.71828183^(-5.3953)*AADT^0.8845
4LD(SPF05-08)	LENGTH*2.71828183^(-6.669)*AADT^1.038
4LU(SPF07-08)	LENGTH*2.71828183^(-6.4516)*AADT^1.0095

2LArterial=two-lane arterial
2LCollect=two-lane collector
2LLCOAL two-lane local
4LD=four-lane divided
4LU=four-lane undivided

Table 5.5. Negative binomial model specification by road type

Variable	Estimate	t-statistic	p-value
2LArterial			
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			
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			
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			
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			
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***

2LArterial=two-lane arterial
2LCollect=two-lane collector
2LLCOAL two-lane local
4LD=four-lane divided
4LU=four-lane undivided
***, **, *=significance at 1%, 5%, 10%, respectively

5.2.3 Empirical Bayes Methodology

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

> EB Estimate of the Expected Crashes for an entity = Weight * Crashes expected on similar entities + (1 – Weight) * Count of crashes on this entity, where $0 \leq \text{Weight} \leq 1$ (5-5)

The weight in equation 5-5 plays an important role in the EB estimate. The weight that is assigned 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):

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

where W = weight applied to model estimate

μ = mean number of crashes/year from model

φ = over-dispersion 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 we built all the SPFs by using average crash data over different years for each type of road as shown in Table 5.3, we only selected the SPFs with the largest over-dispersion parameter (Phi values) in each type of road to calculate the EB estimate.

From equation 5-6, it's easy to understand that the larger the over-dispersion parameter, the larger the weight. By selecting the SPFs with the largest over-dispersion parameter, a heavier weight is assigned to the SPF model estimate, as shown in equation 5-5.

5.3 EB Analysis Results

After we estimated the SPFs by different types of road as shown in Table 5-4, we calculated the EB estimates using these SPFs combined with different years of site observed crash data. We kept using the same SPF results on "*Crashes expected on similar entities*" and changed "*Count of crashes on this entity*" in equation 5-5—from only one year (2008) crash data, two years average crashes (from 2007 through 2008), three years average crashes (from 2006 through 2008), etc., up to seven years average crashes (from 2002 through 2008). With this, we got a total of seven different EB estimations as EB 08, EB 07-08, EB 06-08, etc., up to EB 02-08.

Then, we calculated the corresponding root mean square error (RMSE) using equation 5-7 to compare the EB estimated crash frequency in 2009 with the actual crash frequency in 2009.

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

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

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

We 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.

Table 5.6. Average crash method results versus EB method results using largest Phi value SPFs

Years of data used		**RMSEAVERAGE**		**RMSEEB**
1	Crashes 2008 vs. 2009	1.7345	EB 08 vs. 2009	1.6546
2	Avg. 07-08 vs. 2009	1.5754	EB 07-08 vs. 2009	1.5211
3	Avg. 06-08 vs. 2009	1.5064	EB 06-08 vs. 2009	1.4743
4	Avg. 05-08 vs. 2009	1.5022	EB 05-08 vs. 2009	1.4784
5	Avg. 04-08 vs. 2009	1.4898	EB 04-08 vs. 2009	1.4690
6	Avg. 03-08 vs. 2009	1.5036	EB 03-08 vs. 2009	1.5015
7	Avg. 02-08 vs. 2009	1.5136	EB 02-08 vs. 2009	1.5119

EB estimates are calculated by using the largest Phi value SPFs

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

Table 5.6 and Figures 5.1 and 5.2 show 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 crash data available.

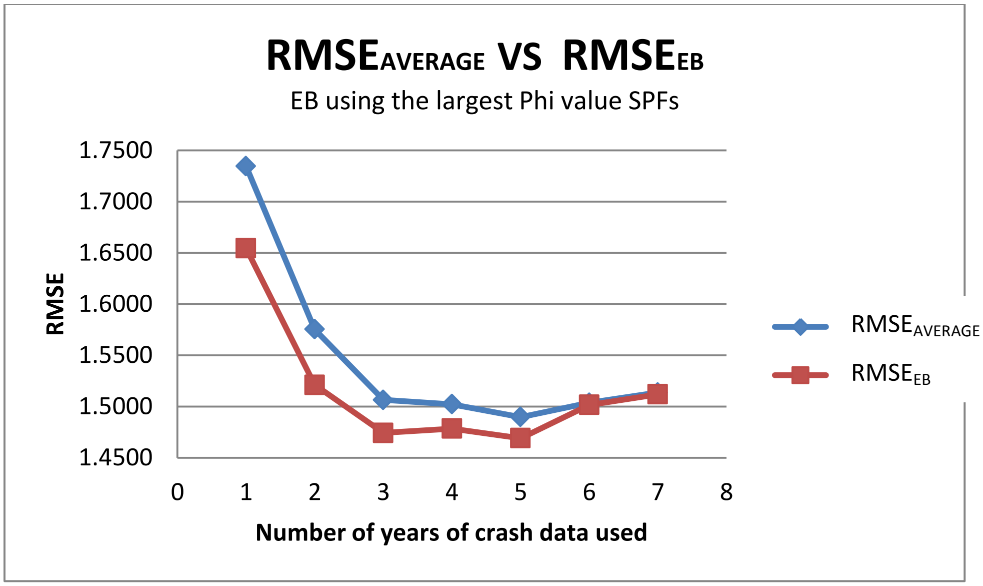

Figure 5.1. RMSE$_{AVERAGE}$ versus RMSE$_{EB}$ with EB using the largest Phi value SPFs

However, this trend only holds true for up to five years of crash data being used. The prediction accuracy does not improve (actually, it is worse) when more than five years of crash data are used. This is probably attributed to the fact that crash data more than five years old cannot accurately represent the current safety situation for the site.

The research team also conducted another EB analysis similar to the first one: the only differences were using the seven years average crash data from 2002 through 2008 to build SPFs for all types of roads and calculating the EB estimates using all year's combination The results are shown in Table 5.7 and Figure 5.2.

The results are similar to the first ones. 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 crash data available. However, this trend only holds true for up to five years of crash data being used.

The only difference with the second set of results is that the RMSE average is closer to RMSE EB, which makes sense, because we used more comprehensive crash data for 2002 through 2008 to build SPFs and develop EB. Hence, the EB prediction will be as effective as the average crash prediction.

Table 5.7. Average crash method results versus EB method results using the most comprehensive crash data to build SPFs

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

EB estimates are calculated by using the most comprehensive crash data from 2002-2008 to build SPFs

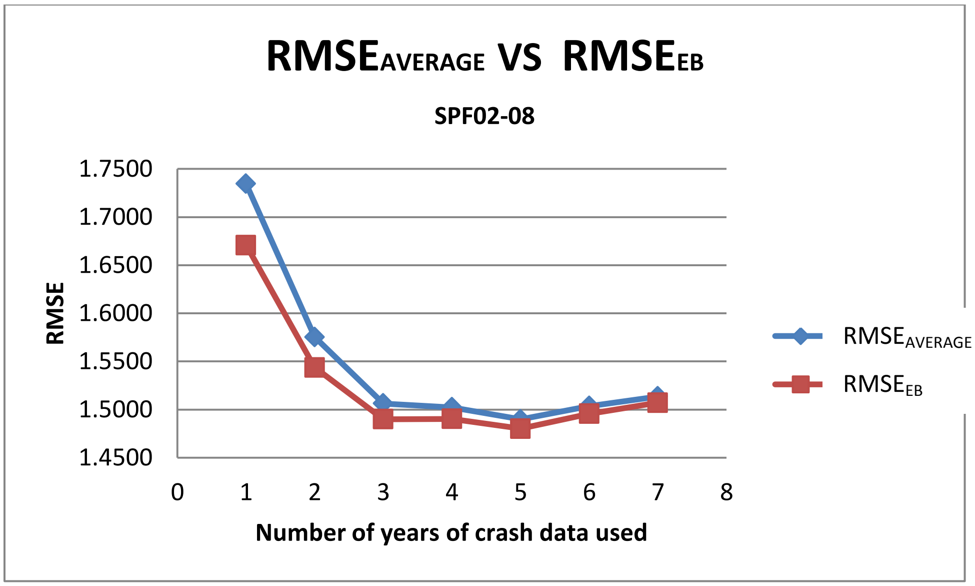

Figure 5.2. $RMSE_{AVERAGE}$ versus $RMSE_{EB}$ with EB using SPF02-08

5.4 Summary/Conclusions

If a long period (at least four years) of site crash data is not available 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 four years.

All SPF model outputs and EB calculations are included in Appendix A.

CHAPTER 6. usRAP-STYLE RISK MAPPING

6.1 Overview

The consideration of safety in metropolitan planning is a requirement of federal highway legislation (such as 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 for explicitly incorporating 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) (Harwood et al. 2010a; 2010b).

usRAP risk mapping and road assessment methods have previously been applied to state highways by the Center for Transportation Research and Education (CTRE) at Iowa State University and the Midwest Research Institute (MRI). usRAP has three safety assessment protocols that are potentially applicable to regional planning: risk mapping, star ratings, and countermeasure program selection (known as Safer Roads Investment Programs). The objective of this chapter is to report on the investigation of applicability of the 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 investments.

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. These were the tasks to accomplish this objective:

1. Invite and assemble an advisory team. Outcome: advisory committee formation.
2. Assemble data for risk mapping. Outcome: GIS crash database in usRAP risk mapping format for Ames area roads.
3. Develop four basic risk maps (crash density, crash rate, crash rate ratio, and potential crash savings) for the City of Ames, Iowa. 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 Methodology

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, the 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 following: street name, AADT category (0-100-400-1000-5000-10000-max), speed category (0-25mph, 30-35mph, 40-45mph, 50-55mph, >55mph), road type (two-lane arterial/2LArterial, two-lane collector/2LCollect, two-lane local/2LLCOAL, four-lane divided/4LD, four-lane undivided/4LU, freeway), and a unique ID for each segment. Next, the new road network and crash data were used to create these usRAP-style maps: crash density, crash rate, crash rate ratio, and potential crash savings.

For the usRAP-style crash maps 1 and 2, which are the crash density map and the crash rate map, we calculated the crash density (in crashes per mile) and the crash rate (in crashes per 100 million vehicle miles traveled/100M VMT). The resulting risk for each road segment, from high to low (as defined in Table 6.1), is shown on the maps.

For the usRAP-style crash map 3, which is the crash rate ratio map, first we calculated the average crash rate for each road type (two-lane arterial/2LArterial, two-lane collector/2LCollect, two-lane local/2LLCOAL, four-lane divided/4LD, four-lane undivided/4LU, freeway). Then, we calculated the crash rate ratio for each road segment and compared it to the average crash rate for the same or similar roads. The resulting risk for each road segment is shown on the maps

For the usRAP-style crash map 4, which is the potential crash savings map, we calculated the number of total crashes saved per mile in seven years for each road segment if the crash rate were reduced to the average crash rate for similar roads. The resulting potential crash savings for each road segment is shown on the map.

6.3 Results

Table 6.1 defines the ratings used to categorize the road segments in the four usRAP-style risk maps in Figures 6.1 through 6.4.

Table 6.1 Definition of map legends

Rating	Density, Rate, Ratio, or Savings
High	In the top five percent
Medium-High	Between the top five and 15 percent
Medium	Between the top 15 and 35 percent
Low-Medium	Between the top 35 and 60 percent
Low	Between the top 60 and 100 percent

The summary risk mapping data is listed in Table 6.2.

Table 6.2. Ames metropolitan area risk mapping data summary for 2002 through 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

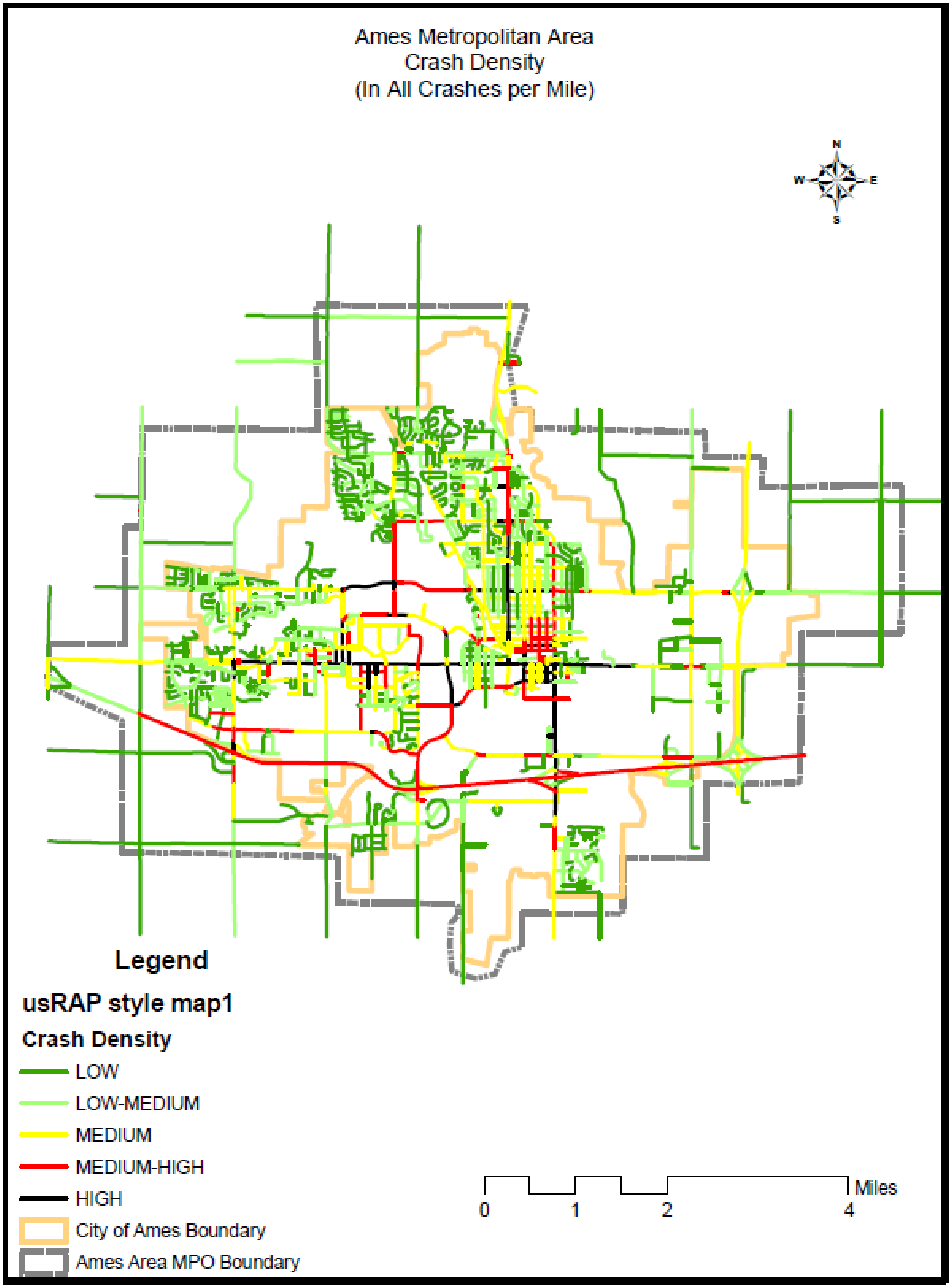

Figure 6.1. usRAP-style crash density map 1

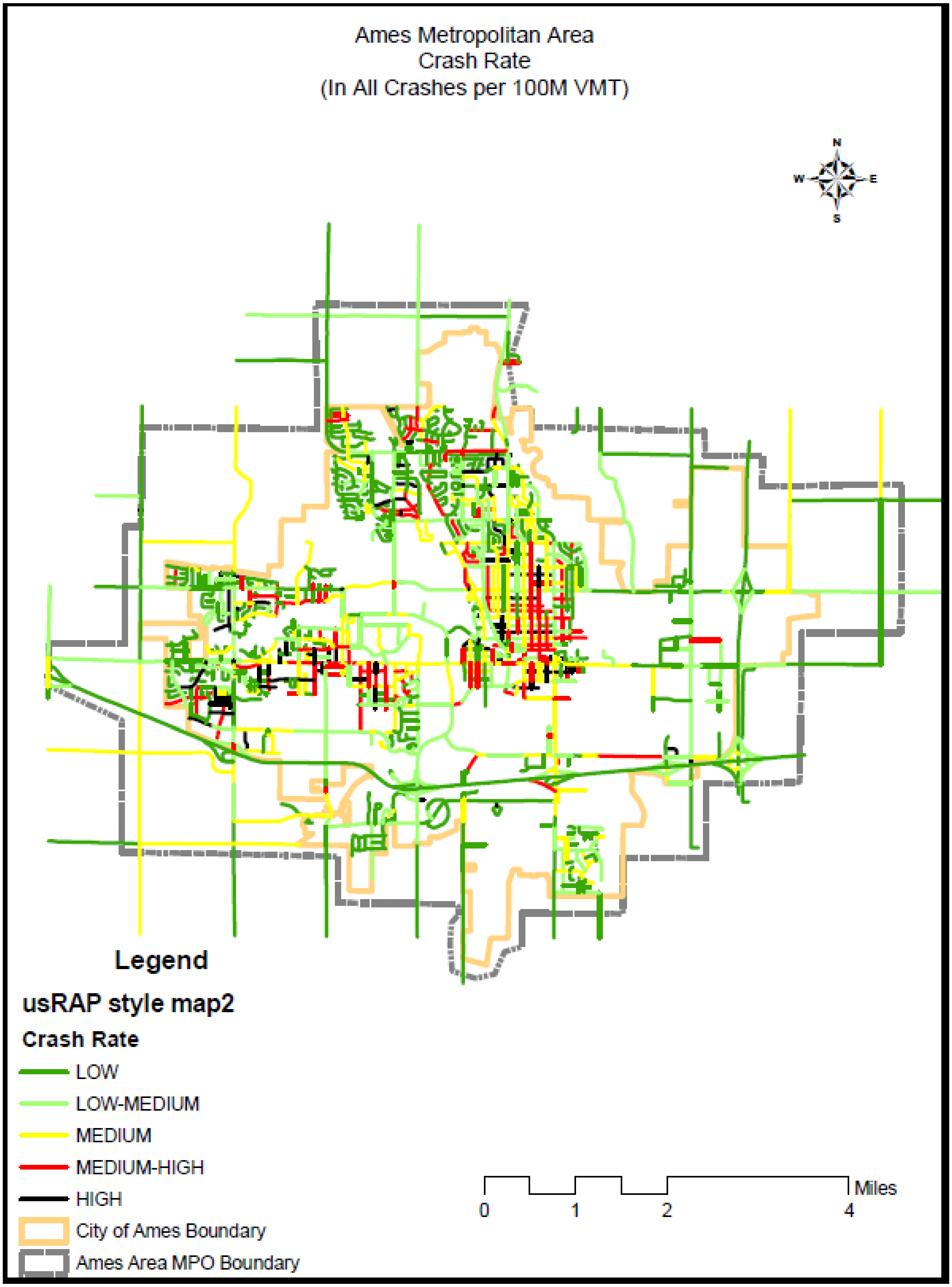

Figure 6.2. usRAP-style crash rate map 2

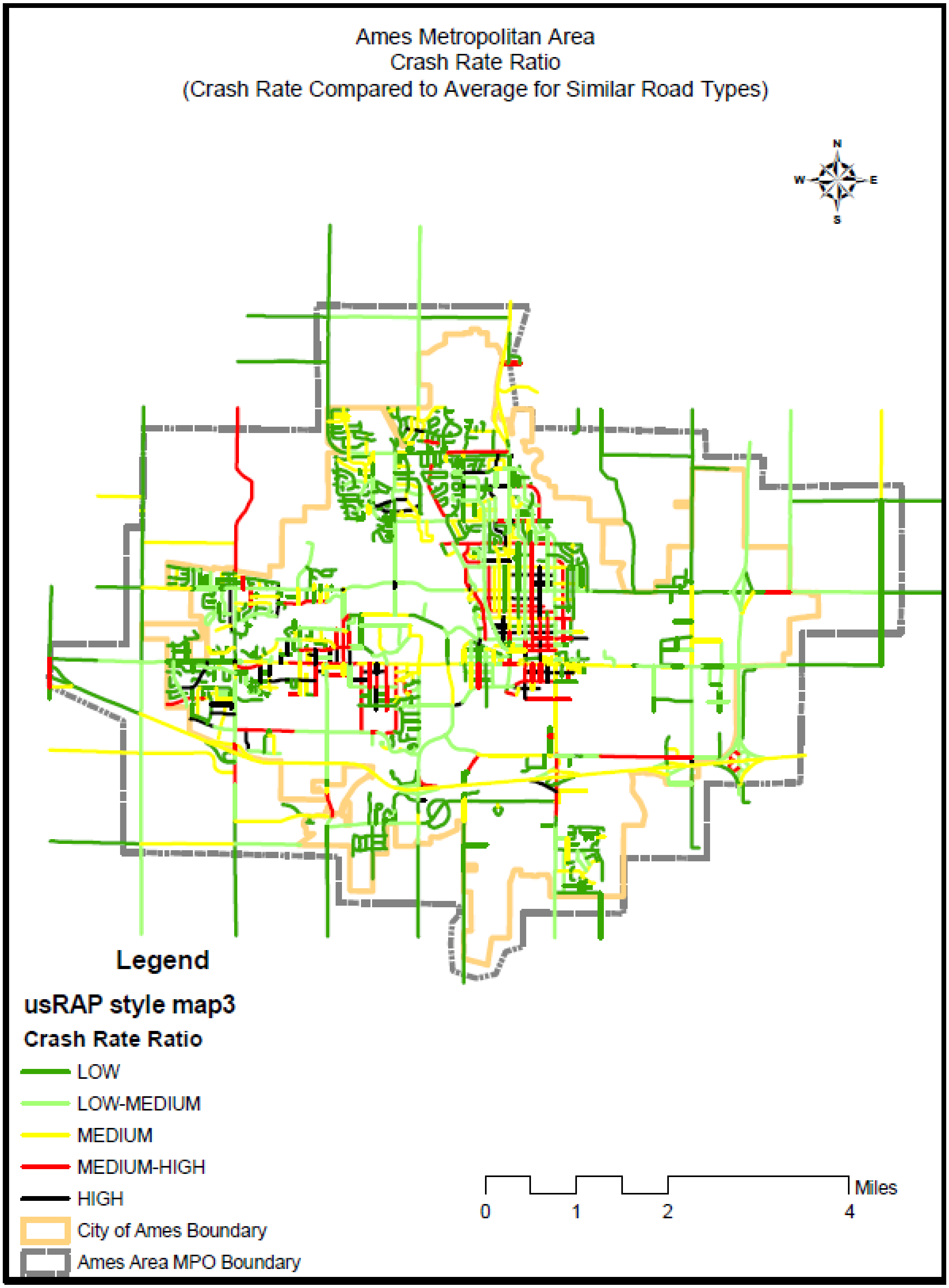

Figure 6.3. usRAP-style crash rate ratio map 3

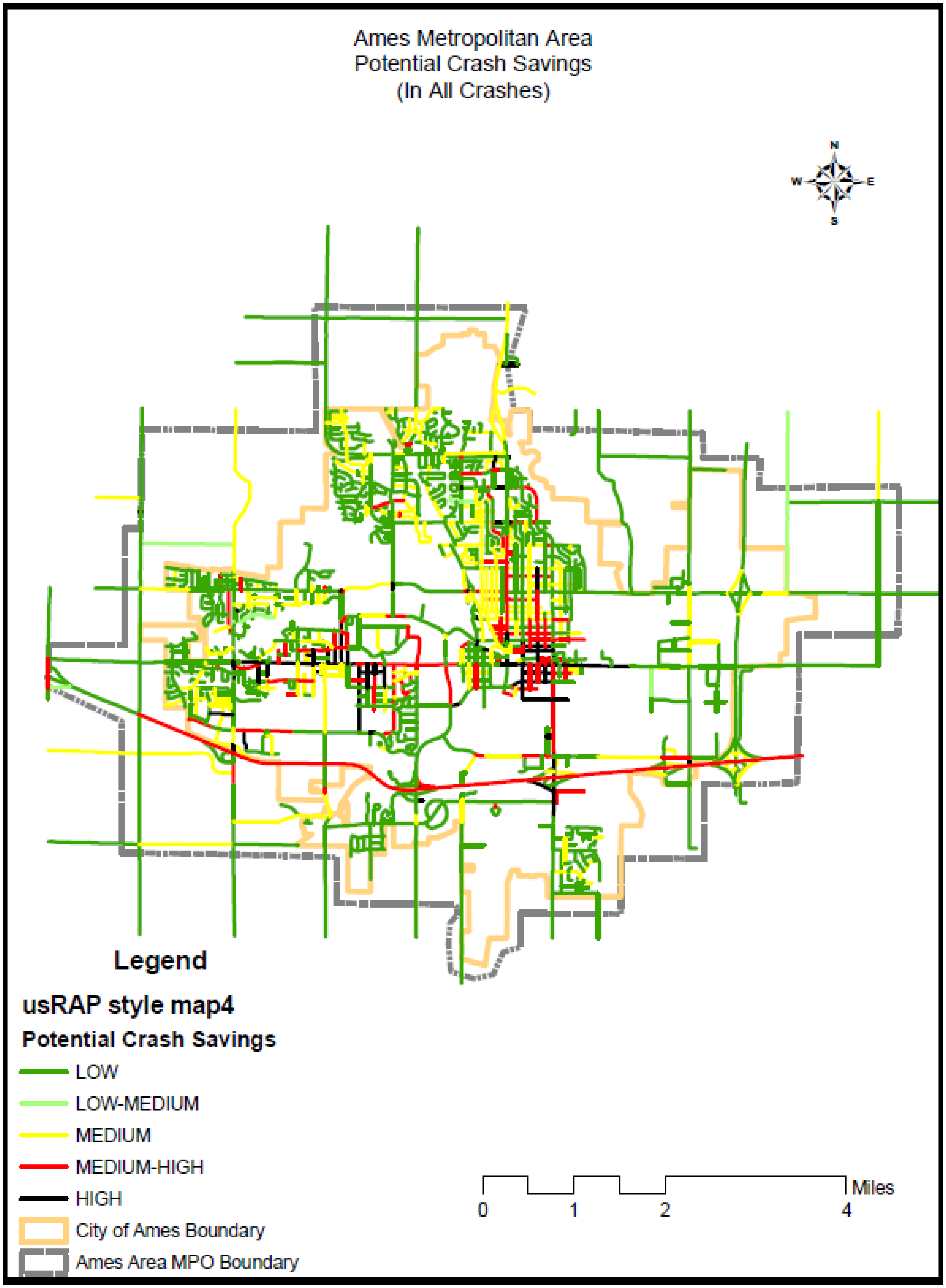

Figure 6.4. usRAP-style potential crash savings map 4

6.4 Summary/Conclusions

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

The usRAP-style map 3, which shows the crash rate ratio, is based on the relative total crash rate per 100M VMT for the road segments when compared 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, which shows the potential crash savings, is based on the number of total crashes saved per mile in seven years for 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 countermeasures, such as infrastructure modifications or enforcement programs.

All four usRAP-style risk maps can help local transportation office and planning staff to identify 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 the general public.

CHAPTER 7. CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS

7.1 Conclusions and Limitations

Although the three safety analysis 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 planners who do not have backgrounds in statistics. 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 EB 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, etc.), demonstrating that no single map can provide all of 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.

Finally, 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 it should be 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 socio-economics 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 A. EB MODEL SPECIFICATION

Key to Tables

2LArterial=two-lane arterial
2LCollect=two-lane collector
2LLCOAL two-lane local
4LD=four-lane divided
4LU=four-lane undivided
***, **, *=significance at 1%, 5%, 10%, respectively

Table A.1. SPF based on 2008 crash data

Variable	Estimate	t-statistic	p-value
2LArterial			
Intercept	-0.6991	-0.266	0.790
logAADT	0.2551	0.852	0.394
Phi φ	0.18315		
-2 x log-likelihood	132.809		
2LCollect			
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			
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			
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			
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		

Table A.2. SPF based on 2007-2008 crash data

Variable	Estimate	t-statistic	p-value
2LArterial			
Intercept	-2.2318	-0.981	0.3264**
logAADT	0.4382	1.698	0.0895***
Phi φ	0.00787		
-2 x log-likelihood	124.864		
2LCollect			
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			
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			
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			
Intercept	-6.4516	-2.426	0.015260 **
logAADT	1.0095	3.488	0.000487 ***
Phi φ	0.704		
-2 x log-likelihood	267.016		

Table A.3. SPF based on 2006-2008 crash data

Variable	Estimate	t-statistic	p-value
2LArterial			
Intercept	-1.7366	-0.759	0.448
logAADT	0.3751	1.443	0.149
Phi φ	0.001305		
-2 x log-likelihood	122.532		
2LCollect			
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			
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			
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			
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		

Table A.4. SPF based on 2005-2008 crash data

Variable	Estimate	t-statistic	p-value
2LArterial			
Intercept	-5.4538	-2.128	0.03334 **
logAADT	0.7933	2.746	0.00603***
Phi φ	0.000234		
-2 x log-likelihood	119.854		
2LCollect			
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			
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			
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			
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		

Table A.5. SPF based on 2004-2008 crash data

Variable	Estimate	t-statistic	p-value
2LArterial			
Intercept	-6.0553	-2.327	0.01998 **
logAADT	0.8654	2.952	0.00315 ***
Phi φ	0.017544		
-2 x log-likelihood	128.637		
2LCollect			
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			
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			
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			
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		

Table A.6. SPF based on 2003-2008 crash data

Variable	Estimate	t-statistic	p-value
2LArterial			
Intercept	-7.8320	-2.832	0.004625 ***
logAADT	1.0622	3.420	0.000625 ***
Phi φ	0.021277		
-2 x log-likelihood	123.395		
2LCollect			
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			
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			
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			
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		

Table A.7. SPF based on 2002-2008 crash data

Variable	Estimate	t-statistic	p-value
2LArterial			
Intercept	-8.3553	-2.707	0.00679 ***
logAADT	1.1155	3.216	0.00130 ***
Phi φ	0.11919		
-2 x log-likelihood	125.425		
2LCollect			
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			
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			
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			
Intercept	-6.0298	-2.676	0.007448 ***
logAADT	0.9457	3.876	0.000106 ***
Phi φ	0.359712		
-2 x log-likelihood	246.376		