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FINAL REPORT

WY-1901F (Vol 2)

UPDATING AND IMPLEMENTING THE GRADE SEVERITY RATING SYSTEM (GSRS) FOR WYOMING MOUNTAIN PASSES: EVALUATING THE SAFETY EFFECTIVENESS OF DOWNGRADE WARNING SIGNS (VOLUME 2)

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16. Abstract:

Truck safety on mountain passes presents a major challenge to most highway agencies in western United States. Large trucks are known to be disproportionately affected on severe downgrades which characterize mountain passes in comparison to other vehicle classes due to large sizes and heavy loads. The Wyoming Department of Transportation in an effort to reduce crash risks on Wyoming mountain passes has among other measures installed warning signs on steep grades in the state. The main purpose of this study is to develop recommendations of the best warning system on Wyoming mountain passes based on an evaluation of the impact of warning signs on truck crashes. Hazardous downgrades in the state were identified and data was collected to build a crash database. Several analyses were then conducted to evaluate the impact of advance downgrade warning signs on truck crashes. The analyses included propensity score matching, negative binomial modeling, and ranking of sites and a hotspot analysis of warning sign placement. The potential use of intelligent transportation systems in reducing downgrade truck crashes was assessed as well. The results of the analyses indicate that the various downgrade warning signs are effective in preventing downgrade crashes on mountain passes.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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LIST OF ACRONYMS

AADT	Average Annual Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
ABS	Anti-lock Braking System
ADTT	Average Daily Truck Traffic
AEBS	Advanced Emergency Braking Systems
ANOVA	Analysis of Variance
ARF	Accident Reduction Factor
ARFF	Aircraft Rescue and Fighting
ATE	Average Treatment Effect
ATRI	American Transportation Research Institute
ATRWS	Automatic Truck Rollover Warning Signs
CALTRANS	California Department of Transportation
CARE	Critical Analysis Reporting Environment
CDC	Center for Diseases Control and Prevention
CMF	Crash Modification Factor
CPM	Crash Prediction Model
CRF	Crash Reduction Factor
DOT	Departments of Transportation
DSRC	Dedicated Short Range Communication
EB	Empirical Bayes
EPDO	Equivalent Property Damage Only
ESC	Electronic Stability Control
ESP	Electronic Stability Program
FHWA	Federal Highway Administration
GIS	Geographic Information System
GSRS	Grade Severity Rating System
HCM	Highway Capacity Manual
HSM	Highway Safety Manual
ITS	Intelligent Transportation Systems
LPR	License Plate Reader
LTCCS	Large Truck Crash Causation Study
M&R	Maintenance and Rehabilitation
ML	Main Line
MUTCD	Manual on Uniform Traffic Control Device
MVMT	Million Vehicle Miles Traveled
NB	Negative Binomial
NHTSA	National Highway Traffic Safety Administration
NN	Nearest Neighbor
OCR	Optical Character Recognition
PDO	Property Damage Only
RR	Relative Risk/Risk Ratio
RSC	Roll Stability Control
RTM	Regression-to-the-mean
SIRIS	Smart Infrared Inspection System
SPF	Safety Performance Function

TRS	Trailer Roll Stability
UMTRI	University of Michigan Transportation Research Institute
USDOT	United States Department of Transportation
VMS	Variable Message Sign
VMT	Vehicle Miles Travelled
WIM	Weigh-in-Motion
WSS	Weight Specific Speed
WYDOT	Wyoming Department of Transportation
WYT^2/LTAP	Wyoming Technology Transfer Center/ Local Technical Assistance Program
ZINB	Zero Inflated Negative Binomial Model

CHAPTER 1: INTRODUCTION

This chapter gives a background of the study by highlighting the issue of truck crashes on downgrades. The problem study, research objective and tasks are discussed in the chapter. The chapter concludes by discussing the organization of the report.

TRUCK SAFETY ON MOUNTAIN PASSES

Mountain passes are characterized by difficult geometry and terrain that increase the risk of a runaway, or out of control trucks. Advance warning signs inform drivers to take special precautions such as reducing speed or using lower gears during descent to counter the incidence of truck crashes on mountain passes. The Wyoming Department of Transportation (WYDOT) has installed steep grade advance warning systems on various Wyoming mountain passes throughout the state. Some highways have experienced varied degrees of improvement over others. However, despite these developments, concerns for out of control trucks on mountain passes persist.

Runaway or out-of-control truck crash frequencies are high on mountain passes compared to other sections of typical routes. WYDOT attributes some of the runaway truck crashes to driver unfamiliarity with the road and terrain. (WYDOT, 2016). Although many Wyoming roads drive through relatively, flat prairie areas, they often traverse mountainous terrain. Such terrain present challenges to inexperienced or ill-prepared drivers handling the severity of the mountainous road geometry. These drivers are more likely to be involved in downgrade crashes.

WYDOT and other highway agencies expend significant resources on the installation, upgrading and maintenance of traffic control devices, such as warning signs. To ascertain that those resources are well invested, it is important to assess the extent to which such traffic control devices serve their intended purpose. Knowing the effectiveness of warning signs for improving safety on mountain passes is important for highway agencies to assess the impact of such safety interventions. Such safety effectiveness analyses are also needed for alternative improvements. This study assessed the effectiveness of downgrade warning signs in reducing the incidence of truck crashes.

PROBLEM STATEMENT

Downgrade truck crashes are a serious problem on mountain passes with an attendant loss of lives and property. WYDOT has installed advance-warning signs on steep downgrades on Wyoming mountain passes to counter this type of crash occurrence. The problem of downgrade truck crashes is however, still present.

In the period from January to September 2014, seven downgrade truck crashes were recorded on United States (US)-14 near Dayton, Wyoming. (VanOstrand, 2014). The number of truck crashes was more than double that recorded from 2004 to 2013. WYDOT suspected truck driver unfamiliarity with the road and terrain to be the cause of these crashes. On December 2015, a fatal truck crash occurred on a section of US-14 despite a recently reduced speed zone of 40 mph. (Burr, 2015). The crash was attributed to brake failure and indicated the need to develop road signs with truck weight specific speed advisories instead of the general speed limit signs.

A report released by the American Transportation Research Institute (ATRI) in 2014, ranked the top 10 states with the highest large truck crash rates as shown in Table 1. Wyoming ranked number one with 0.52 large truck crashes per million vehicles miles traveled (MVMT), which is twice the National average of 0.26, next to New Jersey and Kansas at 0.48 and 0.41, respectively. (Weber, A., Murray, 2014). Based on this information, it is evident that a proper investigation into truck crashes on mountain passes is warranted, which has prompted this study.

Table 1. National Truck Crash Rates (Weber & Murray, 2014)

Crash Rates

National Average	0.26

Top 10

Rank	State	Crashes/MVMT
1	Wyoming	0.52
2	New Jersey	0.48
3	Kansas	0.41
4	Colorado	0.40
5	Virginia	0.39
6	Montana	0.37
7	Kentucky	0.35
8	Minnesota	0.34
9	Iowa	0.32
10	Michigan	0.31

Bottom 10

Rank	State	Crashes/MVMT
39	Washington	0.20
40	South Dakota	0.19
41	Georgia	0.19
42	Oregon	0.18
43	Idaho	0.16
44	Pennsylvania	0.16
45	Mississippi	0.14
46	Florida	0.12
47	Utah	0.11
48	New Mexico	0.08

This study is part of the research aimed at recommending appropriate warning systems to reduce the incidence of truck crashes during downgrade descent on Wyoming mountain passes. This was achieved in two tasks. The first task which is volume 1 of this study involved reviewing, updating and validating the current Grade Severity Rating System (GSRS). The product from this task was an application capable recommending descent speeds based on truck weight and grade characteristics. The second task, which is the focus of this present report, carried out a comprehensive evaluation of the current mountain pass warning systems in Wyoming, as well as the most current state of practice to recommend the best warning system for the state's mountain passes.

An evaluation of the advance warning system was carried out both at the state-wide level and for specific hazardous mountain passes with high incidences of truck crashes. Crash, geometric and other relevant data were collected on the routes and statistical analyses was conducted to determine the systems and signing types effective in preventing downgrade truck crashes. After analyzing the quantitative data of truck crashes on downgrades throughout the state of Wyoming, a total of 157 sections were identified as hazardous and used in the analysis. Five representative downgrades were selected and analyzed in detail in terms of their warning system configurations and placement. These were WY-22 (Teton Pass), US-14 and 16 in the Bighorn Mountains, as well as WY-28 (South Pass).

RESEARCH OBJECTIVES

The research aims to evaluate Wyoming mountain passes and their warning systems with regard to truck crashes on downgrades. The results of the research will be recommending the best means of communicating downgrade information to truck drivers to reduce the incidence of runaway truck crashes. To accomplish this, hazardous mountain pass roadways were first identified. Multiple databases pertaining to crashes on the mountain passes, roadway geometric characteristics as well as the present warning signs systems were developed. This enabled different statistical analyses aimed at identifying the primary factors relating to downgrade truck crashes and the effectiveness of various downgrade warning signs designed for trucks to be evaluated. A propensity score model was used to quantify the safety effectiveness of the presence of warning signs. The routes were then ranked based on two methods; (EB) empirical Bayes adjusted expected crash frequency and equivalent property damage (EPDO). Crash hotspots as well as plots of current warning signs were digitally mapped in ArcMap to evaluate the present warning system and to recommend the best warning sign system. Vital information gained from this research can be used to determine the effectiveness of advanced warning signs systems and to propose recommendations to local WYDOT districts and other agencies operating in mountainous areas to combat downgrade truck crashes based on the results of this study.

RESEARCH TASKS

The study consists of multiple research tasks. The main tasks outlined in the research proposal were to evaluate the safety effectiveness of advanced warning signs on downgrades and recommend the most effective warning system to prevent truck crashes. The following tasks were performed to achieve the study objectives:

- A literature review was conducted to provide insights into the safety effectiveness of countermeasures such as warning signs. The literature review identified methods adopted in previous studies in safety effectiveness evaluation.
- Data was collected on mountain passes identified as hazardous. The criteria set out in the manual on uniform traffic control devices (MUTCD) was used in identifying hazardous downgrades. Data was collected on these hazardous downgrades. The data included information about posted speed limits, grade percent, vertical and horizontal curves, warning sign types installed and their locations and other road geometric characteristics.
- A field assessment of some mountain passes identified in task 2 was undertaken. The field assessment determined the type of warning signs installed and their condition.
- An evaluation of the impact of warning systems on truck crashes was carried out. A propensity score model was utilized to evaluate the safety effectiveness of the presence of warning signs on mountainous downgrades in Wyoming. The method consists of estimating the probabilities of occurrence of a truck crash in a section with the presence

of a warning sign and without. A further analysis was conducted to evaluate the safety effectiveness of individual warning sign types. This was done using a statistical regression modeling. Ranking of mountain passes was done using the expected average crash frequency using the Empirical Bayes (EB) Adjustment. This analysis was undertaken to allow the ranking of each downgrade segment and mountain pass routes to be ranked in terms of safety. The analysis also enabled an evaluation of what safety systems work on the mountain passes.

- The next task involved a hotspot analysis of warning sign locations and crashes on mountain passes. The hotspot analysis was done to assess the relationship between warning sign installation and locations of truck crashes. This also enabled the identification of general trends of crashes and sign placement and also led to recommendations of the best mitigation strategies.
- A review of potential and current Intelligent Transportation Systems (ITS) in reducing the incidence of truck crashes on downgrades was undertaken. Several infrastructure- and vehicle-based ITS applications were reviewed with regards to how applicable they are to reducing downgrade truck crashes.
- Recommendations of the best means to communicate downgrade information to truck drivers were made as the final task.

REPORT ORGANIZATION

This report is organized into seven chapters as follows:

- Chapter 1 of the report is an introduction to the research topic and presents the objectives of the study. It also lists the tasks that were involved in the study.
- Chapter 2 of this report reviews past studies which have been conducted with respect to is warning signs, and evaluation strategies.
- Chapter 3 focuses on the methodologies developed and followed to complete the study. This chapter outlines the various steps that were taken to identify the study areas, development of a safety performance function (SPF) to screen and rank sites, and approaches to outline the safety effectiveness of warning signs.
- Chapter 4 is associated with the data collection process, and describes the database used to complete the study. This chapter also describes the study areas and shows the field work conducted to collect all warnings signs present in the selected study areas. The study areas are described in detail presenting descriptive statistics of traffic volumes, crashes and other roadway characteristics.
- Chapter 5 presents the results of the various analyses. It also includes a discussion of the best warning signs recommended for communicating downgrade information to drivers.
- Chapter 6 discusses the potential and current use of Intelligent Transportation Systems (ITS) in reducing truck crashes on downgrades.
- Chapter 7 summarizes and highlights the conclusions reached in the study. It includes recommendations based on the study findings. Future work to better understand and implement the best warning systems on mountain pass roads is also proposed.

CHAPTER 2: LITERATURE REVIEW

This chapter discusses the main types of warning signs installed on mountainous and other highways in the state of Wyoming. A review of approaches used in evaluating the safety effectiveness of countermeasures in past studies are presented in the chapter. The strength and limitations of the approaches are also highlighted.

TRAFFIC SAFETY

Improving traffic safety is a very important goal of the transportation agencies throughout the United States. In the year 2007, there was an estimated 2.5 million people involved in a transportation-related crash. Crashes on highways account for nearly 99.5 percent of all transportation related crashes, and nearly 95 percent of transportation related fatalities and injuries. (Bureau of Transportation Statistics, 2009). Statistics obtained from the Center of Disease Control and Prevention (CDC) claimed that crashes are the fifth leading cause of deaths in the United States. Highway crashes have been found to be the leading cause of death for ages between 1 and 44. (CDC, 2016). Added to this, the demand for vehicles also capped in 2018 after an 8-year increase. This increase in vehicles and general travel provides the impetus to develop effective and safe transportation safety management programs. (Transportation and Statistics, 2018).

The purposes of traffic safety management programs are to reduce the frequency and severity of crashes by identifying locations with potential for safety improvements, causation of crashes, implementing countermeasures and evaluating the effectiveness of those countermeasures. The implementation of an effective safety countermeasure is a critical process in traffic safety management.

WARNING SIGNS

The definition of warning signs provided in the MUTCD states that:

> "Warning signs call attention to unexpected conditions on or adjacent to a highway, street or private roads open to public travel and to situations that might not be clear to road users. Warning signs alert road users to conditions that might call for a reduction of speed or an action in the interest of safety and efficient traffic operation". (FHWA, 2009).

Warning signs give drivers enough time to react to forthcoming roadway design changes or hazards.

Driver inattention or "recognition failure" of roadway hazards has been estimated to contribute to 25-50 percent of road crashes. (Stutts et al., 2001). This has been attributed to more crashes and a higher social cost than either alcohol or speeding. (Knowles and Tay, 2002). The most prominent method of relaying information regarding road hazards to drivers is by providing types of roadside warning signs. However, the effectiveness and factors such as frequency of warning signs have been called into question by various studies.

Advance Warning Signs

Advance warning signs provide motorists with information relating to roadway hazards, speed limits, and penalties for traffic violations. There are two main types of warning signs used to inform and warn drivers. These are:

- Static warning signs
- Variable message signs (VMS) or dynamic message signs.

Examples of these signs are shown in Figure 1. Static signs by their nature display pre-defined information or symbols on retroflective and/or fluorescent backgrounds. VMS electronically display current roadway information to alert motorists of the present conditions of the traffic environment. These signs are used in conjunction with conspicuous devices and backgrounds to enhance their visibility to motorists. A further discussion on types of advance warning signs is presented in chapter 4.

Figure 1. Photo. VMS and Static Warning Signs.

Truck-Related Warning Signs

Large Trucks (10,000 lb. gross weight or greater) are a major safety problem on the Nation's highways. (Stein and Jones, 1988). Truck-related crashes constitute about 6 percent of police reported crashes but account for 12 percent of all fatal crashes. Trucks are overrepresented in severe crashes, but on a per-mile basis, trucks appear to have fewer crashes than cars because they travel predominantly on interstate highways, which are low-risk roads. (Stein and Jones, 1988).

Due to their hazardous nature, especially for entering trucks, special advance warning signs are installed in advance of downgrades where physical features of the grade such as percent grade, horizontal curvature and other physical characteristics require special precautions. FHWA

Figure 2 shows some downgrade warning signs. The MUTCD also advises that special advance warning signs should be placed in advance of hazardous grades where it is necessary to caution truck drivers to downshift or brake. Signs for truck escape ramps are also to be provided in advance of sections where the facility exists. The MUTCD further recommends supplemental plaques (W7-2 series) to emphasize special roadway characteristics. Mileage plaques (W7-3a or W7-3b) should be used at intervals of one mile to provide additional information to operators of large trucks. (HDR Engineering, 2003). W7-4 and W7-4a signs are provided in advance of truck escape ramps. Additional information signs are helpful for truck pullout areas, at the summit of grades.

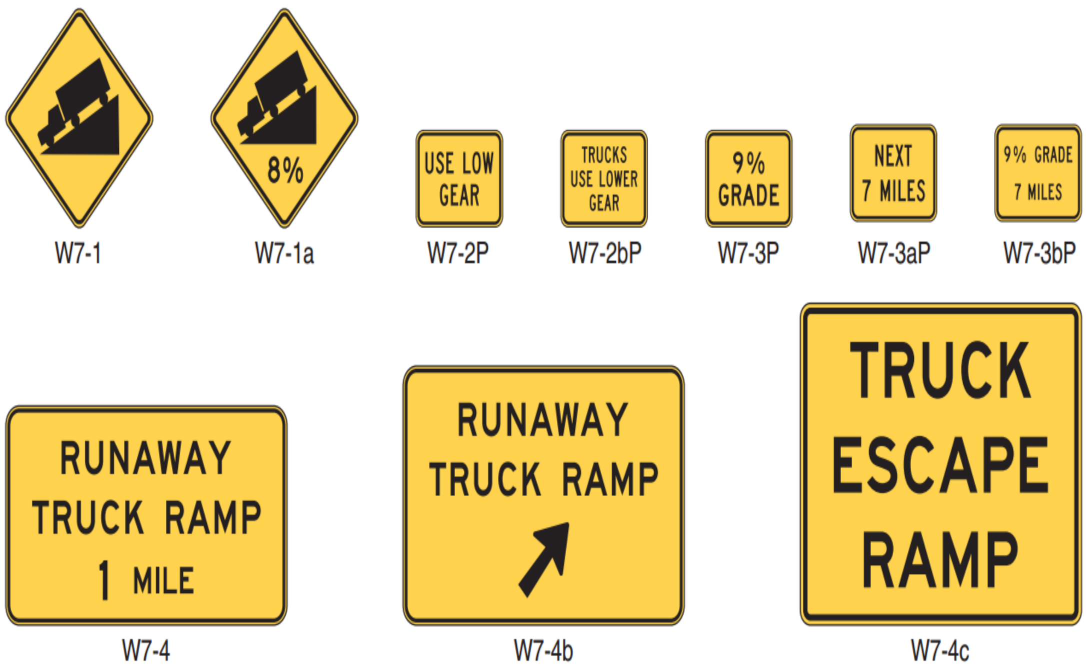

Figure 2. Picture. MUTCD Downgrade Warning Signs. (FHWA, 2009).

Most highway agencies install other advisory signs outside the scope of the MUTCD. These may include truck advisory speed signs, route layout among others. Truck advisory speed signs have been found to be effective in reducing not only downgrade crashes but rollover incidents as well. Research from the Texas Transportation Institute in 1994 revealed that excessive speed is a significant factor in single vehicle large truck crashes. (Middleton, 1994). On the connector of I-610/US-59, five out of seven truck crashes within a period of 8.5 years were reported to have been caused by excessive speed which resulted in rollovers. The investigation prompted the installation of speed reduction signs and since the installation no accident have been reported since. (Middleton, 1994). Statements of Texas truck drivers about advisory speeds suggest that warning speeds are established mainly for automobiles. For safety, trucks should travel even slower than the posted speed limits. An interview conducted with truck drivers in Maryland and Virginia, suggested truck drivers preferred warning signs such as a tipping truck silhouette, and curve arrow and advisory speeds. (Middleton, 1994). The testing also supported the combinations of the symbolic warning signs with separate speed plates underneath as well as the use of advance warning signs in combination with flashing lights. Figure 3 shows some truck warning signs on US-14 in Wyoming.

Figure 3. Photo. Example of Truck Speed Advisory Signs.

Several Departments of Transportation (DOTs) in the United States have recently installed downgrade maps on mountain routes which are hazardous for trucks. The maps indicate the general layout of the highway including curves, grades and their lengths as well as brake check areas and escape ramps. Figure 4 is a downgrade route map installed on US -14. Anecdotal evidence from WYDOT suggests these signs are effective in preventing downgrade truck crashes.

Figure 4. Photo. Route Layout Sign.

Research conducted by Hanscom, (1985), supported by empirical evidence provides the greatest evidence that static signing placed before severe downgrades are effective. (Hanscom, 1985). Well-placed signs, which afford truck drivers an opportunity to make brake inspections, cool heated brakes, and choose safe descent speeds have made an impact in reducing downgrade truck crashes. (Hanscom, 1985).

GSRS Weight Specific Speed Signs

Additional warning signs have been developed from the Grade Severity Rating System (GSRS). Known as weight specific speed (WSS) signs, they were developed by the FHWA and serve to reduce downgrade truck crashes. (Johnson et al., 1982; Myers et al., 1981). WSS signs provide advisory downgrade descent speeds based on truck weights. This is an improvement over traditional signs which only provide downgrade information to drivers and leaves the choice of descent speeds to their discretion and experience. (Myers et al., 1981). Tests conducted by the FHWA determined that the WSS signs are effective in reducing downgrade truck crashes because they simplify the driving task and provide pertinent information highlighting the severity of the downgrades. (Hanscom, 1985). WSS signs are most useful on longer grades and their presence result in brake temperatures not exceeding maximum levels that bring about brake fade and truck runaways. (AASHTO, 1997). An example of a WSS sign is shown in © 1981 FHWA**.**

Figure 5.

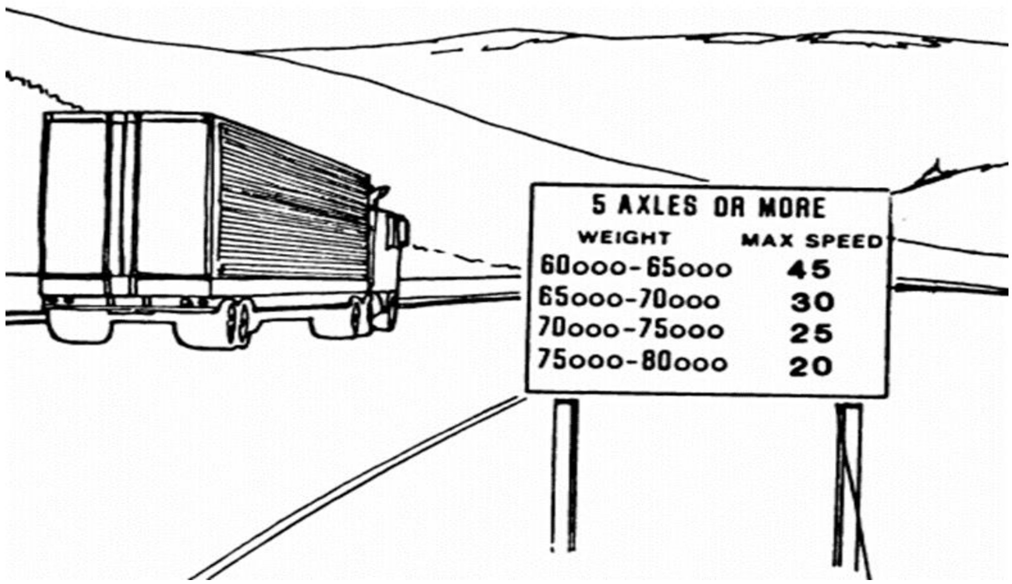

Figure 5. Picture. GSRS based WSS Sign. (Myers et al., 1981).

The GSRS incorporated as part of the VMS has been in use with the Downhill Truck Speed Warning System in the westbound lane of the Eisenhower Tunnel of Colorado. This system has proven to be effective in reducing the occurrence and severity of downgrade truck crashes. (Janson, 2001). A statistical analysis of the system indicated that the speed warning system significantly reduces truck descent speeds for most weight ranges. A similar downhill truck warning system was installed on the I-84 at Emigrant Hill in Oregon. The new system started operations in 2002 and integrates VMS with high speed weigh in motion scales in the roadway and automatic identification devices that recognize in-truck transponder signals. (Robinson, M; McGowen, P; Habets, A; Strong, 2002).

Frequency of Warning Signs

The MUTCD cautions that warning sign use should be kept to a minimum so as not to breed disrespect for all signs. Drivers will pay little attention to warning signs used too frequently, rendering the driving environment unsafe. This idea that the frequent installation of warnings signs can decrease its effectiveness is reiterated by a study conducted by the University of Kansas on the assessing the safety effectiveness of deer warning signs. (Meyer, 2006).

Figure 6 shows an example of an inordinate amount of warning signs before an intersection.

Figure 6. Photo. Misuse of Warning Signs. (Smith, 2011).

Effectiveness of Warning signs

Highway agencies expend significant resources on the installation, upgrading and maintenance of traffic control devices, such as warning signs. To ascertain that those resources are well invested, it is important to know whether traffic control devices serve their intended purpose. The answer may be easy for some devices such as traffic signals, regulatory and guide signs, but more difficult for other devices such as warning signs in general and those intended for occasional hazards in particular. (Al-Kaisy et al., 2008).

Knowing the effectiveness of warning signs, for the purpose of improving safety, is important for highway agencies to assess the feasibility of using conventional signs, or whether alternative warning devices or methods are required for safer highway environments. (Al-Kaisy et al., 2008). Drivers notice few traffic signs because unfamiliar objects attract drivers' attention in relation to familiar signs. (Charlton and Baas, 2006). Therefore, warning signs can be coupled with atypical devices to increase attention such as flags attached to the sign. This alerts drivers in an uncharacteristic manner and forces them slow down or alter their driving behavior. The MUTCD also as an option, mentions that any warning sign can be equipped with a warning beacon. The guidelines for warning sign designs are (Wogalter et al., 2002):

- Salient
- Wording
- Layout and placement
- Pictorial symbols
- Auditory warning.

In other words, the warning should be salient as possible; meaning they should be standing out, prominent and conspicuous to capture the attention of individuals who might be distracted or focused on other tasks. Pictorial symbols in warning signs increase their salience and likelihood of being noticed. The presence of pictorials has also been shown to enhance the memory of a warning.

Effectiveness of Advance Warning Signs

Some of the earliest studies conducted on the effectiveness of warning signs were undertaken in Britain in the 1960s, shortly after the conversion to symbolic signs. These studies were done to estimate how well road signs were understood by drivers. (Mackie, 1966). The studies revealed that comprehension of warning sign messages varied across sign types and motorist ages. However, these studies were largely inaccurate but prompted numerous subsequent investigations.

Another approach to determining the effectiveness of hazard road signs was to assess the driver's ability to recall and recognize the road signs after they had recently been installed. (Johansson and Backlund, 1970; Johansson and Rumar, 1966). The drivers were stopped at roadblocks and questioned about the content of the warning signs. This approach was dubbed the roadblock paradigm and indicated very poor memory of road signs. Earliest studies of recognition and recall results found on average only 50 percent of signs could be recalled. Later studies found even lower results ranging from 2 to 20 percent for single signs and up to 34 percent for serially repeated signs. (Johansson and Rumar, 1966).

In the 1980s, researchers examined how reflectivity, size and placement of warning signs affected the ability to attract a driver's attention. Again, drivers were asked verbally what attracted their attention and found that conspicuity of traffic signs were quite low, only around 10 percent of the traffic signs that were present were reported. These studies made the distinction between search conspicuity and attentional conspicuity and found that visual clutter affected attentional conspicuity more than search conspicuity. Sign formats designed to increase the conspicuity of hazard warnings (larger size, higher contrast or reflectivity) have been put into service, but relatively few studies of their effectiveness have been conducted. (Drory and Shinar, 1982; Hughes and Cole, 1984).

Despite many of the low recognition and recall levels, it was found that consciously noticing, processing the meaning of, and recalling a sign may not be necessary for a hazard warning to be effective. (Fisher, 1992). In his observational study of drivers' reactions to warning signs, Fisher, 1992 noted that recall of a sign was not a reliable indication of whether a driver had reduced their speed, and more importantly, that many drivers who reduced their speed after passing a warning sign were unable to recall having seen the sign 100 meters earlier. (Fisher, 1992).

A priming paradigm has been used by some researchers to investigate the implicit processing of road sign information. With warning signs, drivers are said to be primed to decrease their speed if multiple prior warning signs are apparent (whether or not the driver even recalls having seen the sign). Experienced drivers were found to react positively toward repetitive priming and weaker semantic priming whereas inexperienced drivers experienced little effect. This shows that not only do road signs have an automatic priming function, but that this process is developed with increased experience in the relevant context. (Crundall and Underwood, 2001).

A wide range of methods have been used to assess the effectiveness of warning signs, but few studies have employed multiple measures or have directly compared them. (Martens, 2000). An assessment of a range of hazard warning signs currently in use with regards to their conspicuity, memorability, comprehensibility, how well they prepare drivers to take actions appropriate to the hazards (semantic priming) and to compare the consistency and sensitivity of the measures themselves was conducted in 2006. (Charlton, 2006). The study found that there is no consensus on any single measure to assess the effectiveness of hazard warning signs.

Equally interesting is that there has been no safety effectiveness evaluation for most advance warning signs. Bowman, 1993, indicated that the majority of advance warning signs in use by most highway agencies have not been formally evaluated for their safety effectiveness but are only assumed to be effective. (Bowman, 1993). A study by Veneziano and Knapp, 2016, suggested that the impact of only a few commonly used static warning signs have been studied and documented by any state-of-the-practice approach with robust results. The study rated most previous research on the safety effectiveness of warning signs as having low or medium reliability. (Veneziano and Knapp, 2016). Al-Kaisy conducted a study on the efficacy of static warning signs for occasional hazards by conducting a survey by questionnaires, which were sent to the 50 DOTs and 2 Canadian provinces. (Al-Kaisy et al., 2008). The results from 28 DOTs who responded to the survey, indicated that most states are not assured about the effectiveness of static warning signs for occasional hazards.

Variable message signs (VMS) or dynamic message signs (DMS) have been found to be more effective than traditional static signage in reducing the number of speeding vehicles. (Garber and Srinivasan, 1998). VMS have been found to attract the attention of drivers due to their ability to display flashing or animated symbols, as well as their capacity to show time-specific or event-specific information. (Garber and Srinivasan, 1998). VMS is often combined with a speed measuring device in order to display to drivers their instantaneous speeds and to show messages if they are exceeding the posted limit. (Debnath et al., 2012). A study conducted by Fontaine et al., 2000, suggests VMS, used in conjunction with a speed measuring device may reduce speed by up to 10 mph and lower the percentage of speeding vehicles, whereas using VMS alone decreased speed by 2 mph. (Fontaine et al., 2000).

Static warning signs, on the other hand have been deemed less effective in comparison to VMS. Static warning signs may be coupled with conspicuous devices and materials to improve their visibility. (Debnath et al., 2012). However, static warning signs are the most common types of warning signs installed by most highway agencies. This may be due to their relatively low cost of installation and maintenance.

SAFETY EFFECTIVENESS EVALUATION

The Highway Safety Manual (HSM) describes three fundamental study designs that are used in safety effectiveness evaluations. These are (AASHTO, 2010):

- Experimental before-after studies
- Observational cross-sectional studies
- Observational before-after studies.

Experimental Before-After Studies

Experimental before-after studies revolve around randomly selected sites that will be used for treatment. In experiments, the researcher can intentionally design experiments to control variables. In contrast, for observational studies, the variables of interest cannot be entirely controlled by the researcher. Hence, road safety studies generally fall into the observational type because researchers do not have the luxury of controlling conditions to count accidents. (Transportation Safety Council, 2009). The distinction with observational studies comes from the selection of treatment sites based typically on safety concern reasons. In highway safety, observational studies are more common than experimental studies. (Gross et al., 2016) This is because agencies prefer to use and allocate funds to selected sites for treatment based on crash frequencies or risks.

The foundation for any data-driven decision-making is high-quality data and reliable analytical methods. (Gross et al., 2016). It is important to know that safety of an entity can only be estimated, since what is "expected" cannot be known and estimation is in degrees of precision. The precision of estimates is usually expressed by its standard deviation. Each of the methods described in the following sections have their strengths and weaknesses. It is important to select and use the most appropriate method depending on the circumstance.

Observational Methods

Observational studies can be classified into two distinct groups: before-after studies and cross-sectional studies. A before-after study is generally used to study the safety implications of a countermeasure or operational change. In before-after studies many of the site characteristics remain unchanged, such as an installation of a traffic signal at an intersection. Most of the road geometry will also remain unchanged. (Transportation Safety Council, 2009).

Cross-Sectional Methods

Cross-sectional studies estimate safety effectiveness by using statistical modeling techniques that consider the crashes of sites with and without a particular treatment of interest. (AASHTO, 2010). The difference in number of crashes is attributed to the presence of a discrete feature or different levels of a continuous variable. The use of cross-sectional studies is useful when treatment installation dates are not available, more than one countermeasure is applied to an entity, crash and traffic volume data for the before period are not available and when the data exhibits under, or over-dispersion. Cross-sectional analysis typically uses regression methods that estimate crash frequencies from a large sample of roadway entities in which their characteristics vary systematically. The accuracy of the model is determined by how closely the model expresses the relationship between crash frequencies and its predictor variables. Cross-sectional studies include principal roadway characteristics such as number of lanes, lane width, and shoulder width. Some applications also incorporate traffic volume and composition as covariates. The cross-sectional methods are good analytic tools for sensitivity analysis and evaluations of highway improvement policies. However, these studies do not take into account the effects of the parameters that are not included in the model such as driver population and local conditions. (Gan et al., 2005).

Cross-sectional analysis is accomplished in two steps:

- Selection of a suitable functional form and model type for estimating the relationship between the roadway characteristics and crash frequency
- Developing crash reduction factors (CRFs) for the countermeasures.

For the first step, there are many regression models to choose from. In the traffic safety literature, the most prominent models are the Poisson, zero-inflated Poisson, Negative Binomial and Zero-inflated Negative Binomial models. (Gan et al., 2005).

The second step involves the development of CRFs for the countermeasures that account for a change in a roadway entity such as an implemented treatment. CRFs are determined by calculating the difference in crash predictions within the before-after periods and then dividing by the predicted crashes in the before conditions.

Some advantages of cross-sectional methods are that they can be easily implemented for data that is readily available from state DOTs in addition to reflecting state-specific circumstances. This method can also be undertaken for a fraction of the cost of comparable before-after studies. Although many researchers have used cross sectional methods, the downside of these methods is that they tend to be less reliable than before-after methods. These methods also tend to underestimate the improved safety effectiveness of implemented countermeasures. In addition, cross sectional methods require an extensive amount of data to reach valid conclusions, and rarely are the site characteristics identical in all features except for the ones of interest. (Hawkins, Kuo, & Lord, 2012). These drawbacks may explain why cross-sectional methods have not been widely used.

Also, cross-sectional analyses require that the two entities be characteristically similar except for the feature in question. In practice, this method is difficult to carry out and accomplish. Therefore, cross-sectional methods are typically coupled with multiple variable regression models. Cross-sectional regression models are also called safety performance functions (SPFs), or crash prediction models (CPMs). SPFs and CPMs are essentially mathematical equations that are used to relate the frequency of crashes to roadway characteristics. The coefficients of the variables that are found in these equations are used to estimate the CMFs for various treatments. Estimates of CMFs that have been derived from cross-sectional studies have been criticized for the potential of confounding. Statistical confounding occurs when the independent variables are correlated with both the dependent variable (crash frequency) and the other independent variables in the model.

Observational Before-After Studies

Observational before-after studies are used to evaluate the performance of a safety improvement plan or an operational change to a transportation facility. This is accomplished by the development of CMFs comparing the frequency as well as the severity of crashes before and after the implementation of treatments. The key to before-after studies is to account for the location selection bias as well as changes in time such as changes in traffic and other trends. (Gross et al., 2016).

There are four common observational methods, the advantages and shortcomings of each method will be discussed below:

- Naïve before-after study
- Before-after study with traffic volume correction
- Before-after study with comparison group
- Empirical-Bayes (EB) before-after study
- Before-after study with yoked comparison

It is generally understood by safety research analysts that properly designed before-after studies provide more reliable results than cross-sectional studies for safety evaluation. When considering the methods within observational before-after studies, the EB before-after study is more reliable than the comparison group method. Also, the comparison group method is considered more reliable than the simple before-after method. Reliable safety evaluation methods are those that account for biases that arise due to regression to the mean (RTM), which is described as the fluctuation of successive local high and low crash frequencies.

Figure 7 describes and compares the ability of each method to account for potential biases. The naive before-after methods do not account for the potential biases that occur due to RTM, changes in traffic volume and other general temporal effects. Because of this, they may overestimate or underestimate the safety effects of a treatment.

Figure 7 shows the common sources of bias in before-after studies.

Method	RTM	Changes in Traffic Volume	Nonlinear Relationship	Temporal Trends
Simple Before-After				
Before-After with Linear Traffic Volume Correction		•		
Before-After with Non-Linear Traffic Volume Correction		•	•	
Before-After with Comparison Group		•		•
Empirical Bayes Before-After	•	•	•	•

Figure 7. Diagram. Sources of Bias within Before-After Methods. (Gross et al., 2016).

Regression to the Mean (RTM) Bias

It is a priority of transportation agencies to minimize accident counts, and so when selecting sites for treatment, the selection often revolves around locations with high crash counts based on crash history. This selection procedure is risky due to the potential effects of RTM bias. RTM is described as the situation of periods of subsequent local high and low crash frequencies as shown in

Figure 8 below. This is important to consider because locations that have a high short-term average crash frequency may have a lower crash frequency in subsequent years due to RTM bias, even if those sites are not treated. (AASHTO, 2010). Also, if only a few years of crash data are available, an estimated long term crash estimate obtained by averaging the observed crash rates over a few years, can be easily influenced by a single year with an unusually high or low number of crashes. (Carriquiry and Pawlovich, 2004). This can lead to overestimates or underestimates of safety effectiveness evaluations of treatment effects.

Naïve Before-and-After Study

The naïve (simple) before-after method is frequently used in safety evaluations and is essentially a direct comparison of crash frequency before and after implementation of a countermeasure. It is the simplest technique for an observational study. Accident counts in the period before are used to estimate and predict the expected accident rates and frequency had the safety treatment not been implemented. The change of accident counts between the before and after conditions is considered as the treatment effect. (Transportation Safety Council, 2009). It should be noted that simple before-after techniques do not account for possible bias caused by RTM as well as temporal effects, or trends, due to changes in traffic volume, driver behavior and crash reporting. (Gross et al., 2016). Because of this, simple before-after methods tend to overestimate the safety benefit, which could result in erroneous conclusions at specific locations and at aggregate levels. (Al-masaeid, 1997).

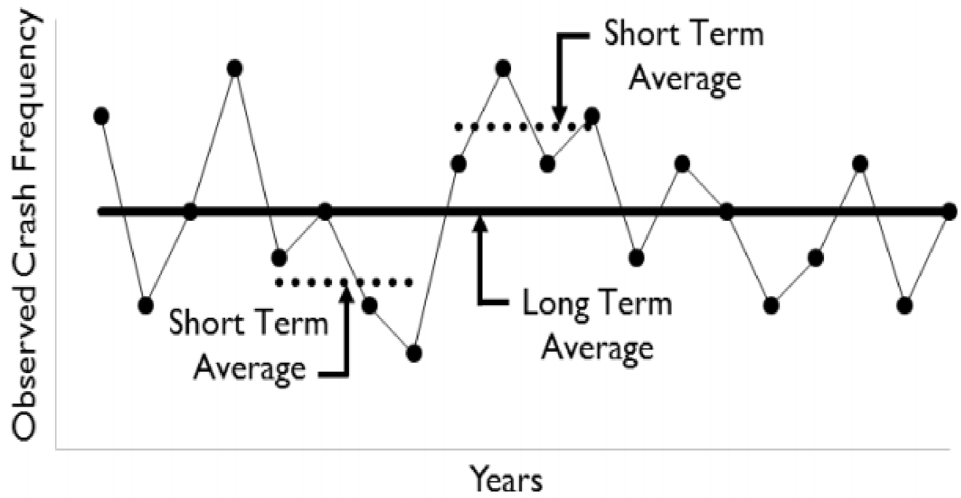

Figure 8. Diagram. Regression-to-the-mean bias Illustration. (Gross et al., 2016).

In a simple before-after study, the accident reduction factor (ARF) is used to measure safety effectiveness (Figure 9). Effectiveness is determined by X_a and X_b, which denote the observed number of accidents in a period before and after improvements respectively. The significance of an ARF at the location level assumes that the number of accidents can be fit with the Poisson distribution. (Al-masaeid, 1997).

$$ARF = \left(\frac{X_b - X_a}{X_b}\right) * 100$$

Figure 9. Equation. Calculation of Accident Reduction Factor.

Before-After with Traffic Volume Correction

The before-after study with traffic volume correction is a modified version of the simple before-after study. It accounts for changes in traffic volume over time. Comparing crash rates helps account for changes in traffic volume as opposed to crash counts.

The traffic volume correction may be based upon a linear or nonlinear trend. When using crash rates, it is implicitly assumed that the relationship between crash frequency and volume is linear. There are studies, however, that show this relationship can be nonlinear. (Gross et al., 2016). In addition, using crash rates does not account for the annual variation in traffic volume within the before and after periods. Corrections of nonlinear traffic volume using SPFs are more accurate than linear traffic volume correction methods such as crash rates. This method does not account for possible bias due to RTM, and does not also account for temporal effects or trends such as changes in driver behavior. (Transportation Safety Council, 2009).

Figure 10 below shows the nonlinear trend of crash frequency versus traffic volume.

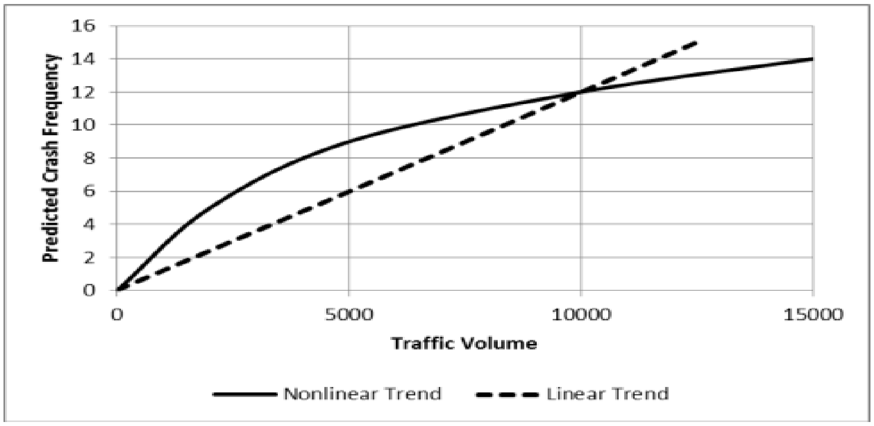

Figure 10. Diagram. Relationship between Crash Frequency and Traffic Volume. (Transportation Safety Council, 2009).

Before-After with Yoked Comparison

The before-after with yoked comparison needs treated and untreated sites to carry out the comparison. The technique requires a group of similar entities to be selected so that a one-to-one correspondence between each member of the treated and untreated entities exists. This method requires the treated site to have similar characteristics to the comparison group. The area type (commercial, urban, rural), intersection type (three or four legged), traffic control (signalized, two-way stop), geometric design, and traffic volume should be similar between the treated group and comparison group in order to carry out this method. (Transportation Safety Council, 2009).

Figure 11 shows a graphical illustration of the yoked comparisons between the treated and comparison group.

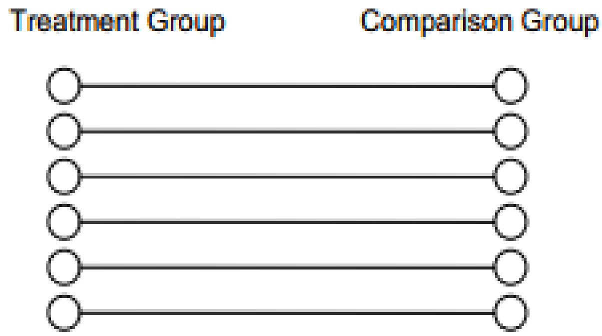

Figure 11. Diagram. Before-After with Yoked Comparison. (Transportation Safety Council, 2009).

By making a one-to-one comparison, it is hoped that the unknown factors that affect the comparison group should affect the treated group in the same manner. In this way, the change in the number of accidents between the before-after groups, had the treatment not happened, should have the same proportions as the corresponding comparison site. To predict the expected number of accidents in the period after the treated site without the improvement, simply multiply the accident frequency at each treatment site in the before-period by the ratio of the after-to-before accidents at the comparison site. (Transportation Safety Council, 2009).

This approach is considerably better than the naïve before-after method. However, the yoked comparison still suffers from three issues. First, the comparison is only made between one comparison site, so it is possible to come to different results and conclusions when different sites are used. These problems make findings of the evaluation variable and with wide limits. Second, this method does not account for RTM bias, making the distinction difficult between lower accident frequency caused by the treatment or the intrinsic randomness of accidents. Finally, this method cannot be used when the comparison site does not have a history of accidents. (Transportation Safety Council, 2009).

Before-After with Comparison Group

This method is also known as the "before-after with control group" (© 2009 ITE.

Figure 12). The rationale for this method is the same as the yoked comparison. However, there is no need for the one-to-one matching between the comparison and treatment group. The philosophy is, the larger the comparison group, the better the assessment. (Transportation Safety Council, 2009). It incorporates information from an untreated group of entities to compensate for temporal effects and changes in average daily traffic (ADT). The before-after method with comparison yields accurate results given that information on the comparison locations have similar characteristics to the locations that have been improved. (Al-masaeid, 1997). In the study by Al-masaeid (1997), the similar characteristics were in terms of physical characteristics and traffic flow, and the unimproved state was identified as the comparison group. (Al-masaeid, 1997).

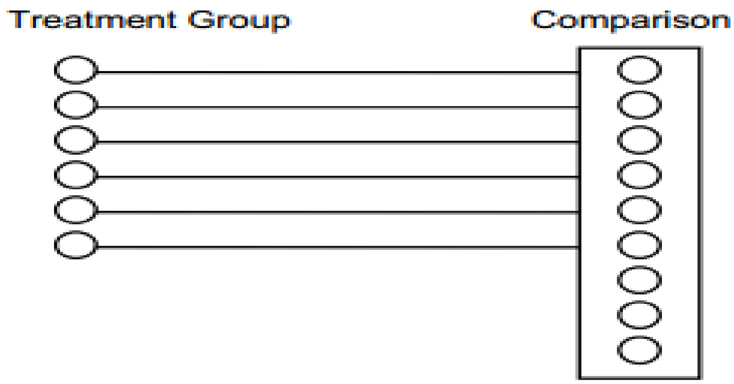

Figure 12. Diagram. Before-After with Comparison Group. (Transportation Safety Council, 2009).

There are several ways to use this method. One is to calculate comparison ratio, which is the ratio of the observed crashes in the before-after period. After the treatment has been completed, the frequency before is multiplied by the comparison ratio to determine the crash frequency as if the treatment had not been done. This estimates the crash frequency of the entities as if the treatment had not occurred, which can be compared with observed crash frequency of the site after treatment. (Gross et al., 2016).

For this approach to work, there needs to be an assumption made that the crash counts in both the treatment and comparison groups are similar. It is common for analysts to use comparison entities in the same jurisdiction with the treatment site to increase the likelihood that the comparison and treatment entities have similar trends.

The other possible approach is to develop SPFs from the data of the comparison group. This approach also estimates a comparison ratio but uses the SPFs. By using SPFs, changes in traffic volume, as well as the nonlinear relationship between traffic volume and crashes within the before-after periods, can be accounted for. However, the comparison group approach does not account for RTM. Therefore, this method can be used if treatment sites are not selected based on crash history, which reduces the concern of possible bias due to RTM.

Empirical Bayes Before-After Studies

The Empirical Bayes (EB) methodology has been applied for over 20 years in the field of transportation safety engineering and studies. The validity of this methodology is widely accepted. However, there are many skeptics who suggest that the complexity of data needed for the EB methodology is not worth the effort since there are less complex methods that can produce equally valid results. (Persaud and Lyon, 2007).

The method was proposed by Hauer in 1986 to overcome the problems associated with naïve-

before-after studies and before-after studies with comparison group. (Hauer, 1986). In the EB

method (© 2009 ITE.

Figure 13), crash counts from the entity of interest along with the safety performance of other similar entities are used to determine the safety performance of the entity. The expected number of crashes at the treatment site in the after-period, as if the treatment had not been applied, is calculated from the observed number of crashes at the treatment site during the before-period and the expected number of crashes at similar sites. (Sasidharan, 2011).

In practice, there is a natural tendency to select entities with a high accident frequency for treatment. However, if the accident frequency was based on short-term high prevalence of accidents, a low accident rate would be expected in the period after, even if no improvements were made. (Transportation Safety Council, 2009). The EB method is used frequently in safety estimation because it addresses the bias caused by RTM, as well as accounts for changes in traffic volume and accounts for temporal effects. The theory of the EB method is to estimate the expected number of crashes had the treatment not been performed and compare that to the number of observed crashes after treatment. (Gross et al., 2016).

The EB method heavily depends on safety performance functions (SPFs) and thus an incorrectly specified SPF can adversely affect the precision of the results. Additionally, the EB method cannot account for site selection bias in the analysis. Even though the EB method is widely used by traffic safety analysts, it is unclear how neglecting considerations of the site selection mechanism affects the results of safety effect estimates. (Sasidharan, 2011).

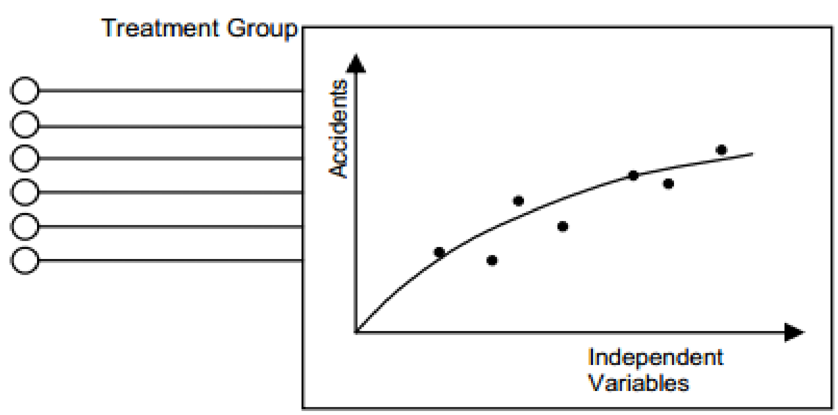

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Figure 13. Diagram. Before-After with Empirical Bayesian Method. (Transportation Safety Council, 2009).

EPIDEMIOLOGICAL STUDIES

Epidemiological case-control studies have recently gained popularity in traffic safety research. (Gross & Jovanis, 2007; Majdzadeh et al., 2008). These studies are used to isolate the treatment effect of a countermeasure from the effect of other potential confounding variables. Epidemiological studies measure statistical association rather than causal relationships. The epidemiological definition of a case-control study in the context of traffic safety can be defined as the comparison of entities that experience crash "cases" with a group of entities that did not experience a crash "control" during the same period. (Sasidharan, 2011).

One major limitation of the matched case-control studies is that the results are mainly binary outcomes of occurrence or non-occurrence. It is still unclear whether the method can be modified to consider multiple crash events when estimating CMFs. (Gross and Donnell, 2011). While it is true that case-control studies can produce an unbiased treatment effect estimates by matching cases and controls or all potential confounding variables, matching can become difficult when the number of confounders is large. Another major disadvantage of case control studies is its inability to determine the causal effect of a treatment. (Sasidharan, 2011).

Propensity Scores Matching Approach

Propensity scores matching is a type of causal inference method used to determine the effect of treatment based on observational, non-randomized data. (Sasidharan and Donnell, 2014). These models are common in medical, economic, political and educational research. (Gelman, A., Meng, 2004). Propensity score modeling considers the probability of an entity receiving treatment given covariates (X) and outcomes (Y). When the treatment is uncounfounded, the propensity score, P is as expressed in Figure 14 (Sasidharan, 2011):

$$P = ((T = 1|X)$$

Figure 14. Equation. Definition of Propensity Score.

Where, *T* is the treatment status (T=1, site treated with countermeasure and T=0, site untreated, no countermeasure); X is the covariate influencing treatment selection.

Randomized experiments, where entities are assigned randomly to treatments and controls, is the best way to estimate treatment effects. In this method, all entities are assumed to have an equal probability of receiving the countermeasure. Furthermore, random assignment ensures that the treated and untreated groups with respect to probability were the same before the treatment and assumes that any difference in the outcomes is due to treatment effect. (Sasidharan and Donnell, 2014). It has been suggested that no differences exist in the estimated treatment effect between randomized control experiments and studies using propensity score matching. (Hallmark et al., 2015). An added strength of the propensity score technique is that the estimated treatment effect is doubly robust. This means that the bias in the estimated treatment effect will disappear, if either of the two models (propensity score or safety estimate) is wrong due to the use of the dual modeling approach. (Elliot and Little, 2000; Schafer and Kang, 2008).

It has been suggested that the risk ratio is a good measure to report the safety effectiveness of a treatment. (Karwa et al., 2011). The risk ratio (RR) or relative risk, is the ratio of the probability of occurrence of target crashes at an untreated entity to the probability of a crash at a treated entity. An unbiased estimate of RR can be determined from observational data as long as it follows the following three assumptions. (Rubin, 1978;Rubin, 1990):

- *Stable unit treatment value assumptions (SUTVA):*
  The SUTVA states that when a treatment is applied to an entity, it does not affect the outcome of any other entity
- *Positivity:*
  This assumption implies that there can be a non-zero probability of receiving every level of treatment for any value combination of exposure and covariates.
- *Unconfoundedness:*

This states that the treatment assignment is unconfounded if the treatment status is unconditionally independent of the potential outcomes. (Sasidharan and Donnell, 2014).

CHAPTER SUMMARY

The methods of this research necessitate a well-grounded understanding of downgrade signs and the statistical methods to evaluate the safety effectiveness of warning signs in preventing downgrade truck crashes. Hence, the selection of an appropriate statistical method is required for the study. The chapter was essentially split into two sections. The first describes the types and use of downgrade warning signs. The second section discusses in depth the many approaches to safety effectiveness research, the advantages, disadvantages, and appropriate use of the methods, as well as the requirements. Based on the findings of the literature and initial analysis of the data collection process, the most appropriate methods were selected for this research and are described in the following chapters.

CHAPTER 3: METHODOLOGY

This chapter presents the methodology that was followed to achieve the objectives of the study. This study used data collected from WYDOT databases, the Critical Analysis Reporting Environment (CARE) package, and a field assessment of warning signs installed on identified hazardous downgrades. Supplementary data from the video logs were also used to ensure data accuracy. Each step is described in detail in the next subsections. Figure 15 is a flowchart of the methodology adopted for the entire study of updating and implementing the GSRS for Wyoming mountain passes. Only the left side of the flowchart is applicable to this report.

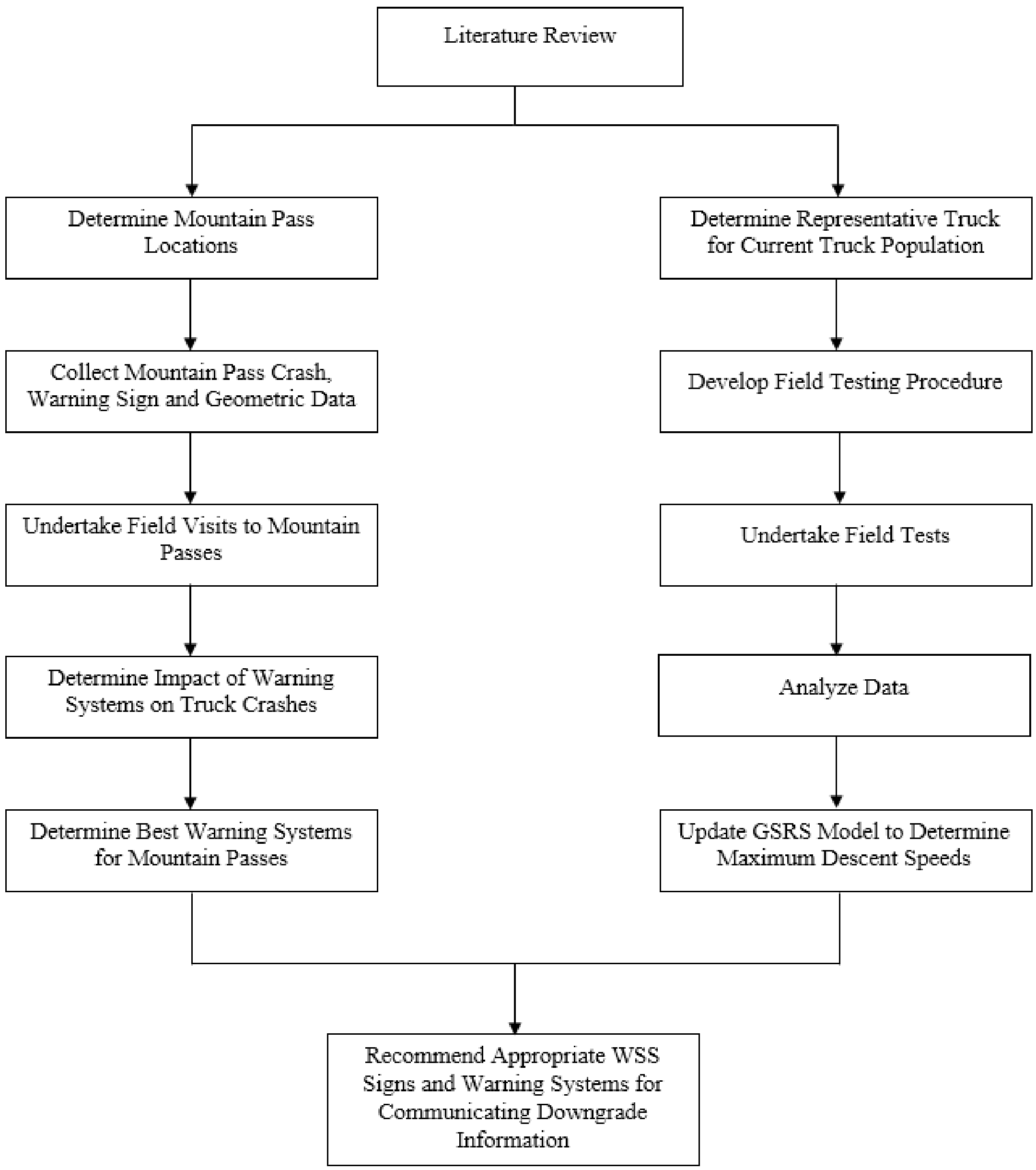


Figure 15. Flowchart. Study Methodology.

Mountain pass locations were identified according to criteria from the MUTCD. The minimum requirement for the downgrades to be considered in the study was for them to have at least a 5 percent downgrade of 3,000 feet in length. Mountain pass data warning systems data were then collected both on field and using the pathway video logs. The warning sign data was merged with a crash database compiled from the critical analysis reporting environment (CARE) package and geometric data from WYDOT.

The impact of the warning systems on truck crashes was evaluated using statistical analyses. This was accomplished using propensity score matching to assess the effectiveness of warning signs. Individual warning sign types were then evaluated using the negative binomial (NB) model. A ranking of sites was done using the expected average crash frequency with Empirical Bayes (EB) adjustments in terms of their safety evaluations. Another evaluation undertaken was a hotspot analysis. It was done to correlate warning sign placement with locations of high truck crashes. Finally, current and potential use of intelligent transportation (ITS) was reviewed. Recommendations for safety improvement and the use of warning signs for communicating downgrade information to drivers were made.

PROPENSITY SCORES POTENTIAL FRAMEWORK

Propensity scores-potential estimates the probability of a truck crash occurrence on mountain passes with and without the presence of advanced warning signs. Defined simply, the propensity score is a conditional probability of selecting an entity for treatment given observed covariates. Propensity scores are used to match treated and untreated entities. Logistic regression or probit models are mostly used to estimate propensity scores. The two model types are preferred over the linear model which may produce probabilities outside the 0,1 bounds. (Li et al., 2013). Other studies have estimated propensity scores using probit models, classification trees, and neural networks. (Breiman et al., 1984; King et al., 2007; Liu, 2005; Luellen et al., 2005). Propensity scores were estimated for this study using the logistic regression model where the presence of an advance warning sign is the response variable. The independent variables are covariates influencing the installation of warning signs such as downgrade length, grade percent, ADTT, etc. The use of the propensity scores framework to assess the safety effectiveness of advance downgrade warning signs, in Wyoming was achieved by:

- Mimicking randomization using propensity scores in identifying comparable treated and untreated downgrade segments,
- Estimating the treatment effect using logistic regression and RR estimated as the ratio of the probability of a target crash occurring on an untreated segment to a treated segment from the segments identified in the first step.

The flowchart for the propensity score procedure is shown in Figure 16.

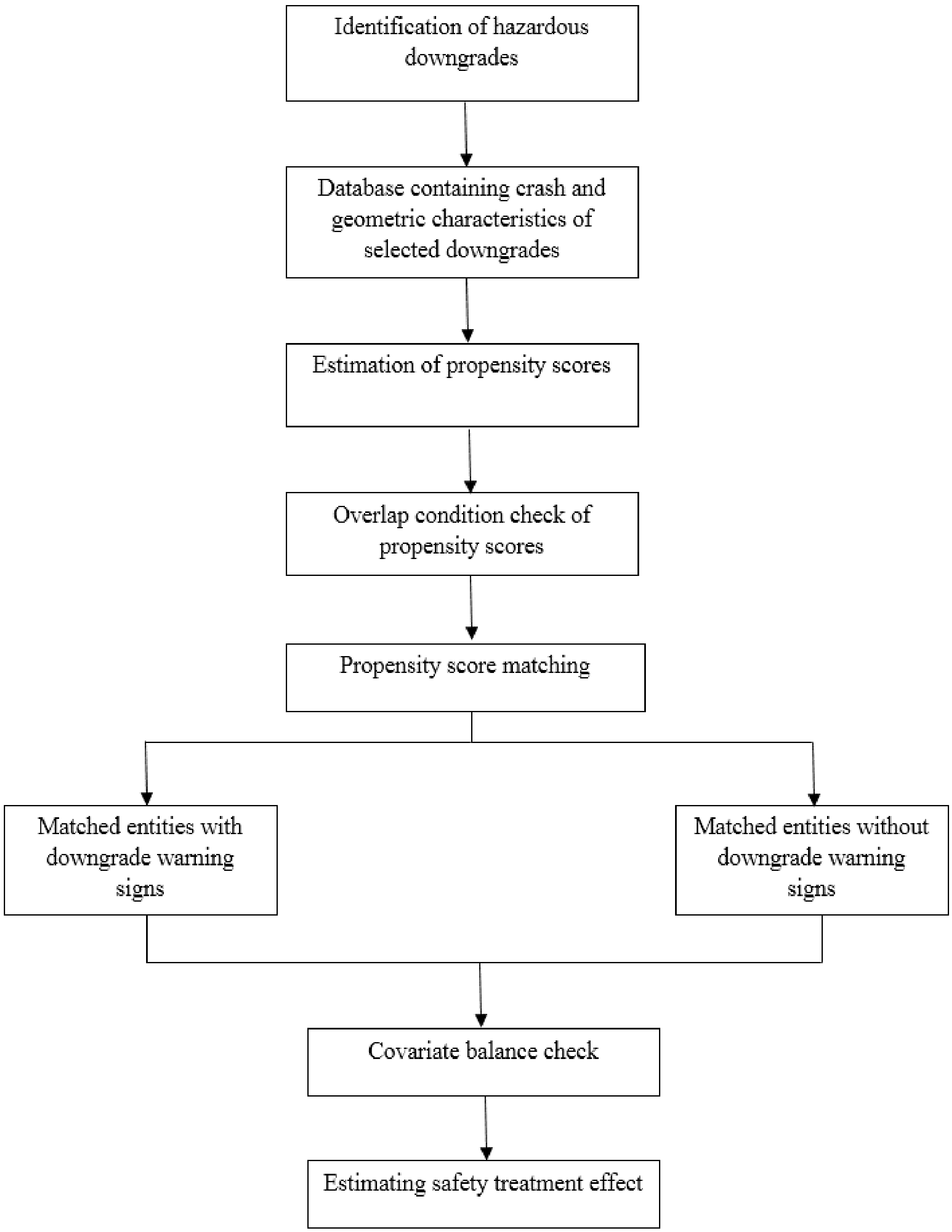


Figure 16. Flowchart. Propensity Score Methodology.

Propensity Score Estimation

Propensity scores were estimated using a binary logistic regression. The presence of a warning sign at a distance of at least 0.5 miles before the downgrade was considered the response variable. The presence of a warning sign was assigned a value of 1, while 0 indicated the absence of an advance downgrade sign. The response variable was regressed against several independent variables thought to influence the placement of downgrade warning signs.

Once the propensity scores are estimated, homogenous groups of treated and untreated groups can be identified and the average causal effect or average treatment effect (ATE) determined using methods such as matching, sub-classification or stratification, inverse propensity weighting, or regression estimation with propensity related covariates. (Sasidharan, 2011).

Overlap Analysis

Before matching is done using the propensity scores, the overlap of propensity scores should be checked between the treated and untreated groups. Checking the overlap is used to assess the distributional similarity between the score distributions. (Olmos and Govindasamy, 2015). A complete overlap in terms of range and density implies the treatment and untreated group are identical with respect to the covariate distribution, which is expected for a randomized experiment, but unlikely in observational studies. (Harder et al., 2010). When there is no overlap between the treated and untreated groups, the implication is that significant differences exist between the two groups and another technique for analyzing the treatment effect is required. Thus, matching and outcome analysis is best if there is a high degree of overlap. Overlap between treated and untreated groups are usually checked graphically using histograms, though other methods exist.

The balance check of covariates is undertaken after matching to assess the matching quality and to verify that the treatment is independent of the covariates after matching. (Li et al., 2013). A well-applied propensity score matching should result in the balance of characteristics between the treated and untreated groups. Significant differences should not exist between the covariate means of the treated and untreated groups. The balance of covariates can be checked for the matched sample using the standardized bias. (Li et al., 2013). It is as shown in Figure 17. (Sasidharan and Donnell, 2014):

$$Standardized\ bias = \frac{100\ \times (\bar{x}_T - \bar{x}_{UT})}{\sqrt{\frac{(S_T^2 + S_{UT}^2)}{2}}}$$

Figure 17. Equation. Standardized Bias.

where $\bar{x}_T$ is the sample mean of the treated group, $\bar{x}_{UT}$ is the sample mean of the untreated group, S_T^2 is the sample variance of the treated group, and S_{UT}^2 is the sample variance of the untreated group.

Propensity Score Matching Methods

The most direct and intuitive method for adjusting for overt biases is matching. Matching is done to control for confounding variables. A variable is considered a confounder if it is a risk factor for the outcome and is associated with, but not a consequence of, the risk factor in question. (Collett, 2003).

Numerous matching algorithms exist in the literature. These include nearest neighbor (NN) (with and without calipers) matching, Mahalanobis, K-nearest neighbor, optimal, radius, kernel and genetic matching. (Guo and Fraser, 2010; Olmos and Govindasamy, 2015). A 1:1 (one treated to one untreated) matching or 1:n (1 treated to *n* untreated) matching can be done with either NN or Mahalanobis matching. For similar sample sizes for treated and untreated groups, a 1:1 matching is often an appropriate choice. (Guo and Fraser, 2010). A 1:1 matching using the NN algorithm was selected for this study due to the similarity of sample sizes for the treated and untreated groups. The NN algorithm matches entities from the treated and untreated groups based on closeness in terms of Euclidean distance. (Olmos and Govindasamy, 2015). Caliper widths are used with NN matching to ensure that the differences between matched treated and untreated observations are similar. (Guo and Fraser, 2010). Common caliper widths selected for outcome analysis are 0.20 and 0.25 multiplied by the standard deviation of the propensity scores of the treated group (σ). (Sasidharan and Donnell, 2013; Wood and Donnell, 2016). Other caliper widths may be used, but larger widths are likely to maintain some selection bias in the data due to larger differences between treated and comparison groups. (Wood and Donnell, 2016). Smaller caliper widths result in close matches and minimize the differences between the treated and comparison groups, but this comes at the cost of dropping observations.

When using a matching method to determine the Average Treatment Effect (ATE), the entire sample is first divided into treated and untreated groups. Then each treated entity is compared to untreated entities which appear comparable in terms of observed covariates. The unmatched treated and untreated entities are not considered for further analysis. In the matching method, the first step is to match each treated entity to an untreated entity which appears nearly the same in terms of observed covariates. However, this is impractical when there are many covariates. Matching based on propensity scores can solve the problem of matching based on the covariates. Matching on propensity scores mimics the results of a randomized block experiment in which entities having the same propensity scores are randomly assigned to treated or untreated groups. (Schafer , Kang, 2008).

Outcome Analysis (Safety Treatment Effect)

Outcome analysis was evaluated by using the matched treated and untreated data. Separate binary logistic regression models were developed for the treated and untreated groups. A risk ratio was then computed from estimated probabilities derived from the binary logistic regression models. The probability from the logistic regression (θ) is defined as (Figure 18):

$$\theta = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 \dots \dots . \beta_n x_n)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 \dots \dots . \beta_n x_n)}$$

Figure 18. Equation. Estimated Probability from Logistic Regression Models.

where, $\beta_0, \beta_1, \beta_2, \dots, \beta_n$ are coefficient estimates by maximum likelihood; $x_1, x_2, \dots, x_n$ are the covariates, and *n* is the number of covariates. The risk ratio was estimated using the equation in Figure 19:

$$RR = \frac{E[\theta_{iUT}(1)]}{E[\theta_{iT}(1)]}$$

Figure 19. Equation. Estimation of Relative Risk.

where, RR is the risk ratio; $E[\theta_{iT}(1)]$ is the expected probability of a truck crash of the treated group; and $E[\theta_{iUT}(1)]$ is the expected probability of truck crash for the untreated control group. A value greater than 1 resulting from the above equation indicates that probability of a truck crash is higher on entities without the treatment compared to those with the treatment. This will indicate that the warning signs are effective. A sensitivity analysis was conducted by varying the caliper value to assess the effect of the caliper width on the estimated treatment effect. The caliper values considered for the sensitivity analysis were from 0.1 to 1.0 times the standard deviation (σ) of the propensity scores of the treatment group at intervals of 0.1.

NEGATIVE BINOMIAL REGRESSION MODELING

The negative binomial (NB) regression model has been commonly applied in safety effectiveness studies. (Gross et al., 2010; Strathman et al., 2001; Tarko et al., 1998). As discussed in the literature review, NB and its extensions have been used extensively for modeling crash occurrence. Two crash prediction models were developed using the NB model with truck and other vehicle crash frequencies as the dependent variables and the various roadway geometric characteristics, traffic volumes and advanced warning signs as independent variables. The NB regression model is derived from the Poisson regression model which is specified as (Figure 20). (Lord and Mannering, 2010):

$$P(y_i) = \frac{Exp(-\lambda_i)\lambda_i^{yi}}{y_i!}$$

Figure 20. Equation. Negative Binomial Regression Model.

where, $P(y_i)$ is the probability of a roadway entity *i* having y_i crashes within a time and λ_i is the population mean with over-dispersion for roadway entity *i*.

After developing the SPF, the safety effectiveness of the warning signs were estimated from the parameter estimates and by applying the concept of elasticity. (Donnell et al., 2010; Labi, 2011). Elasticity is defined as the responsiveness of one variable change to a change in another. (Washington et al., 2011). In the context of warning signs, elasticity is interpreted as the percentage change in expected crash frequency resulting from a one percent change in an explanatory variable. The elasticity of the dependent variable Y with respect to an independent variable X is given by (Figure 21):

$$e_i = \frac{\partial Y}{\partial x_i} \times \frac{x_i}{Y} = \beta_i x_i$$

Figure 21. Equation. Estimation of Elasticity for Continuous Variables.

where, e_i is the elasticity, β_i is an estimated coefficient. For indicator variables, the computed elasticity is known as pseudo-elasticity. This refers to the percent change in expected crash frequency given a change in the value of the indicator variable from zero to unity. (Donnell et al., 2010). This is defined as (Figure 22):

$$e_i = \exp(\beta_i) - 1$$

Figure 22. Equation. Estimation of Elasticity for Category Variables.

The use of elasticity to measure safety effectiveness is beneficial because it is dimensionless unlike an estimated regression parameter, which is dependent on the units of measurement. (Washington et al., 2011).

Safety effectiveness was also estimated from the parameter estimates of the NB model. The safety effectiveness estimated as a crash reduction factor (CRF) for a given countermeasure from parameter estimates is defined as (Figure 23):

$$CRF_i = (\beta_i \ x \ \Delta X_i) \ x \ 100$$

Figure 23. Equation. Crash Reduction Factor.

where, CRF_i is the estimated CRF for countermeasure i, β_i is the estimated parameter for the countermeasure, and ΔX_i is the change in the attribute i associated with the countermeasure implementation.

NETWORK SCREENING – RANKING OF SITES

The ranking of routes and road segments was needed to evaluate the performance of mountain passes estimated from methods provided in the HSM. (AASHTO, 2010). Network screening, as described in the HSM, is a process used for reviewing a transportation network to identify and rank sites from most likely to least likely, to realize a reduction in crash frequencies with implementation of a countermeasure. By following the methods laid out in the HSM, the road segments that are most hazardous can be identified and investigated further. In this study, the (EB) adjusted expected crash frequencies and EPDO methods were used.

Ranking Using Expected Average Crash Frequency with EB Adjustment

In this method, the observed average crash frequency and the predicted crash frequency from a SPF are combined to calculate the expected average crash frequency and to account for RTM bias. (AASHTO, 2010). The ability to account for regression-to-the-mean (RTM) bias and using a site specific SPF makes this method superior to others listed in the HSM. The sites are then ranked from high to low based on the expected average crash frequency. The prediction is adjusted using an annual correction factor and an EB weight. The adjustment accounts for annual fluctuations in crashes due to variability in roadway conditions as well as other similar factors while also incorporating historical crash data specific to each site. The annual correction factor captures the effects of yearly variation in traffic, weather, and vehicle mix being dealt within the crashes. Figure 28 shows a flowchart describing the expected average crash frequency with EB adjustment ranking procedure. Initially, it was planned to conduct a separate ranking for segments with grades between 5-7 percent and segments with grades greater than 7 percent. In practice, it was more pragmatic to include all sections together in the ranking due to data limitations.

The annual correction factor is calculated by dividing the predicted annual average crash frequency from an SPF for year *n* by the predicted annual average crash frequency from an SPF for year 1 as given as (Figure 24):

$$C_{n(total)} = \frac{N_{predicted,n(total)}}{N_{predicted,1(total)}}$$

Figure 24. Equation. Annual Correction Factor.

where, $C_{n(total)}$ represents the annual correction factor for total crashes, $N_{predicted,n(total)}$ is the predicted number of total crashes for year *n*, and $N_{predicted,1(total)}$ is the predicted number of total crashes for year one.

The weight adjustment is needed to account for the reliability of the safety performance function. Lower over-dispersion parameters produce crash estimates through SPFs that exhibit higher reliability and therefore have a larger weighted adjustment. The larger weighting factors contribute to a heavier reliance on the SPF estimates (AASHTO, 2010), as seen in Figure 25:

$$w_{total} = \frac{1}{1 + k_{total} * \sum_{n=1}^{N} N_{predicted,n(total)}}$$

Figure 25. Equation. Weight Adjustment.

where, w_{total} represents the EB weight, and k_{total} is the over-dispersion parameter of the SPF. To predict the adjusted expected crash frequency, the observed crash frequencies are integrated with the predicted average crash frequency from an SPF. As mentioned before, the larger the weighing factor, the greater reliance on the SPF to estimate the predicted crash frequencies at each site per year as shown in the equation in Figure 26:

$$N_{expected,1(total)} = w_{total} * N_{predicted,1(total)} + (1 - w_{total}) * \left(\frac{\sum_{n=1}^{N} N_{observed,y(total)}}{\sum_{n=1}^{N} C_{n(total)}} \right)$$

Figure 26. Equation. Expected Crash Frequency.

where, $N_{expected,1(total)}$ is EB-adjusted estimated average crash frequency for year one, and $N_{observed,y(total)}$ represents the observed crash frequencies on the roadway segment. The expected average crash frequency with EB adjustment is calculated by multiplying the first year expected crashes with the final year annual correction factor as shown in Figure 27. The expected average crash frequency with EB adjustment for the final years are then compiled and ranked from highest to lowest in order to determine the segments that require the most attention.

$$N_{expected,n(total)} = N_{expected,1(total)} * C_{n(total)}$$

Figure 27. Equation. Final Year Expected Average Crash Frequency.

where, $N_{expected,n(total)}$ is the EB adjusted expected average crash frequency for final year, $N_{expected,1(total)}$ is the EB adjusted expected average crash frequency for year 1, and $C_{n(total)}$ is an annual correction factor. The flowchart for the EB adjusted expected average crash frequency is shown in Figure 28.

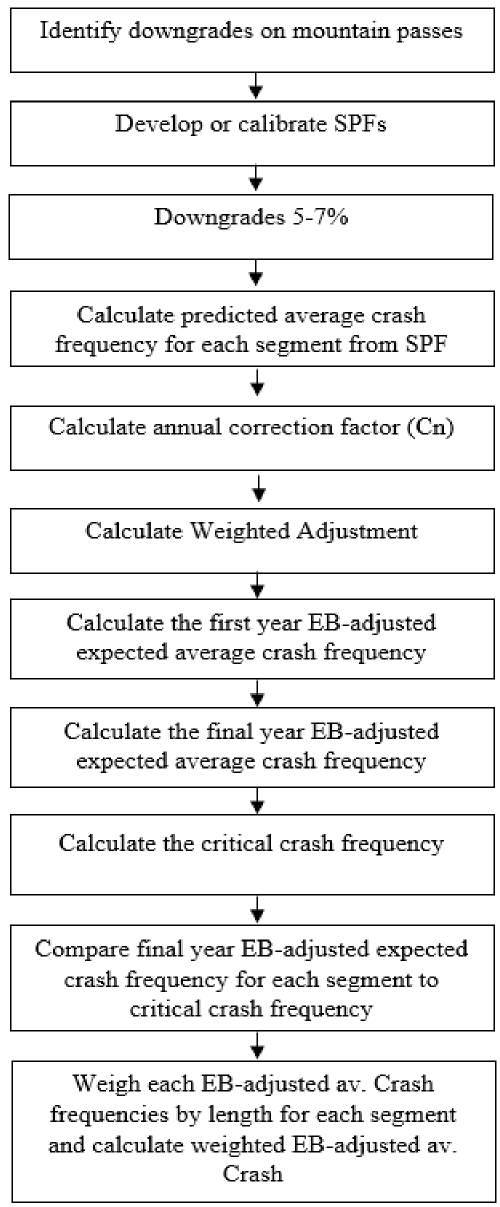


Figure 28. Flowchart. Ranking of Sites using the Expected Av. Crash Frequency with EB Adjustment.

Ranking using Equivalent Property Damage Only (EPDO)

The weighing system of the EPDO method is based on societal crash costs. It was also important to rank the sites based on EPDO and not solely on the hazardousness of the roadway. This allows for identifying which roadways incurs the most cost in equivalence to property damage. State and local jurisdictions generally accept societal crash costs by type, severity, or both. Local crash information was used in the analysis. Table 2 list the societal crash cost by type and cost.

Table 2 EPDO Societal Crash Costs (HSM, 2010)

Severity	Cost	Weight
Fatal (k)	$4,008,900	542
Injury(A/B/C)	$82,600	11
Property Damage Only (PDO) (O)	$7,400	1

A weighing factor was calculated by dividing the crash cost for any given severity by that of the crash cost for PDOs. The equation calculating the weighting factor is shown in Figure 29:

$$f_{y(Weight)} = \frac{CC_y}{CC_{PDO}}$$

Figure 29. Equation. Weighting Factor Used in EPDO Analysis.

where, $f_{y(Weight)}$ is the weighing factor based on the crash severity, y, CC_y represents the crash cost for severity, CC_{PDO} represents the crash cost for PDO crash severity. The total EPDO score is then calculated for each segment and ranked in descending order by the EPDO score. The total EPDO score is expressed as (Figure 30):

$$Total\ EPDO\ Score = f_{k(weight)}\left(N_{(observed,i(f)}\right) + f_{inf(weight),i(f)}\left(N_{(observed,i(f)}\right) + f_{PDO(weight),i}\left(N_{(observed,i(PDO)}\right)$$

Figure 30. Equation. Estimation of EPDO Score.

where, $\left(N_{observed,i(F)}\right)$ is the observed number of fatal crashes per segment, i, $\left(N_{observed,i(i)}\right)$ is the observed number of injury crashes per segment, i, and $\left(N_{observed,i(PDO)}\right)$ is the observed number of PDO crashes per segment, i.

HOTSPOT ANALYSIS

The hotspot analysis assessed the placement of warning sign in relation to truck crash hotspots. The analysis utilized the kernel density spatial analysis function in the ArcGIS software. Intersections of warning sign and truck crash hotspots indicated good placement of downgrade warning signs in relation to hazardous downgrades. The analysis allowed the placement of all warning sign types to be evaluated. A threshold kernel density (k) was defined for analyzing each downgrade section.

This threshold is different for each downgrade identified. This was expressed as (Figure 31):

$$k = 5\,x\,\frac{\sum Number\ of\ Crashes\ or\ signs}{\sum Downgrade\ length}$$

Figure 31. Equation. Threshold for Hotspot Analysis.

CHAPTER SUMMARY

Several approaches were adopted to achieve the goal of evaluating the safety effectiveness of advance warning signs to reduce truck crashes on downgrades. This chapter is a discussion of the approaches used in the study. The propensity score matching analysis was chosen to assess the general safety effectiveness of downgrade warning signs. The use of propensity scores removes bias due to confounding factors and results in unbiased safety effect estimates. The NB modeling approach was proposed to assess the safety effectiveness of individual sign types. Safety effectiveness evaluations using the NB model can be evaluated from parameter estimates and elasticity. Ranking of mountain routes was discussed as part of the chapter. This was done using the expected average crash frequency with EB adjustment and the equivalent property damage only (EPDO) methods adopted from the HSM. Finally, a brief discussion of warning sign and truck crash hotspot analysis was discussed. The hotspot analysis was utilized in assessing if warning sign placement is ideal in relation to locations of the high truck crash frequencies.

CHAPTER 4: DATA COLLECTION

The data needed for this study can broadly be classified into four types: warning sign, geometric, traffic and crash data. To accomplish the data collection task, three main avenues were explored. Primarily, data was collected from the Critical Analysis Reporting Environment (CARE) package, WYDOT database, field and video logs. A summary can be seen below in Table 3.

Table 3. Data Sources Summary

Geometric Characteristics	Crash Data	Field Assessment/Video Logs
WYDOT Database: • Route Numbers • MP • Elevation • Geometry	(CARE) Package: • Severity • Location • Vehicle Type • Date	• Traffic Operations • Sign Types • Downgrade Characteristics • Safety Infrastructure

A field assessment of advanced warning signs was carried out on five specific mountain passes; identified by having high frequencies of truck related crashes. The field assessment enabled an evaluation of the site conditions to gain a familiarity with the downgrades, traffic operations and traffic control devices. Also, notes were taken of possible safety deficiencies and verification of actual downgrade characteristics. Data was collected during the field assessment based on road characteristics, geometry, system of warning signs, truck escape ramps etc. Downgrade characteristics and warning systems installed on downgrades which were not part of the field assessment were collected from video logs. Crash and geometric data were obtained from the CARE package and WYDOT respectively. A total of 11 years of crash data was obtained from the CARE package.

The roadway and traffic volume information were collected to form basic roadway files. The files contained information on homogenous sections of roadway, which are stretches of road with consistent roadway characteristics. When any of the characteristics changed, a new section was defined. Based on the data for this study, the roadway file contained the following information among others:

- Road name
- Route
- Milepost (MP) direction
- Beginning and ending MP
- Length
- Grade
- Number of horizontal and vertical Curves
- Number of lanes
- Road width
- Shoulder width
- Average Annual Daily Traffic (AADT) and Average Daily Truck Traffic (ADTT)

WYDOT CRASH DATA

One of the first steps to crash analysis and safety effectiveness assessments is to compile the crash records of the specific segments of the roadway in interest. This information was extracted from the CARE package. This is a database maintained by WYDOT, in which crashes in Wyoming are found. Eleven years of crash data were compiled from 2005-2015 for crash safety analysis purposes. Data extracted from the CARE package combined with other data sources to carry out the investigation included:

- MP
- Crash date
- Crash severity
- Vehicle type (heavy and medium trucks)
- First harmful event
- Number of vehicles involved
- Road conditions at time of crash, etc.

The title sheet of each project was also compiled because it was necessary to match the construction stations to the MP of the road network.

VIDEO LOGS

Video logs were used extensively in determining the signage of the segments of interest. They were also used to correct and validate the data collection process. WYDOT has compiled statewide video logs of most major roadways. There is about 10 years of video logs, with current conditions of approximately half of the roadways updated each year.

WYDOT SIGN DATABASE

To carry out the safety effectiveness comparison of downgrade warning signs in Wyoming, the construction layout, maintenance and types of signs within the segments of interest were gathered. Several trips to WYDOT headquarters were necessary to compile the constructed summary files of all maintenance activities undertaken in the roadway segments of interest. The highway sign construction of each project was filtered for truck related or downgrade specific signs and compiled into a database.

FIELD ASSESSMENT

The field assessment was carried out in the summer of 2017. The data collection on the field consisted of:

- Highway section
- MP marker
- Downgrade direction
- Start and end of downgrade
- Posted speed limits
- Number of lanes
- Presence of passing lanes and median
- Roadway conditions
- Locations of rest/brake check areas

- Presence of skid marks
- For three miles before and within the downgrade section
    - Type of sign
    - Milepost
    - Sign direction
    - State of maintenance
    - Last installation date

A blank copy of the field data collection form can be found in Appendix 1. The segments and routes that were assessed contained the highest number of truck crashes.

Field Data Collection

This section describes the processes and procedures followed to select the study areas investigated in this report. Descriptive statistics are given for the five study areas namely, WY-28, US-14, US-16, WY-22 and US-287 including ADTT and truck crash statistics. The purpose of this section is to familiarize the reader with the areas of focus in terms of the current warning system, geometry and other characteristics of the downgrades.

Selection of Study Areas

The first step in the analysis involved the identification of hazardous downgrade sections. According to the Highway Capacity Manual (HCM), downgrades steeper than 5 percent and greater than 6 kilometers length exert almost double the passenger car equivalency. (TRB, 2010). The MUTCD specifies the combination of downgrades and lengths deemed hazardous to road users. These hazardous downgrades must meet at least one of the following criteria. (FHWA, 2009):

- a five percent grade that is more than 3,000 ft. (914.4 m) in length
- a six percent grade that is more than 2,000 ft. (609.6 m) in length
- a seven percent grade that is more than 1,000 ft. (304.8 m) in length
- an eight percent grade that is more than 750 ft. (228.6 m) in length, or
- a nine percent grade that is more than 500 ft. (152.4 m) in length.

This is the criteria adopted by the MUTCD in identifying downgrades requiring the installation of downgrade warning signs. WYDOT maintains a database containing general roadway geometric characteristics, route numbers, MPs, elevations, and vertical and horizontal alignment information. Grades for different sections were computed using information from the WYDOT database. The grade between two different locations was calculated from their elevations and MPs as (Figure 32):

$$Gradient = \frac{Elevation_i - Elevation_{(i-1)}}{MP_i - MP_{(i-1)}} \times 100$$

Figure 32. Equation. Calculation of Gradient.

The calculations allowed a graphical plot of gradient against mileposts to be generated for each route to help identify grades that exceeded the MUTCD criteria of five percent; the grade at which advanced warning signs may be required. A typical plot on US-16 [Main line (ML) 36] is shown in Figure 33. The sections identified were then examined further to determine if they met the MUTCD criteria for installation of a steep grade advanced warning sign as described above. Crashes which occurred a mile beyond the end of selected downgrades were included in the analysis. This was to account for runaway truck crash events that originate within the downgrade but occur beyond it. (Bowman, 1989). A total of 157 downgrades were identified for the study. Data collected for selected downgrades were merged to form a crash database. Figure 34 shows the truck crash frequency for downgrades, on Wyoming 28.

To select mountain routes on which to focus the field assessment, crashes were compiled into a table and summed based on routes. They were then ordered from highest to lowest based on frequencies of truck crashes. Table 4 lists the ten routes with the highest truck crash frequencies. Five of the routes with the highest truck crash frequencies were chosen as a focus of the field assessment. The five study areas were, WY-28, US-14, US-16, WY-22 and US-287. The remaining were considered in the extended study group and were also used in the analysis to primarily bolster the database.

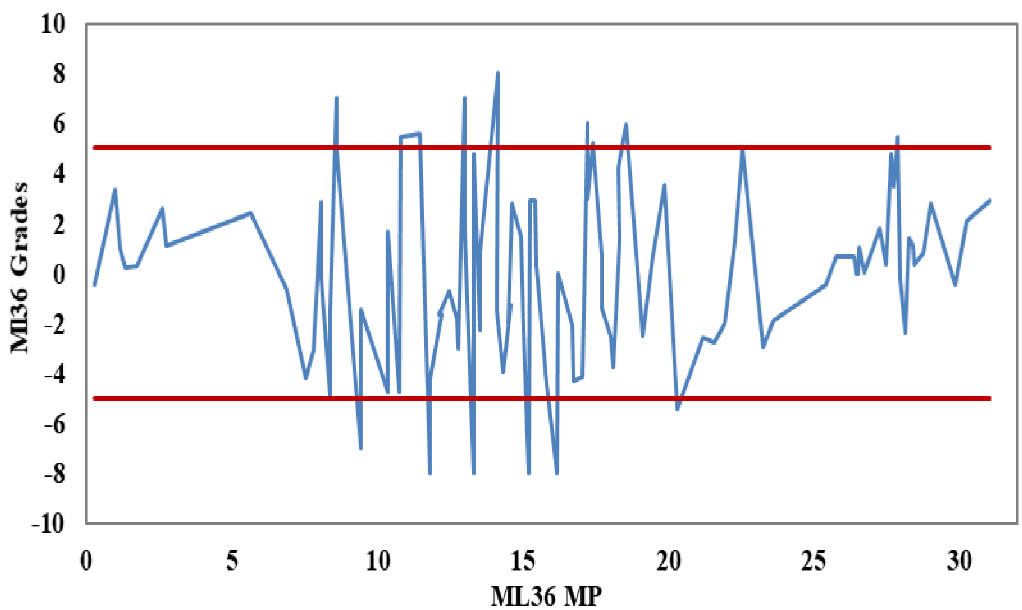


Figure 33. Graph. Grade Profile by MP for Route ML36 (US-16).

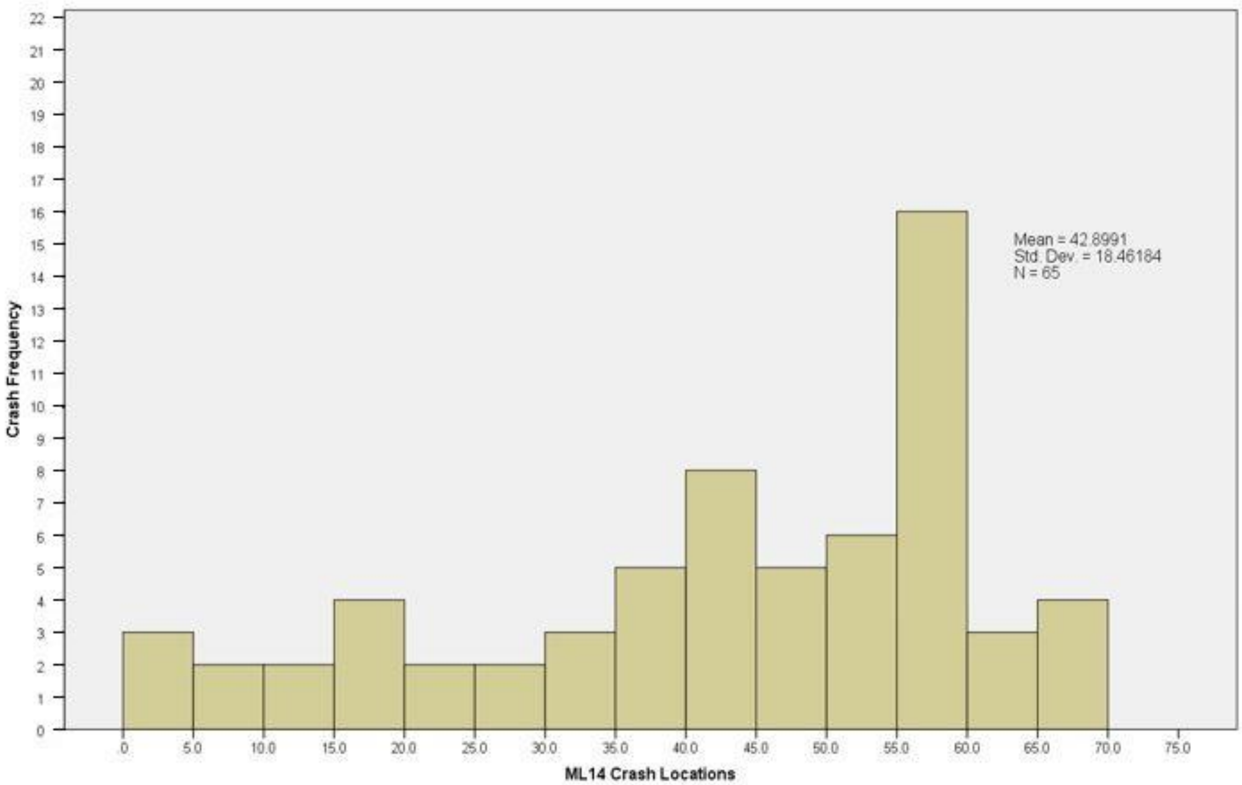
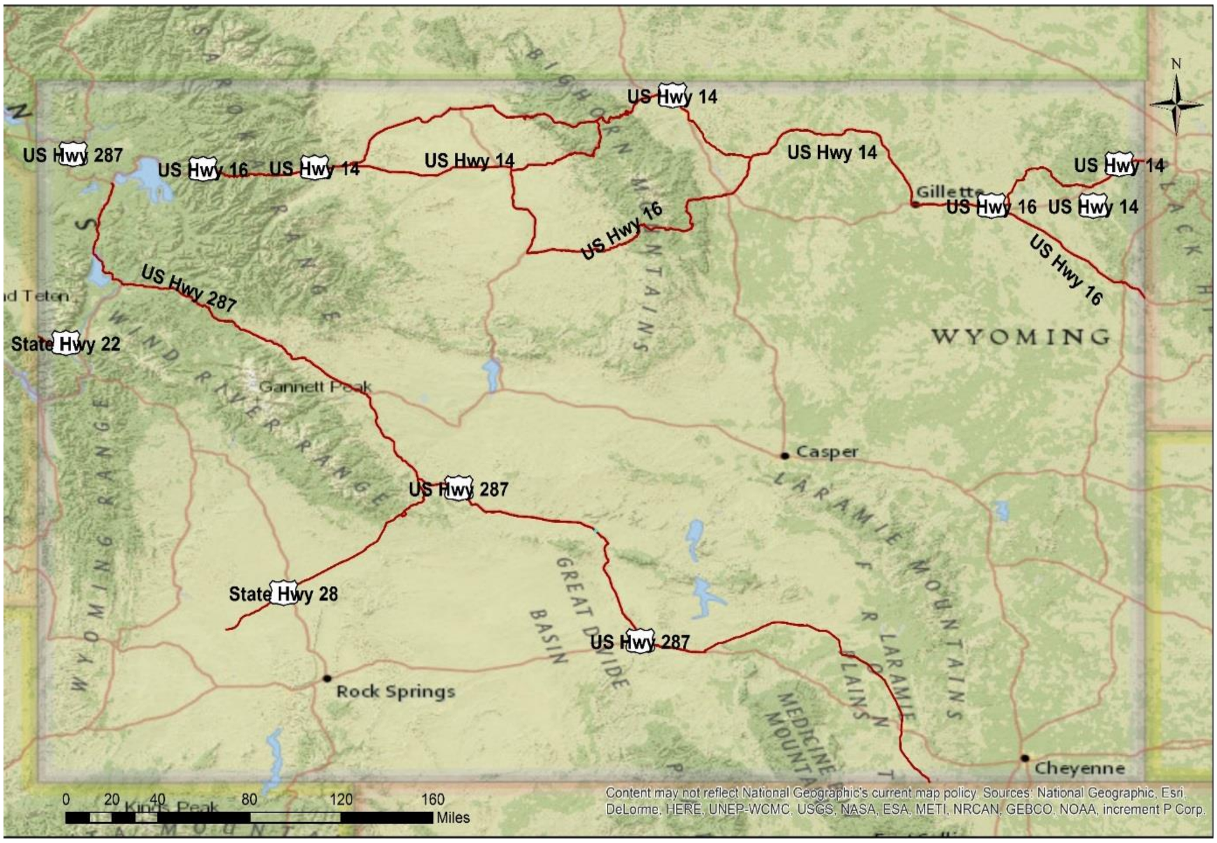


Figure 34. Graph. Truck crash frequency by MP for Route ML14 (WY-28).

Table 4. Mountain Pass Crash Summary by Route

No.	Route	All Crashes	Truck Crashes
1	WY-28	191	33
2	US-14	190	32
3	US-16	212	30
4	WY-22	313	23
5	US-287	111	21
6	WY-258	211	18
7	US-191	58	18
8	WY-230	35	11
9	US-189	64	10
10	US-26	17	8



Original Photo: © 2018 ArcGIS® (see Acknowledgements section.)

Figure 35. Diagram. Mountain Pass Routes (ESRI, 2018).

A total of 39 routes were identified in the mountain pass route selected. The complete lists of the routes can be found in Appendix 2.

Study Areas

This section describes the five mountain pass routes (WY-28, US-14, US-16, WY-22 and US-287) that were identified for the field assessment. Charts displaying ten years of truck crashes as well as the average daily truck traffic (ADTT) are shown below and are used to analyze general traffic and crash rate trends. A general description of the route is also provided. Maps containing grade information, crash location, and warning sign placement can be found for the five routes are located in Appendix 6.

WY-28 (South Pass)

WY-28, also known as South Pass, lies between Lander and Farson, Wyoming. A total of seven downgrade sections were on this route. The route is located in WYDOT district 5 and falls within Fremont County. The general trend identified was that ADTT steadily decreased over the period of analysis while truck crash rates increased. This phenomena is apparent on several routes. Figure 36 shows the truck crash rates and ADTT trends for WY-28.

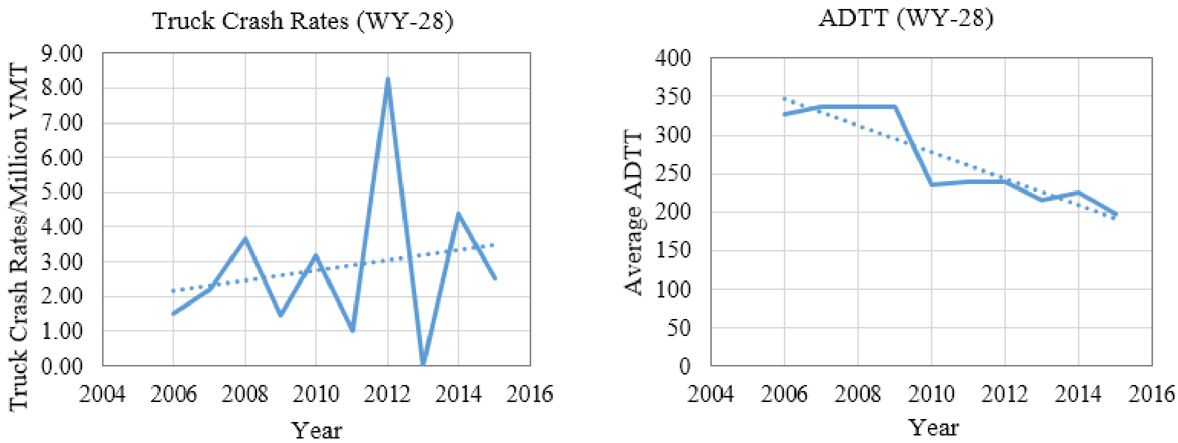


Figure 36. Graph. WY-28 Truck Crash Rates and ADTT Trend.

US-14

The segments of US-14 that are of interest are divided into two locations. The primary locations were situated north of Sheridan, Wyoming, going through Ranchester to Dayton, Wyoming. The highway splits into two routes at Burgess Junction, Wyoming with US-14 going to Greybull, Wyoming and US-14 Alternative (Alt.) going to Lovell. During the winter (December to June) US-14 Alt. to Lovell, Wyoming is closed. These two roads run within the Bighorn National Forest and fall within WYDOT districts 4 and 5. The other group of segments are located on the northeast corner of Wyoming, in the vicinity of Devil's Tower spanning from Moorcroft, Wyoming to Sundance, Wyoming. Between these two sections, there are over 36.05 miles of hazardous downgrades divided among 21 road segments. This road network contained the most segments of interest and had the most miles considered within the assessment. US-14 has experienced an increase in truck crashes over the past decade and constitutes one of the most hazardous routes under investigation in this study. Figure 37 shows the truck crash and ADTT trend for US-14. The trend shows that as truck crash rates have increased, ADTT has decreased over the analysis period.

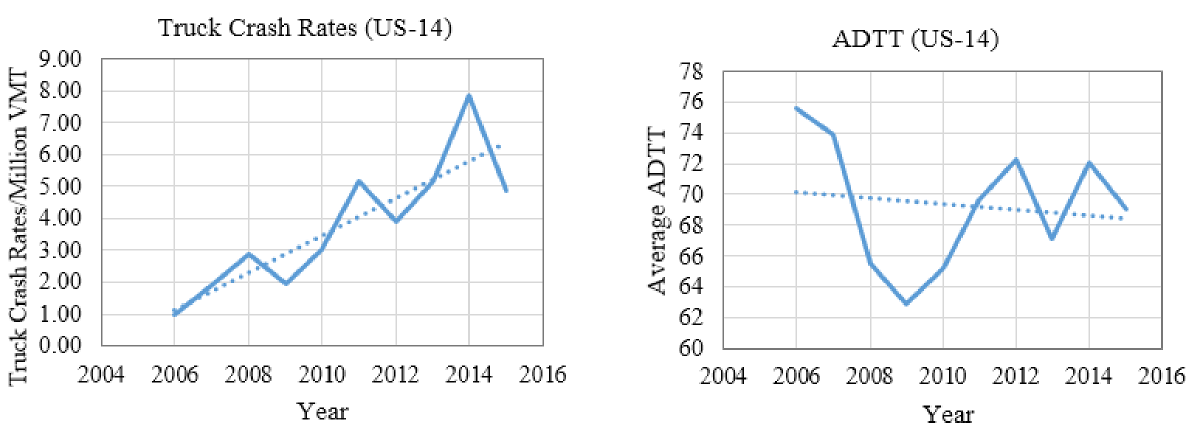


Figure 37. Graph. US-14 Truck Crash Rates and ADTT Trend.

US-16

US-16 is located between Buffalo and Ten Sleep, Wyoming, and runs within the Bighorn National Forest. It contains 25.42 miles of downgrades contained within 13 segments. The road closer to Buffalo, Wyoming, is within Johnson County with the west side of the pass running through Washakie County. The downgrade sections of interest are located in both WYDOT districts 4 and 5. The road leading into Ten Sleep Canyon traverses through steep switchbacks. The downgrade leading into Buffalo, Wyoming is a long steady downgrade with intermittent curvy sections and features one of the two catch-net runaway ramp for this study. Mandatory brake check areas are located at the start of this downgrade.

US-16 is one of the roadways that received a significant upgrade in its safety infrastructure in the past decade, with positive results. With the implementation of an updated catch-net escape ramp and an increase in warning signs, this route managed to decrease the severity and frequency of truck crashes. Figure 38 shows that truck crash rates on US-16 have decreased within the study for an almost constant ADTT trend.

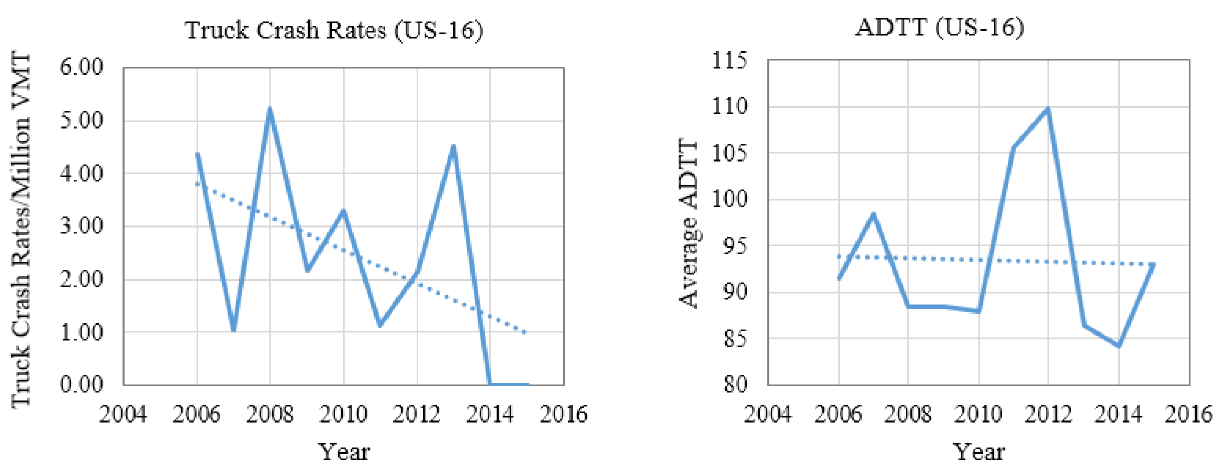


Figure 38. Graph. US-16 Truck Crash Rates and ADTT Trend.

WY-22 (Teton Pass)

WY-22**,** also known as Teton Pass**,** is located in Jackson, Wyoming, and crosses the state border into Victor, Idaho. This route has two long sections totaling about eight miles and has a very good downgrade facility (signage, brake check, turnouts and runaway ramps). The segment is located within Teton county, WYDOT district 3. WY-22 also currently has the highest amount of ADTT among the routes. A large amount of potatoes are transported from Idaho through Teton Pass to be distributed across the country. The general trend of the truck crash rate and average ADTT indicates an increase in truck crashes with increasing ADTT. This is shown in Figure 39. This is a common observation among the downgrades studied apart from US-16, which exhibited a decreasing crash rate trend.

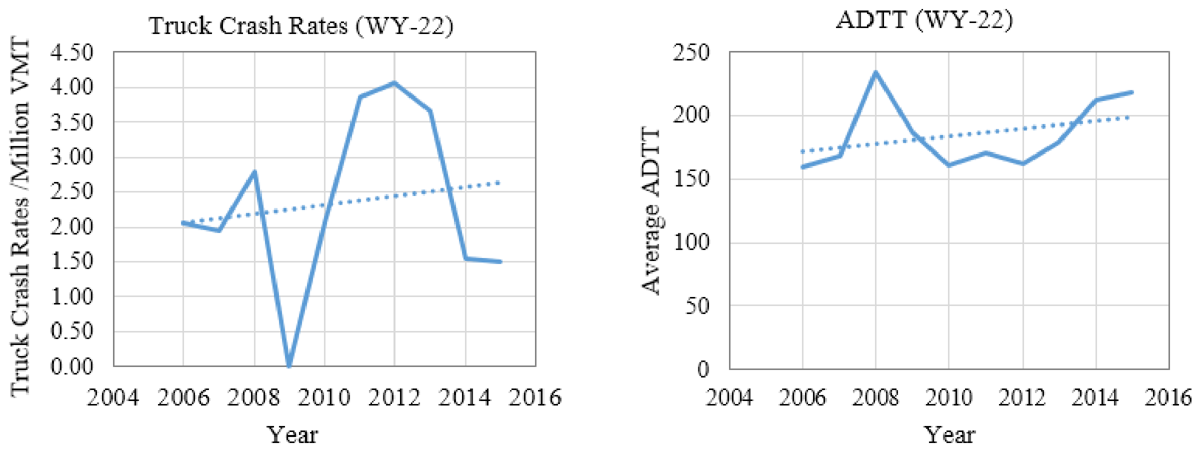


Figure 39. Graph. WY-22 Truck US-16 Truck Crash Rates and ADTT Trend.

US – 287

US-287 is the longest route by miles traveled within the assessment group. It stretches from Laramie to Jackson, Wyoming. There are 10 segments that have downgrades falling within the MUTCD criteria. Being the longest road in terms of miles traveled, the road is the most diverse. Some downgrade segments around Medicine Bow, Wyoming did not have warning signs and other segments such as those between Dubois and Jackson, Wyoming along Togwotee Pass have very good downgrade facilities (signage, brake check and turnouts). This route is separated into three segments and is within WYDOT districts, 1, 2 and 5 and passes through three counties; Albany, Carbon and Fremont. The ADTT for this route was found to have a decreasing trend while truck crash rates increase in the analysis period (Figure 40).

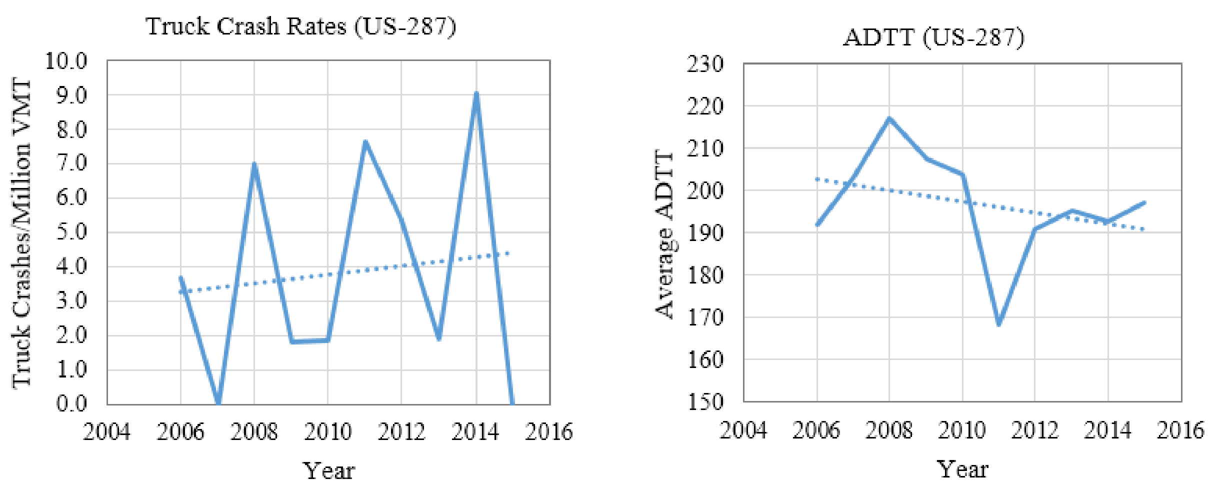


Figure 40. Graph. US-287 Truck US-16 Truck Crash Rates and ADTT Trend.

DATA SUMMARY

A comprehensive data collection effort was undertaken for all downgrades that were identified as hazardous on Wyoming highways based on the MUTCD grade criteria for installing advance downgrade warning signs. An 11-year crash data was extracted from the Critical Analysis Reporting Environment (CARE) software. Vertical, horizontal, cross sectional elements as well as traffic volumes were also obtained from WYDOT sources. Data on the current warning sign systems on five mountain routes was collected during a field assessment in the summer of 2017. The datasets were merged into a single database to satisfy the information needs of the research tasks of this study.

Table 5 shows an example of a sample database.

Table 5. Sample Database

No.	ID No.	Route	Road Name	Direction	From_RM	To_RM	Length (mi)	Grade (Percent)
1	10	ML10B	US-89	Dec MP	65.325	65.919	0.594	6.25
2	10	ML10B	US-89	Dec MP	66.607	68.969	2.362	6.23
3	10	ML10B	US-89	Inc MP	68.969	70.484	1.515	6.24
4	10	ML10B	US-89	Dec MP	201.815	203.869	2.054	5.01
5	10	ML10B	US-89	Inc MP	205.995	207.443	1.448	5.81
6	13	ML13B	US-189	Inc MP	129.814	131.789	1.975	5.73
7	13	ML13B	US-189	Inc MP	155.463	156.278	0.815	6.69
8	13	ML13B	US-189	Inc MP	163.556	164.183	0.627	15.43
9	14	ML14B	WY-28	Dec MP	30.903	31.771	0.868	5.00
10	14	ML14B	WY-28	Inc MP	34.394	35.037	0.643	7.12
11	14	ML14B	WY-28	Inc MP	45.597	46.607	1.01	5.33

Homogeneous Segmentation of Identified Road Segments

The HSM recommends that to obtain accurate results from cross-sectional analysis studies using regression, it is necessary to homogeneously segment roadway sections. Segmentation is done to produce roadway segments with varying lengths, each of which is homogeneous with respect to characteristics such as traffic volumes, roadway design, and traffic control features. The minimum length of a segment is defined by the HSM to be 0.1 mile. (AASHTO, 2010). Segmentation was undertaken on the downgrade entities, such that variations in in geometric and traffic characteristics (horizontal curves, vertical curves, traffic volumes, cross section elements, and other varying roadway elements) between homogeneous entities will be minimum. A sample database after the segmentation procedure is displayed below in

Table 6.

Table 6. Sample of Segmented Database

Site	ID No.	Route	Road Name	Direction	From_RM	To_RM	Length (mi)	Grade (Percent)
1	10	ML10B	US89	Dec MP	65.325	65.530	0.205	6.25
1	10	ML10B	US89	Dec MP	65.530	65.720	0.189	6.25
1	10	ML10B	US89	Dec MP	65.720	65.843	0.123	6.25
1	10	ML10B	US89	Dec MP	65.843	65.995	0.152	6.25
2	10	ML10B	US89	Dec MP	66.607	66.830	0.223	6.23
2	10	ML10B	US89	Dec MP	66.831	66.983	0.152	6.23
2	10	ML10B	US89	Dec MP	66.950	67.100	0.150	6.23

Types of advance warning signs

The types and number of installed warning signs were collected on the 51 sections of the five routes selected. The warning sign data was collected three miles before and within the downgrade section. Warning sign information collected related not only to downgrade signs but other signs including directional, speed limit, Chevron, miscellaneous warning signs, etc. The warning signs were placed in six categories. These are:

Hill signs/Hill Signs with advisory grade or distance plaques

Hill signs (W7-1, W7-1a) are usually placed in advance of downgrades to warn drivers of a steep decline. These signs are frequently used in combination with supplemental signs (W7-2bP, W7-3P, W7-3aP, and W7-3bP). (FHWA, 2009). Supplemental signs emphasize the use of lower gears and speed at locations where conditions justify extra caution. Hill warning signs are installed on locations where crash experience, or engineering judgment indicate a need. These warning signs were divided into the hill signs alone or the combinations of the hill signs and supplement signs. The hill sign categories are shown in Figure 41.

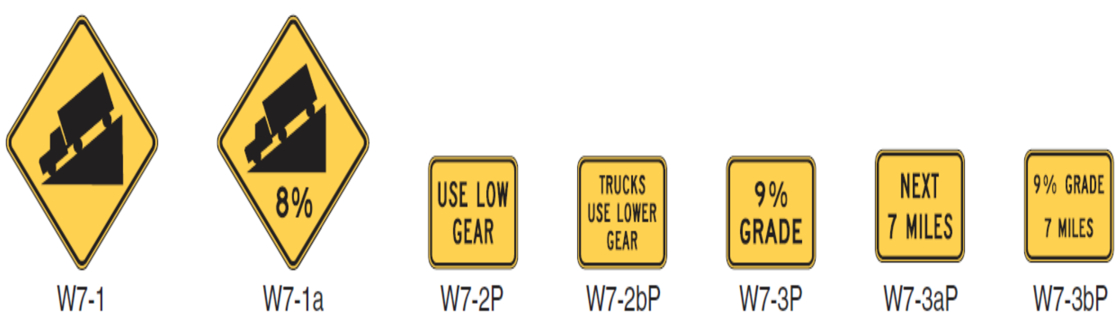


Figure 41. Hill Signs with Speed/Advisory Plaque (FHWA, 2009).

Truck escape ramp signs

As can be seen in Figure 42, this category includes W7-4, W7-4b, and W7-4c. These signs inform drivers, especially truck drivers of the provision of truck escape ramp facilities for use of out of control vehicles. Truck escape ramp signs can be seen in Figure 42.

W7-4 W7-4b W7-4c

Figure 42. Truck Escape Ramp Signs (FHWA, 2009).

Directional warning signs

Warning signs of this type are installed on mountain passes to inform drivers of changes in horizontal alignment and route direction. Directional sign types are varied and their shape depends on the section in question. An example of a directional warning sign is shown in Figure 43.

Directional Sign/Directional Sign and Advisory Speed Plaque

Most often, directional warning signs were combined with advisory speed plaques or were installed close to speed signs for emphasis on reducing speed. These two groups were combined for the analysis. Directional warning signs/advisory speed plaques are shown in Figure 43.

Truck speed sign Directional sign Speed and directional sign

Figure 43. Speed and Directional Signs.

Chevron warning signs

These are signs installed to show the edge of the road in dangerous curves and provide an emphasis for sudden changes in horizontal curves. Chevron signs are placed at the actual location of the curve change or bend to assist in safely negotiating such sections. They are usually black arrows placed on a yellow background. An example of Chevron signs can be seen in Figure 44.

Figure 44. Chevron warning signs.

Miscellaneous warning signs

Several other downgrade warning signs were identified during the data collection warning drivers of approaching downgrades. Some of these signs did not have enough observations to be categorized into individual groups. These included lane merges, high wind, route layout, and rollover signs among others. Due to their assorted nature, these signs were placed in a miscellaneous category. Some miscellaneous downgrade signs are shown in Figure 45.

Steep grades sign | Lane merges sign | Sharp curves sign

Figure 45. Miscellaneous Downgrade Signs.

CHAPTER SUMMARY

This chapter discussed the data collection process and datasets used in the study. Other supplementary data sources such as video logs and trips to WYDOT headquarters to retrieve sign construction data were described. The databases created were described as well. Five mountain passes, identified in terms of truck crash frequency were visited for detailed analysis of warning systems installed. Truck traffic and crash trends were also shown to help understand the current safety circumstances of the roadways. The types of warning signs identified during the field trip and from video logs were described as well. These were classified into six categories. Also, steps in the database preparation including segmentation was discussed. The database developed from this chapter was used in the analyses described in the next chapter.

CHAPTER 5: DATA ANALYSIS

This chapter discusses the analyses and results of the study. Five analyses are presented in this chapter. These are:

- A propensity score matching analysis providing a general quantitative measure of the safety effectiveness of advance downgrade warning signs. The propensity score model, matching method, binary logistic models and sensitivity results are discussed therein.
- A negative binomial (NB) model to estimate the safety effectiveness of individual types of downgrade warning signs. This analysis is useful in determining the type of warning signs that are effective in reducing the frequency of downgrade truck crashes.
- Ranking of hazardous sites based on two methods; expected average crash frequency with Empirical Bayes (EB) adjustment and equivalent property damage only (EPDO) based on the HSM. (AASHTO, 2010). To conduct the ranking using the EB method, a SPF was calibrated using the NB model for predicting the expected number of truck crashes on the study routes.
- A hotspot analysis was undertaken to assess the placement of warning signs in relation to the location of hazardous downgrades. GIS maps were produced from the analysis using warning sign data hazardous downgrades found in analysis 3. These GIS maps were used to analyze hotspots of truck crashes and warning sign densities and were generated from a kernel density spatial analysis. Additionally, this analysis aimed to evaluate the present warning sign system, evaluate inadequacies, and to ultimately recommend the best warning system for downgrade mountain passes.

Descriptive statistics are presented for the five study areas that were focused on during the field assessment, namely; WY-28, US-14, US-16, WY-22, and US-287. Table 7 is a brief description of some mountain pass routes including number of sections making up the route, cumulative length, average grades, ADTT, truck crash rates and frequencies.

Table 7. Summary Statistics on Some Mountain Pass Routes

Route	Number of Segments	Cumulative Length (mi)	Av. Grade (Percent)	ADTT	Truck Crash Frequency	Crash Rate (MVMT)
WY-28	7	11.0	5.65	269	33	2.70
US-14	21	36.1	6.19	69	32	3.47
US-16	13	25.4	6.62	93	30	2.39
WY-22	2	8.4	7.12	185	23	2.35
US-287	10	10.0	5.96	197	21	3.83

The descriptive statistics found in Table 7 indicate that US-14 has almost double the number of segments of any other route analyzed in the study and has the longest cumulative length. WY-22 and US-16 have the most severe average downgrade decline of over 6.5 percent. WY-28 has the largest ADTT out of the other routes and also has the largest truck crash frequencies. The routes with the highest crash rate/MVMT are US-287 and US-14. Figure 46 and Figure 47 are graphs of truck crash and total crash frequencies of the mountain passes in the study.

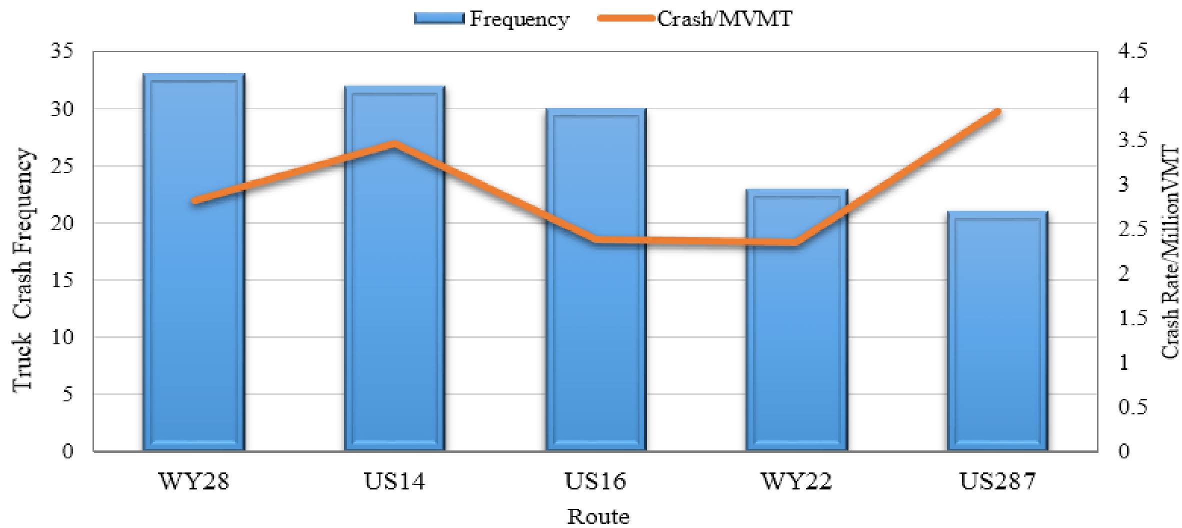


Figure 46. Graph. Truck Crash Rates and Frequencies.

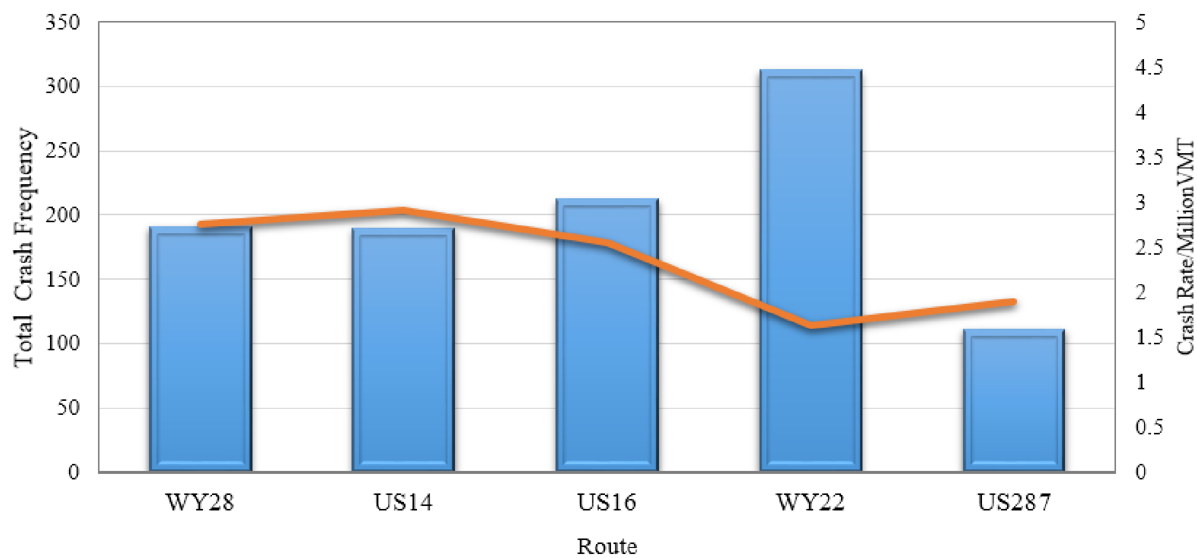
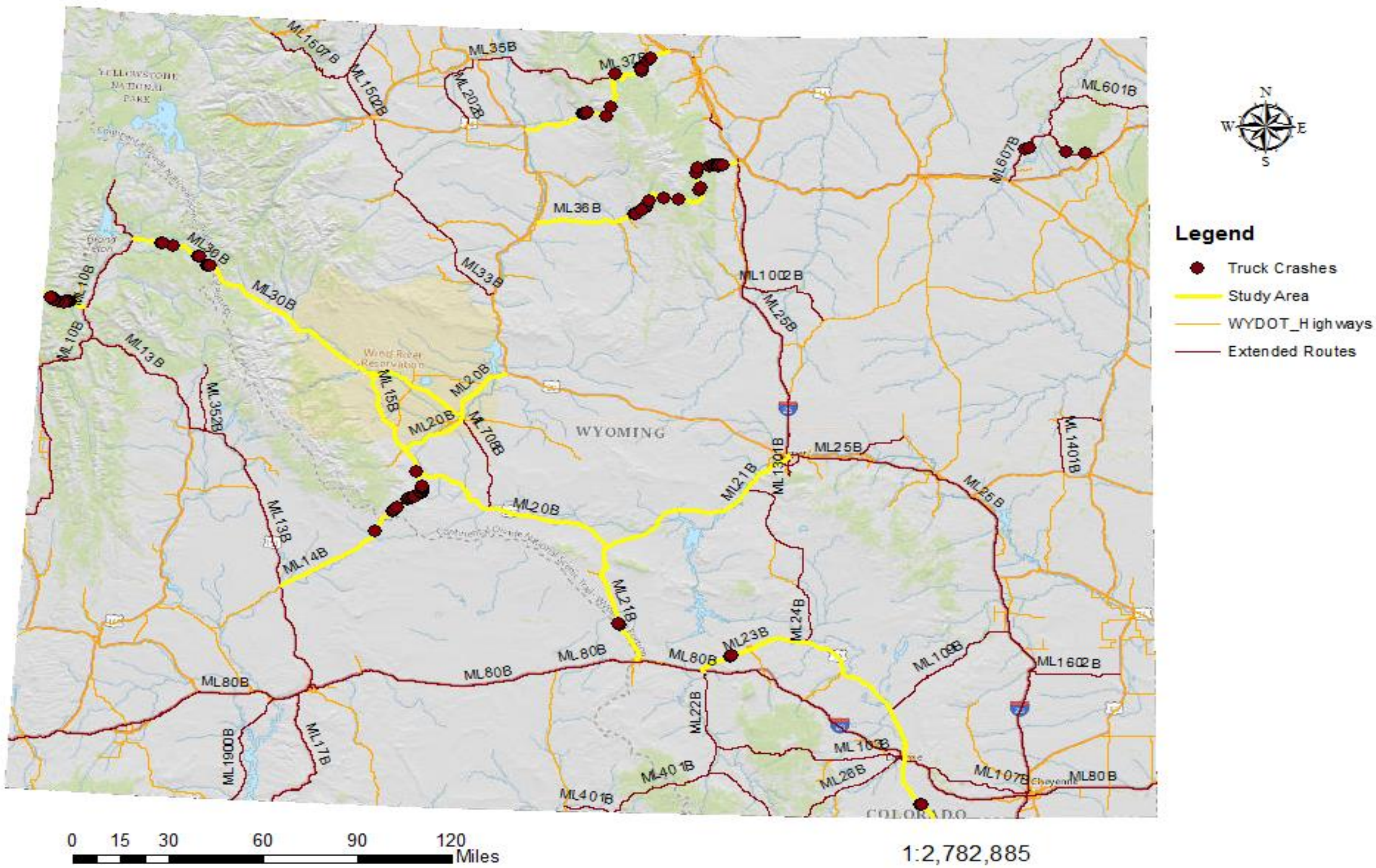


Figure 47. Graph. Total Crash Rates and Frequencies. **Original Photo: © 2018 ArcGIS® (see Acknowledgements section.)**

Figure 48 is a larger map showing the concentration of truck crashes along US highways within Wyoming. The study groups were also highlighted in different colors. Yellow represents the five routes with the highest crash frequency, red being the extended group consisting of the other mountainous routes, and orange representing other US highways running through Wyoming.



Original Photo: © 2018 ArcGIS® (see Acknowledgements section.)

Figure 48. Diagram. Study Areas and Locations of Truck Crashes (ESRI, 2018).

PROPENSITY SCORE MATCHING FOR ASSESSING SAFETY EFFECTIVENESS OF ADVANCE DOWNGRADE WARNING SIGNS

A propensity score model was calibrated from the crash database of all hazardous downgrades identified for the study. The response variable for the model was the presence of an advance downgrade warning sign. This was regressed against several explanatory variables including downgrade length, average grade, average curve length, number of access points, number of lanes, shoulder width, log of ADTT [LN(ADTT)], presence of passing lane, presence of traffic control, speed limit, etc. Table 8 shows the descriptive statistics of some of the variables selected for the analysis.

Table 8. Descriptive Statistics of Variables used in Propensity Score Model

Continuous Variables				
Variable Name	**Min.**	**Max.**	**Mean**	**Std. Dev.**
Downgrade length (miles)	0.15	5.73	1.79	1.599
Average grade (percent)	5.00	9.61	6.9	1.016
Average curve length/1000 (ft)	0.1	16.45	1.67	3.809
Lane width (ft)	7.5	18	11.93	1.134
Number of access points	0	6.00	0.96	1.614
Number of lanes	2.00	4.00	2.46	0.702
Shoulder width (ft)	0	12	4.26	2.655
LN(ADTT)	1.00	6.00	4.14	0.868
Categorical Variables				
Variable Name	**Frequency**	**Percentage of sample**	**Sample size**	
Presence of advance downgrade warning sign	1536	51.63	2974	
Truck crashes	253	8.51	2974	
Presence of passing lane	828	27.83	2974	
Presence of traffic control	2099	70.58	2974	
Speed limit (1 if greater than 50 mph, 0 otherwise)	2236	75.16	2974	

In terms of statistical significance, there is no clear direction as to what variables to retain in the propensity score model. It has been argued by some researchers that all relevant variables that account for the response variable of interest should be included in the model regardless of significance. (Austin et al., 2007; Caliendo and Kopenig, 2008). This approach was used in calibrating the propensity score model for this study. The propensity score model is shown in Table 9. To assess the validity of the propensity score matching in analyzing the crash database, the overlap of the propensity scores of crashes occurring on the treated and untreated sites were evaluated. This was done by visually inspecting the propensity score distributions of the two groups using a back-to-back histogram. Figure 49 shows the back-to-back histogram of the propensity score distribution of the two groups.

Table 9. Propensity Score Model

Variable	Estimate	Std. Error	Z-value	p-value
Intercept	2.828	0.710	3.98	<0.001
Downgrade length	0.771	0.041	18.67	<0.001
Grade	0.070	0.038	1.85	0.064
Average curve length	0.664	0.075	8.82	<0.001
Lane width	0.036	0.036	1.00	0.316
Number of access points	-0.053	0.035	-1.53	0.126
Presence of passing lane	-1.881	0.153	-12.30	<0.001
Number of lanes	-1.752	0.157	-11.15	<0.001
Shoulder width	-0.127	0.022	-5.81	<0.001
LN(ADTT)	0.034	0.069	0.50	0.619
Presence of traffic control	-0.053	0.101	-0.52	0.601
Speed limit (1 if greater than 50 mph, 0 otherwise)	0.741	0.138	5.38	<0.001
Number of observations	2974			
Log Likelihood	-2850.814			
AIC	2874.814			

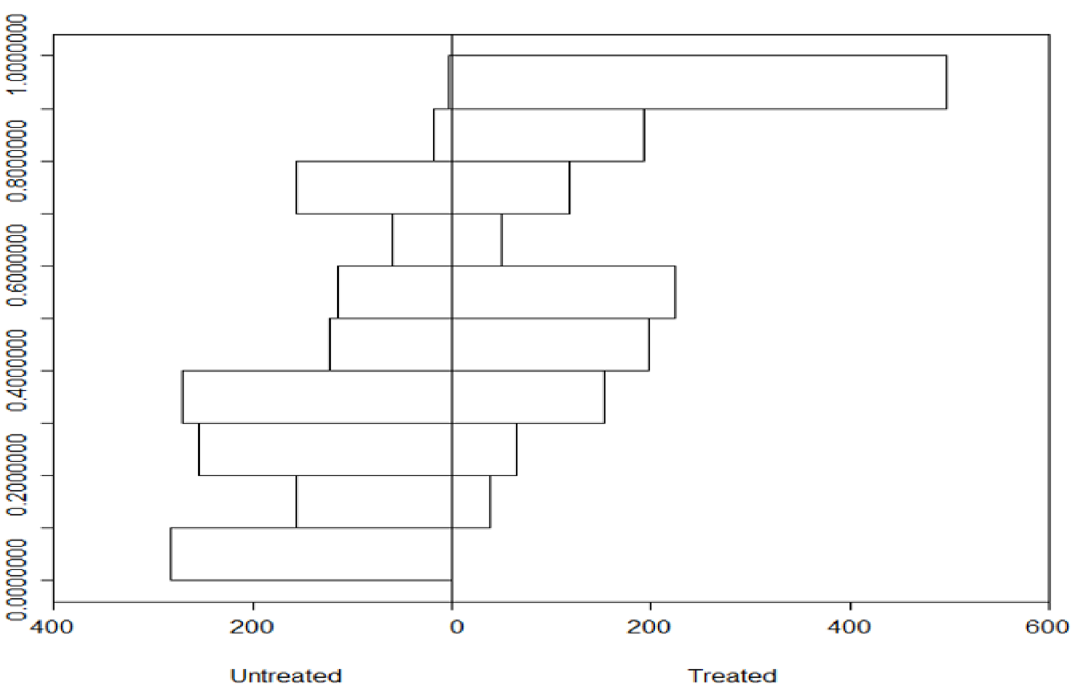


Figure 49. Graph. Back-to-Back Histogram of Propensity Scores before Matching.

The plot of propensity score distribution in Figure 49 shows that there is a good overlap between the two groups. Thus, the propensity score framework is suitable for implementation using the database developed. The histogram of propensity scores after matching is shown in Figure 50.

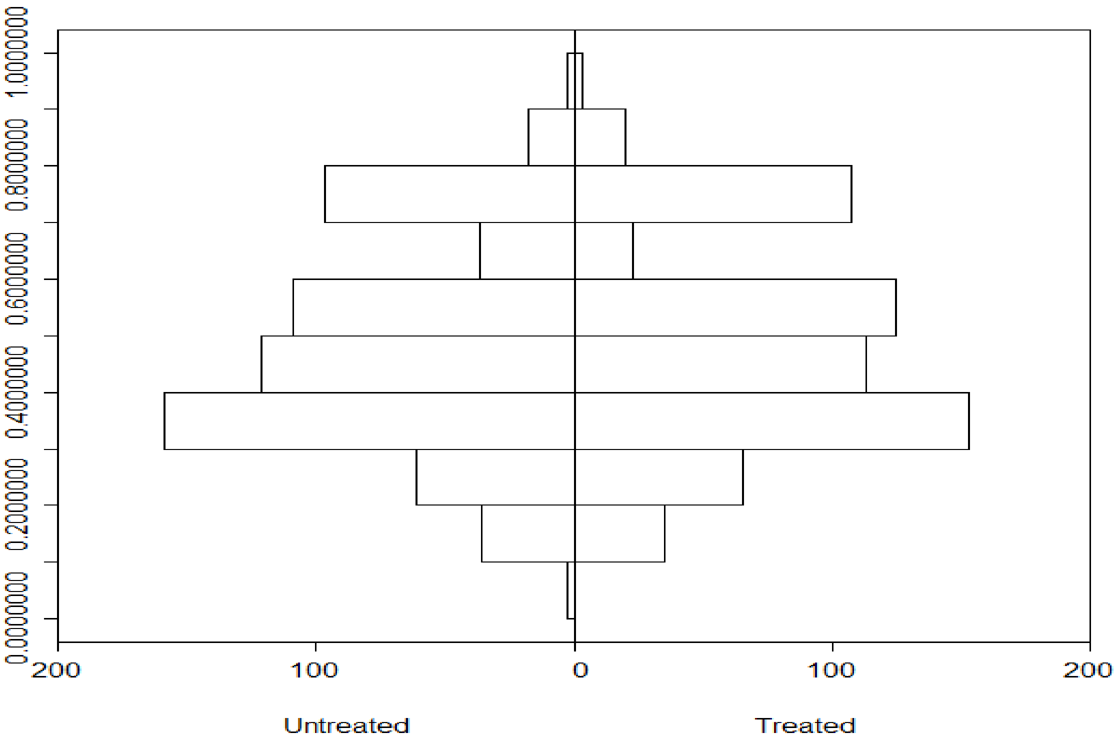


Figure 50. Graph. Back-to-Back Histogram of Propensity Scores after Matching.

Propensity Score Matching and Covariate Balance Check

Matching was done by 1:1 matching with the NN algorithm using defined caliper widths. The NN matching algorithm was chosen due to the comparable number of treated and untreated segments. The default caliper width of 0.25 times the standard deviation (σ) of the propensity scores of the treatment group was used for the analysis (caliper width = 0.064).

Covariate balance was evaluated by calculating the absolute standardized bias of the variables before and after matching using the equation in Figure 17. The analysis shows matching resulted in a reduction of the standardized bias for most of the variables. The results suggest the absolute standardized difference in means for most of the variables is less than five percent. This indicates that the use of the matching algorithm resulted in a good balance of the covariates. Figure 51 is a plot of the covariate balance before and after matching using the default caliper width of 0.064.

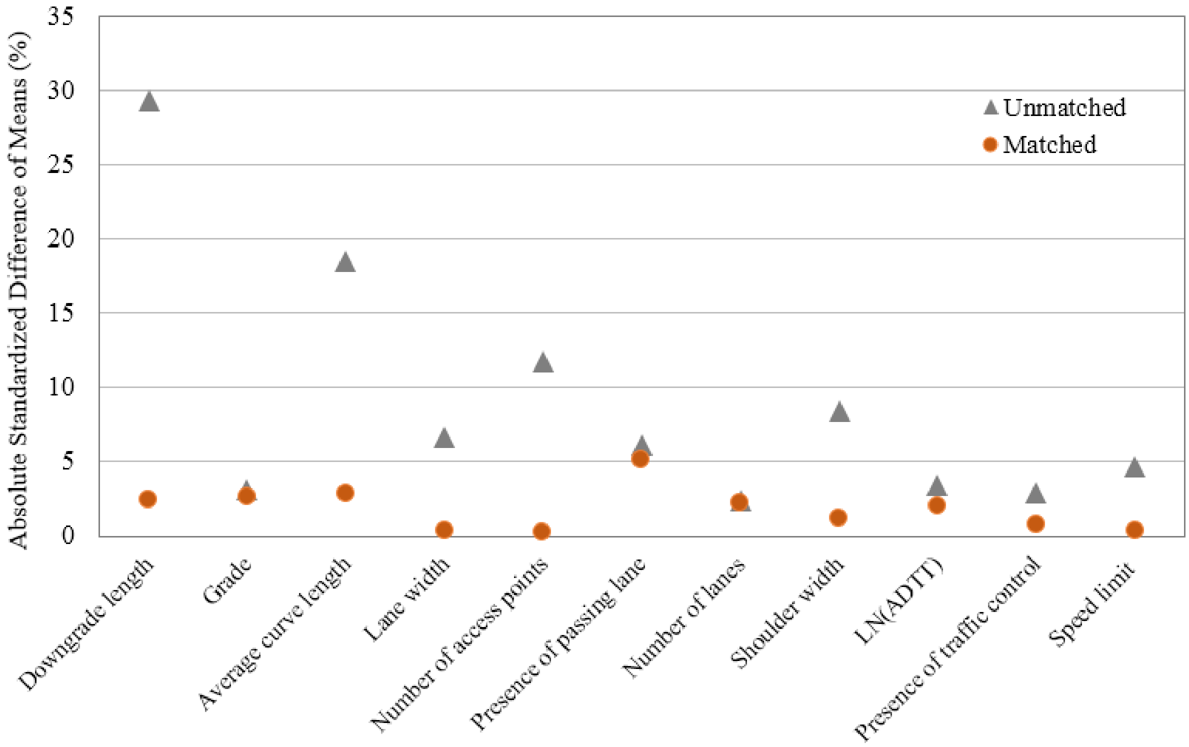


Figure 51. Graph. Covariate Balance Analysis of Matched and Unmatched Data.

Effect of Advance Downgrade Warning Signs on Truck Crashes

The safety effectiveness of advance downgrade signs on truck crashes was estimated using logistic regression models calibrated separately for crashes occurring on treated and untreated segments. The probability of a truck crash occurrence on downgrades with and without an advance downgrade warning sign is the potential outcome for the study. The dependent variable for the logistic regression models was therefore the occurrence of a truck crash. The logistic regression models predicting the occurrence of a truck crash on treated and untreated segments are shown on

Table 10.

It may be observed that the logistic regression models in

Table 10 include variables that are not statistically significant at the 0.05 or 0.10 significance level. It has been argued that for observational studies, statistical significance should not be the primary concern. (Rosenbaum, 2010).

The results indicate that the estimated probability of a truck crash occurring on a downgrade segment with a downgrade warning was 0.072 (i.e., one in every 14 crashes on segments with advance downgrade signs). For downgrades without downgrade warning signs, the estimated probability was found to be 0.082 (i.e., one in every 12 crashes on segments without advance downgrade signs). The risk ratio (RR) was thus estimated to be 0.082/0.071 = 1.15. This indicates that the probability of a target crash occurring on segments without advance downgrade signs is an estimated 15 percent higher compared to segments with advance downgrade signs.

Table 10. Binary Logit Model for Treated and Untreated Groups (0.25σ Caliper Width)

Variable	Downgrades with advance warning signs				Downgrades with no advance warning signs		
	Estimate	Std. error	Z		Estimate	Std. error	Z
Intercept	-4.965	2.888	-1.72		-4.848	2.428	-2.00
Downgrade length	0.270	0.250	1.08		0.338	0.183	1.85
Grade	0.204	0.102	2.01		0.124	0.108	1.14
Average curve length	0.547	0.322	1.70		-0.270	0.391	-0.69
Lane width	0.048	0.150	0.32		0.117	0.117	1.00
Number of access points	-0.746	0.304	-2.46		-0.273	0.154	-1.77
Presence of passing lane	-0.811	0.682	-1.19		-0.439	0.586	-0.75
Number of lanes	-0.019	0.760	-0.03		-0.710	0.663	-1.07
Shoulder width	0.105	0.160	0.66		0.075	0.067	1.13
LN(ADTT)	0.524	0.311	1.69		0.520	0.287	1.82
Presence of traffic control	-3.023	1.024	-2.96		-2.551	0.734	-3.48
Speed limit (1 if greater than 50 mph, 0 otherwise)	0.156	0.593	0.26		-0.152	0.490	-0.31
Number of observations	643				643		
Log Likelihood	-260.44				-316.42		
AIC	284.44				340.42		

To assess the reliance of the RR on sample size, a 90 percent bootstrap confidence interval was computed for the mean risk ratio at the caliper width of 0.064. Resampling for bootstrapping was achieved by repeatedly drawing samples a hundred times with replacement from the original sample. The 90 percent bootstrap confidence interval was 1.04 to 1.53. The absence of 1 within the confidence interval suggests a high reliability of the treatment effect estimated using the propensity scores technique. A confidence interval of 90 percent was selected for this study because of the relatively smaller sample size of the matched data. (Zajac and Ivan, 2003).

Sensitivity Analysis

A series of binary logistic regression models for calipers ranging from 0.1 to 1σ were calibrated to evaluate the sensitivity of the analysis with respect to sample size. The models evaluated the probability of occurrence of a truck crash on downgrade segments with advance downgrade signs. These models for matched treated and untreated groups for different calipers can be found in Appendix 4. RRs were then computed based on the logistic regression models calibrated. Figure 52 shows the RR estimates values for the truck crash probabilities at different caliper widths.

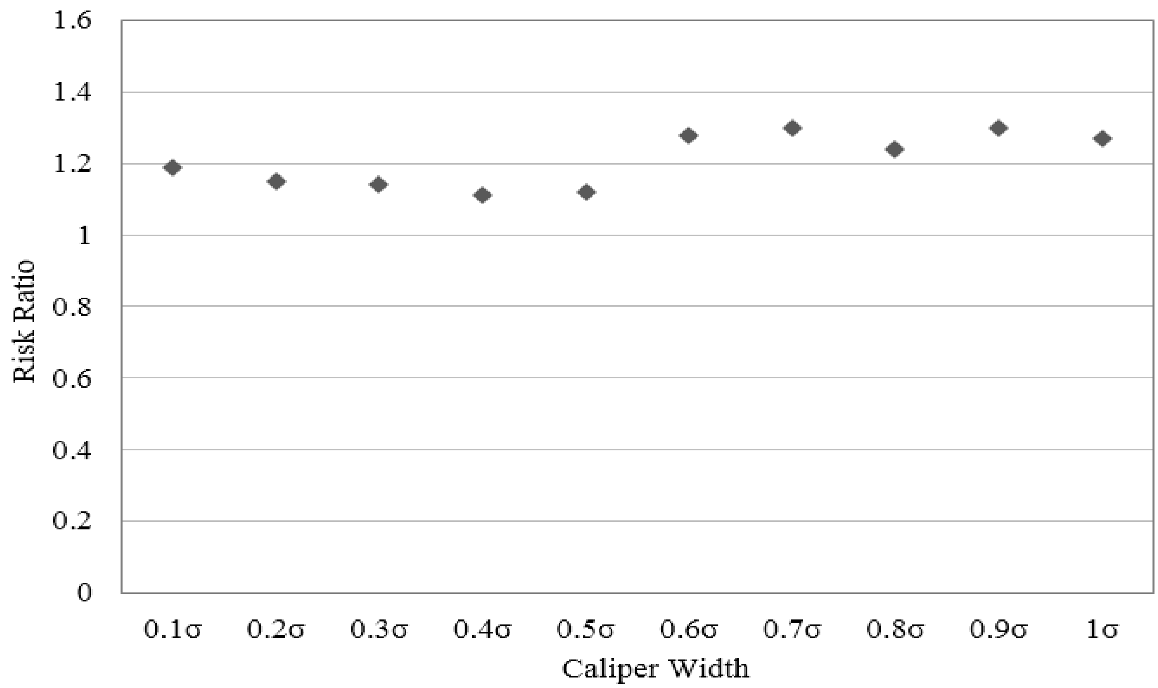


Figure 52. Graph. Risk Ratio for Different Caliper Widths.

The sensitivity analysis shows that the estimates of RR for the occurrence of truck crashes at matched downgrades are comparable for different caliper widths. The results indicate that the RR estimates vary from 1.11 to 1.30 for the different caliper widths. The RR range is relatively small and suggests the propensity score matching adopted for the analysis is sound.

SAFETY EFFECTIVENESS OF CURRENT WARNING SIGN TYPES

The safety effectiveness of current downgrade warning signs installed on Wyoming mountain passes were evaluated using the NB model. Two crash prediction models were calibrated for truck and non-truck crashes respectively. The total length of downgrades considered for the study was 172 miles, segmented into 1,416 homogeneous entities. Due to data limitations and unavailability of warning sign information on some segments, the number of observations used for the actual analysis was 1232. Three miles of advance warning signs were collected before the start of downgrades along with warning signs within the downgrades. This meant that the total length used for frequency analysis of the advance warning signs was 3,696 miles. Because warning signs were mostly installed in advance of the downgrade, signs within the downgrade were found to have low frequencies. Warning signs within the downgrade were therefore combined into a single category in the modeling process. A complete list of variables related to warning sign along with their frequencies and normalized information (frequency/mile), are presented in Table 11.

Other variables related to the geometric and traffic characteristics of the segments were considered for the analysis as well. These variables included number of crest curves, lane width, number of sag curves within segments, curve radius and length, average daily truck traffic (ADT) among others. Descriptive statistics of some variables are shown on

Table 12.

Estimation Results

The effect of warning signs on truck and other (non-truck) crash frequency will be discussed in this section. The safety effects were evaluated based on the parameter estimates and elasticity values from NB prediction models calibrated for truck and non-truck crashes. The results from the models were found to be sound and intuitive. Interpreting the effect of an explanatory variable for NB models is done in terms of the exponent of the parameter estimate. For instance, a parameter estimate of 0.20 implies that for a unit increase in that independent variable, the expected number of crashes will increase by a factor of exp(0.20) = 1.22 or 22 percent while holding all the other variables in the model constant. Conversely, a parameter estimate of -0.20 implies that for a unit increase in the independent variable of interest, the expected crash frequency is expected to decrease by 1-exp(-0.20) = 0.18 or 18 percent while holding all other variables in the model constant. Safety improvements estimated from regression parameters are also discussed in this section.

Table 11. Descriptive Statistics of Advanced Warning Signs

Advance warning sign type	Frequency	Frequency/mile
Hill Sign W7-1	96	0.026
Hill Sign with grade value advisory sign (W7-1a)	43	0.012
Hill sign with lower gear advisory plaque (W7-1 + W7-2P)	619	0.168
Hill sign combination with downgrade distance advisory plaque (W7-1 + W7-3aP)	176	0.048
Hill sign with downgrade value advisory and distance advisory plaque W7-1a + W7-3aP	534	0.145
Truck Escape Ramp Sign (W7-4b)	544	0.147
Speed sign	377	0.102
Directional sign	1201	0.325
Directional and advisory speed plaque	2706	0.732
Chevron sign	362	0.098
Miscellaneous	1234	0.334
Warning signs within downgrade	305	1.773

Effects of Variables on Truck Crash Frequency

This analysis was conducted by only incorporating truck crashes into the model. It was hypothesized that because trucks are especially vulnerable on downgrades, due to their sizes and loads, truck drivers pay more attention to downgrade-specific warning signs than other vehicle drivers. Also, the literature suggests that unique contributory factors are responsible for truck and other vehicular crashes. This formed the basis for analyzing the two crash types separately. The predictive model and elasticities for truck crashes on downgrades are shown on Table 13 and

Table 14.

Table 12. Descriptive Statistics of Some Variables for NB Model

Variable	Mean	Std. Dev.	Minimum	Maximum
Length (x 1000 miles)	139.74	97.25	100	2460
ADTT	90.57	87	9	646
Average grade (percent)	6.90	1.016	5	9.6
Superelevation (percent)	0.0107	0.027	0	0.6
Deflection angle (radians)	26.31	32.393	0	205.2

Table 13. Prediction Model for Truck Crash Frequency

Parameter	Estimate	Standard Error	Wald chi-square	P-value
Intercept	-3.614	0.7431	21.78	<.0001
Average grade	0.277	0.0946	8.59	0.0027
Superelevation	0.047	0.0235	3.92	0.0385
Deflection angle	0.883	0.2080	18.02	<.0001
Passing lane	-0.641	0.3142	4.16	0.0408
ADTT	0.009	0.0012	54.51	<.0001
Warning signs within downgrade	0.452	0.1712	6.97	0.0084
Miscellaneous warning signs	0.705	0.2558	7.59	0.0059
Truck escape ramp sign	-0.572	0.2644	4.68	0.0305
Directional and speed plaque sign	-0.380	0.0613	38.41	0.0244
Hill sign with downgrade combination and distance advisory plaque (W7-1 + W7-3aP)	-0.452	0.1827	3.20	0.0190
Model fit statistics				
Dispersion	3.654	0.66007	30.65	<.0001
AIC	1028.07			
Log Likelihood	-389.480			

Table 14. Elasticities of Variables Influencing Truck Crashes

Parameter	Elasticity or Pseudo Elasticity (percent)
Average grade	171.40
Superelevation	1.94
Deflection angle	22.50
Passing lane	-47.32
ADTT	155.70
Warning signs within downgrade	7.47
Miscellaneous warning signs	29.37
Truck escape ramp sign	-5.69
Directional and speed plaque sign	-16.80
Hill sign with downgrade percent and distance plaque combination sign (W7-1 + W7-3aP)	-11.10

Roadway and Traffic Characteristics Impacts on Downgrade Truck Crashes

For the roadway characteristics, average grade, superelevation, deflection angle, and passing lane were found to significantly impact the frequency of truck crashes on downgrades. The results suggest that an increase in the vertical grade by one percent will lead to an increase in truck crashes by a factor of 1.32 [exp (0.277)] given that the other variables are held constant. Similarly, it was found that superelevation was positively associated with an increase in truck crash frequency on downgrades. A one percent increase in superelevation will result in an increase in truck crash frequencies by up to a factor of 1.05 [exp (0.047)] while holding all other variables in the model constant.

A positive coefficient was found for deflection angle indicating a positive association with truck crash frequency. A one degree increase in deflection angle was related to a 2.4 factor increase in truck crash frequency. This finding was attributed to increased speeding on sections with higher deflection angles, and thus, smoother curves. The presence of a passing lane was found to decrease the frequency of truck crashes on downgrades. The coefficient for the passing lane variable indicates that having a passing lane decreases truck crashes by about 47 percent. This was attributed to an increase in passing opportunities on downgrades.

The traffic variable ADTT was found to be positively associated with truck crash frequency. An increase in truck traffic was found to increase truck crash frequency. However, this increase was found to be marginal [exp (0.009)].

In terms of elasticity of the significant roadway and traffic variables, the average grade was found to have the highest impact on downgrade truck crashes (171.40 percent) while superelevation had the least impact (1.94 percent). The results suggest a one percent increase in average grade, superelevation, deflection angle and ADTT will lead to 171.40, 1.94 percent, 22.5 percent, and 155.7 percent increase in truck crash frequency, and a 47.32 percent decrease in truck crashes for passing lanes.

Warning Sign Impacts on Downgrade Truck Crashes

The effect of warning signs on truck crashes were assessed in a similar fashion as the other variables discussed above.

Warning signs within downgrade

Due to the low frequency of warning signs within the downgrade, a category was created to combine all such signs. The analysis (Table 13) indicated a positive association ($\beta = 0.452$) between warning signs installed within the downgrade and truck crash frequency. This does not mean these warning signs increase truck crash frequency, but may only suggest that such warning signs are installed on black spots; areas known to have high truck crashes. The positive parameter estimate of this variable may also be the result of confounding brought about by the different groupings of warning signs in this category.

Miscellaneous warning signs

Miscellaneous downgrade signs installed in advance of hazardous downgrades were found to be associated with an increase in truck crash frequency. This result is unexpected but may be due to the reasons explained above.

Hill sign with downgrade percent and distance plaque combination signs

The results indicated that the hill sign with downgrade percent and distance plaque combination signs (W7-1 + W7-3aP) are associated with a decrease in truck crash frequency. Increasing the number of this sign will lead to an estimated decrease of truck crashes by 36 percent while holding all the variables in the model constant. This decrease may be due to the easily recognizable characteristic of these signs and the extra information (with regards to speed) that they provide.

Truck escape ramp signs

The results of the analysis indicates that truck escape ramp signs are associated with a decrease in truck crash frequency on downgrades ($\beta = -0.572$). Truck escape ramps allow trucks that have run out of control due to brake issues to come to a safe stop. Truck escape ramps are installed on downgrades where the incidence of truck runaways is high. (Witherford, 1992). The parameter estimate suggests an increase in the truck escape ramp sign will reduce truck crashes by 36 percent while holding the other variables in the model constant. This decrease may not be due to only the presence of the truck escape ramp signs, but also the presence of the escape ramps themselves. The effect of the truck escape ramp sign on truck crashes may be due to its presence being considered as a signal to truck drivers that they are approaching a steep downgrade. The sign may therefore be thought of as a surrogate for steep downgrade signs.

Directional and speed combination advisory sign

The directional and speed plaque advisory sign was found to be related to a decrease in truck crashes on downgrades. A unit increase in the frequency of this sign is associated with a 32 percent decrease in the number of truck crashes while holding all variables in the model constant. This warning sign is important on downgrades due to the winding nature of such terrain that also require low operating speeds.

Elasticity Analysis of Warning Signs Impact on Truck Crashes

An analysis of the elasticities suggests the directional and speed advisory sign have the highest effect on decreasing truck crashes. A one percent increase in the frequency of directional and advisory speed sign was found to be associated with a 16.8 percent reduction in truck crashes. Hill combination with downgrade and distance advisory signs were found to be associated with an 11.1 percent reduction in truck crash frequency, while truck escape ramp signs decreased truck crashes by 5.7 percent. Figure 53 shows a bar chart of elasticity of variables associated with decreasing truck crashes on downgrades.

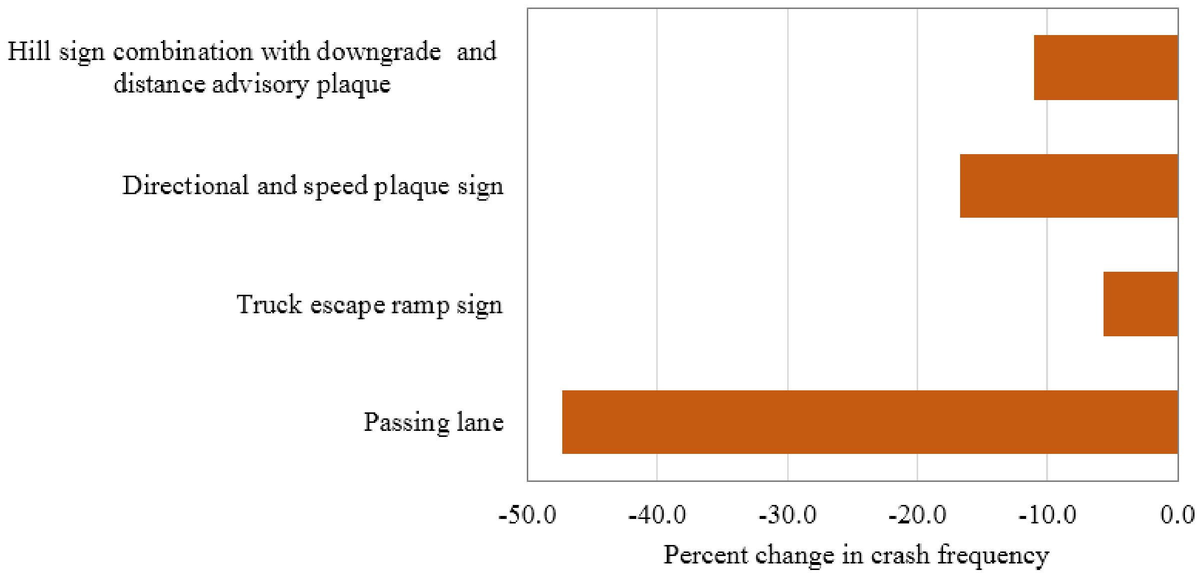


Figure 53. Graph. Bar Chart for Elasticities of Variables (Truck Crashes).

Effects of Variables on Other Vehicular (Non-Truck) Crash Frequency

The second analysis identified variables that impact other vehicular crash frequency on downgrades, and these variables included curve length and type, superelevation, tangent length, presence of passing land, ADTT, hill sign, directional and speed advisory sign, and Chevron warning sign. Table 15 and Table 16 show the negative binomial model and elasticity results for variables impacting non-truck crashes on downgrades.

Roadway and Traffic Characteristics Impacts on Downgrade Non-Truck Crashes

The analysis of the results (Table 15) suggests that downgrade length, superelevation, and ADTT are associated with an increase in non-truck crash frequency. Horizontal tangent length, curve type, and passing lane presence decrease the frequency of non-truck crashes.

The results indicate that a unit increase in downgrade length will increase the frequency of truck crashes by a factor of 38.6, while superelevation increases crashes by a factor of 1.08, and ADTT was found to increase crash frequency by a factor of 1.02 while holding other variables in the model constant. The results suggest sag and crest curves decrease non-truck crash frequency by 12.1 percent and 15.7 percent respectively in comparison to level sections. Horizontal tangent length and the presence of a passing lane were found to decreases non-truck crashes by 1.19 and 17 percent respectively while holding all other variables in the model constant.

Table 15. Prediction Model for Non-Truck Crash Frequency

Parameter	Category	Estimate	Standard Error	Wald chi-square	P-value
Intercept		1.538	0.1456	111.59	<.0001
Downgrade length		0.036	0.0053	46.29	<.0001
Curve type	Sag	0.130	0.0852	2.33	0.1266
	Crest	-0.171	0.0863	3.92	0.0477
Superelevation		0.074	0.0174	17.86	<.0001
Horizontal tangent length		-0.012	0.0006	4.98	0.0257
Passing lane		-0.190	0.1010	3.55	0.0595
ADTT		0.002	0.0005	16.50	<.0001
Presence of downgrade warning sign		-0.3271	0.0965	11.49	0.0007
Hill Sign (W7-1)		-0.506	0.1381	13.43	0.0002
Directional and speed advisory sign		-0.0842	0.0170	24.5	<.0001
Chevron warning sign		-0.1129	0.0578	3.82	0.0501
Model Fit Statistics					
Dispersion		1.2593	0.062	440.51	<.0001
AIC		6540			
Log Likelihood		8621			

Table 16. Elasticity of Variables Influencing Non-Truck Crashes

Parameter	Elasticity or Pseudo Elasticity (percent)
Downgrade length	19.90
Curve type (sag)	12.19
Curve type (crest)	-15.72
Superelevation	2.90
Horizontal tangent length	8.63
Passing lane	-17.30
ADTT	34.60
Presence of warning sign	-27.89
Hill Sign (W7-1)	-9.11
Directional and speed advisory sign	-9.50
Chevron warning sign	-2.42

The elasticity of the significant variables show that ADTT had the highest impact on non-truck crash frequency. A one percent increase in truck traffic was found to be associated with a 34.6 percent increase in non-truck crash frequency. Downgrade length, the presence of a sag curve, horizontal curve length and superelevation were associated with 19.9 percent, 13.9 percent, 8.6

percent, and 2.9 percent increase in non-truck crashes respectively for an associated one percent increase in these variables. The presence of a crest curve was associated with a decrease in non-truck crashes by 15.72 percent in comparison to level sections on the downgrade.

Warning Sign Impacts on Downgrade Non-Truck Crashes

The effects of warning signs on non-truck crash frequency is discussed below.

Presence of downgrade warning signs

This category of warning signs include only downgrade-specific or truck-specific warning signs (truck escape ramp signs, truck speed signs, etc.) installed predominantly on hills. For this analysis, the advance signs were considered present if they were installed 0.5 miles or less in advance of downgrades. They exclude speed limit, directional, Chevron, lane merges, and high wind warning signs. This categorical variable was created to assess the impact of general downgrade signs on crashes. The analysis of the results indicate the presence of downgrade warning signs decreases non-truck related crashes ($\beta = -0.3271$). Increasing the presence of such signs was found to decrease crashes by 27.89 percent while holding all variables constant. This is an indication that the downgrade warning signs specified are effective in preventing non-truck crashes even though they are targeted at larger vehicles crashes.

Directional and Speed Combination Advisory Sign

The results of the analysis indicate that there is a negative association between the directional and speed combination advisory sign and non-truck crashes. The parameter estimate ($\beta = -0.0842$) suggests a unit increase in signs of this type will result in a decrease in non-truck crash frequency by 8.1 percent while holding all the other variables in the model constant.

Hill Signs (W7-1)

The hill sign was found to be negatively related to non-truck crashes on downgrades. The results show that by adding a hill sign, the expected frequency of non-truck crashes will decrease by about 43 percent. The impact of hill signs on non-truck crashes may be because the presence of this sign indicates locations with truck presence. This may in turn lead to a reduction in speeds and an adoption of caution by drivers of vehicles leading to an improved safety on sections with the warning sign.

Chevron Warning Sign

The negative association of Chevron warning signs installed before downgrades with non-truck crashes indicates that sections with higher numbers of Chevron warning signs generally experience fewer crashes. The results suggest installing a Chevron sign in advance of a downgrade will lead to about an 11 percent reduction in non-truck crashes while holding all other variables constant (Table 15). This is expected because Chevron warning signs which alert drivers to sudden changes in horizontal alignment are associated with a decrease in travel speeds in order to safely negotiate such geometric changes. Reducing speed while traveling over mountain passes is highly recommended to decrease the probability of run-off road crashes. Other studies have confirmed this finding where Chevron signs have been found to reduce crashes by up to 50 percent. (Lalani, 1992).

Elasticity Analysis of Warning Signs Impact on Non-Truck Crashes

The elasticity analysis shows that the presence of general downgrade warning signs have the highest impact on non-truck crashes (27.89 percent). Hill, directional and speed advisory, and Chevron warning signs were found to decrease crash frequency by 9.11 percent, 9.50 percent and 2.42 percent respectively for a one percent increase in the frequency of those signs. A bar chart showing the elasticity of those variables which decrease the frequency on non-truck crashes on downgrades is shown on Figure 54.

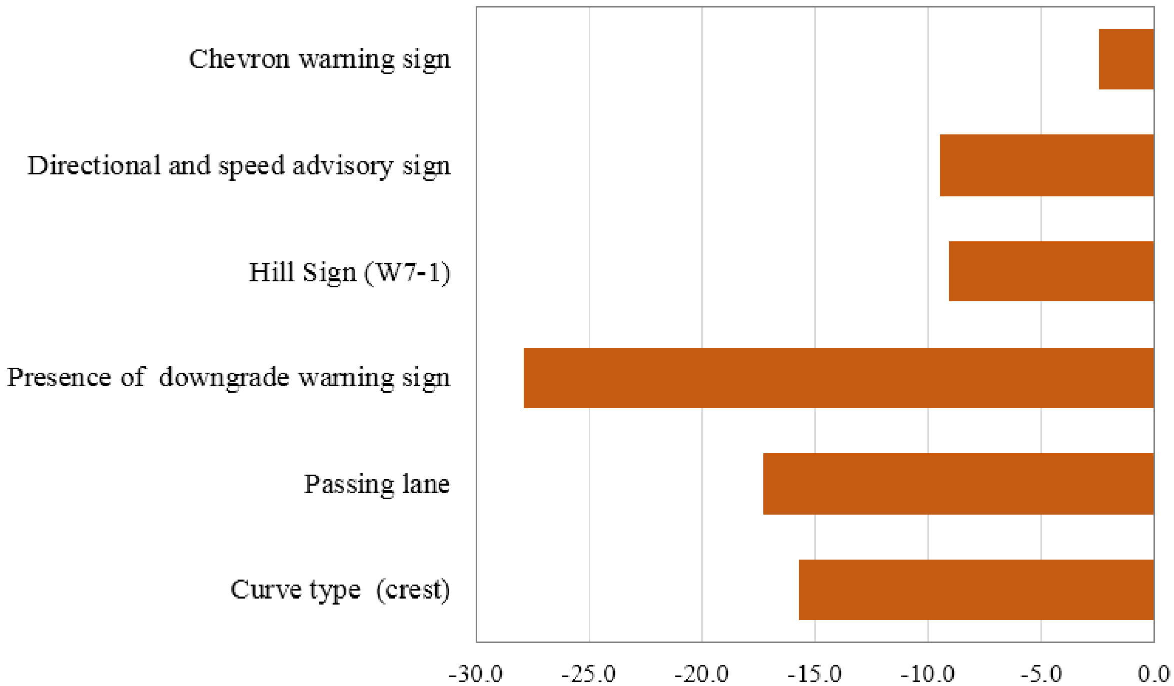


Figure 54. Graph. Bar Chart for Elasticities of Variables (Non-Truck Crashes).

Summary of Warning Sign Effectiveness Analysis using the NB Model

The analysis of the safety effectiveness of warning signs in reducing both truck and non-truck crashes revealed both expected and unexpected results. For truck crashes, warning signs within the downgrade section, and miscellaneous signs were found to be associated with an increase in truck crashes. This was attributed to their possible installation on hotspots. Truck escape ramp signs, directional and speed signs, and hill sign combinations with downgrade percentage plaques decreased truck crash frequency on downgrades. An analysis of the elasticity of the variables indicated that directional and speed warning, truck escape ramp and hill sign combinations were most effective in decreasing truck crashes.

For non-truck crashes, Chevron, directional and speed advisory plaques, hill, and presence of downgrade warning signs were found to be effective in reducing non-truck crash frequency. In terms of the elasticity analysis, the presence of a downgrade warning sign had the highest impact on reducing crashes (27.89 percent), with directional and speed advisory signs and the hill sign having decreasing effects of about 9 percent each for a one percent increase in the frequency of those warning signs. Chevron warning signs had a 2.42 percent decreasing effect on non-truck crashes for a one percent increase in their numbers installed.

RANKING OF SEGMENTS

This section discusses the ranking of downgrade segments of mountain passes in terms of safety. An SPF was calibrated using the NB model to predict truck crash frequencies on mountain passes in Wyoming as part of the ranking procedure.

A comprehensive discussion on the steps outlined in the HSM for the ranking procedure can be found in the methodology chapter. Table 17 shows the statistical results for the NB fitted estimates for truck crashes. The dependent variable used to calibrate the SPF was the frequency of truck crashes in a segment and the independent variables were various roadway features. The fitted estimates show that length, number of access points, presence of a passing lane and ADTT are significant predictors of the number of truck crashes on mountainous roads.

Negative Binomial Safety Performance Function Calibration

From the calibration of the SPF, length and LN(ADTT) have positive estimates indicating a positive relationship with truck crash frequency (Table 17). Number of access points and passing lane are negatively associated with truck crash frequency. The negative effect of the number of access points on truck crashes may be due to increased urbanization which results in caution and a reduction of speed. The presence of passing lanes also reduces crashes as driving conditions improve due to an increase in the number of lanes. The exposure variables downgrade length and LN(ADTT) have a positive relationship with truck crash frequency as expected.

Table 17. Calibrated Safety Performance Function

Total Crashes				
Variable	**Estimate**	**Standard Error**	**Wald Chi-Squared**	**p-Value**
Intercept	-3.7385	0.5002	55.87	<.0001
Downgrade length	0.4633	0.0787	34.66	<.0001
Number of driveways	-0.2232	0.0838	7.09	0.0077
Presence of passing lane	-0.7182	0.2383	9.08	0.0026
LN(ADTT)	1.041	0.1259	68.36	<.0001
Dispersion	0.603	0.1759		

The equation in Figure 55 shows the mathematical representation of the SPF used to predict crash frequencies for 2-lane highways on mountainous roads in Wyoming.

$$SPF = [\exp(-3.739 + 0.4633 * Downgrade\ length - 0.223 * Number\ of\ Driveways \\ - 0.718 * Passing\ Lane + 1.041 * LN(ADTT)]$$

Figure 55. Equation. Safety Performance Function.

Ranking of Sites Based on the Expected Av. Crash Frequency with EB Adjustment

The SPF equation in Figure 55 was used in the analysis of the expected average crash frequency with EB adjustment method. The calibrated SPF was used to calculate the expected crash frequency for the study segments using this approach.

From the results, segments with adjusted crash frequencies greater than the overall crash average of 0.52 were flagged for further investigation. Table 18 shows the ranking results for those segments (with final year frequencies above the average) based on the expected average crash frequency with EB adjustment. It may be noted from Table 18 that US-14 is the only road with multiple segments having adjusted crash frequencies greater than 2, which makes this route a safety concern for truck traffic. Other notable routes were WY-28 and US-16 having multiple sections with crash frequencies greater than one.

Table 18. Ranking Based on the Expected Av. Crash Frequency with EB Adjustment.

Rank	Section Number	Route Name	Downgrade Beginning MP	Downgrade Ending MP	Length	Final Year Expected Average Crash Frequency
1	48	US14	72.88	75.17	2.29	2.92
2	49	US14	75.20	75.70	0.50	2.23
3	44	US14	68.70	71.90	3.20	2.05
4	14	WY28	56.15	57.31	1.16	1.63
5	41	US14	25.94	21.56	4.38	1.41
6	15	WY28	58.38	62.34	3.96	1.32
7	52	WY22	11.08	5.35	5.73	1.23
8	29	US16	83.10	86.93	3.83	1.13
9	22	US16	38.35	33.70	4.65	1.09
10	46	US14 Alt.	68.44	73.59	5.15	0.78
11	53	WY22	11.08	13.68	2.60	0.77
12	21	US16	42.01	39.03	2.98	0.56
13	12	WY28	45.60	46.60	1.00	0.54
14	23	US16	55.63	58.99	3.36	0.52
15	7	US287	419.48	419.20	0.28	0.52
16	13	WY28	53.55	55.24	1.69	0.52

After the flagging of hazardous segments, the routes were weighted using length.

Table 19 presents the weighted score of the combined segments of each route based on a weighted average of length and EB adjusted crash frequencies. The results indicate that WY-22 has the highest rank score followed by WY-28, US-14, US-16 and US-287. This indicates that WY-22 has the highest potential for improvement in terms of reducing truck crashes. US-287 requires the least improvement based on these results. What this indicates is that the warning sign types and placement on US-16 and US-287 may be contributing to safety on these mountain routes.

Table 19. Route Ranking based on Expected Av. Crash Frequency with EB Adjustment

Route Name	Rank Score
WY-22	1.08
WY-28	0.82
US-14	0.77
US-16	0.60
US-287	0.32

Ranking of Sites Based on Equivalent Property Damage Only (EPDO) Scores

An EPDO ranking was carried out as a supplement to the EB adjusted expected crash frequency ranking procedure by providing an economic value to the ranking. Table 20 shows the cost and weight based on the severity of each crash as defined in the HSM. (AASHTO, 2010). The results from the EPDO analysis are shown below in

Table 21. The EPDO results were normalized with length and are shown in Table 22.

Table 20. EPDO Severity Weights (AASHTO, 2010)

Severity	Cost	Weight
Fatal (k)	$4,008,900	542
Injury(A/B/C)	$82,600	11
PDO (O)	$7,400	1

Based on the results shown in Table 23, ML2000B from WY-22 is attributed as the most hazardous segment in economic terms; more than three times higher than the consecutive segments. All five routes considered are represented in the top five flagged segments, with US-14 contributing five out of the top 10 hazardous segments based on the EPDO results.

WY-22 had several recorded fatalities. It also has very challenging terrain with average grades of 6 percent and 8 percent in two different directions. It is therefore no surprise it has the highest EPDO rank score. US-14 is the second most hazardous route followed by WY-28, US-16, and lastly, US-287. Table 23 shows the normalized EPDO results. WY-22 has the highest weighted rank score for all the road segments, and second is US-14. The results of the EPDO analysis was found to be similar to the expected average crash frequency with EB adjustment. US-287 consistently has the lowest rank score from the two methods, meaning this section has the least potential for improvement. This also implies US-287 may be the most safe highway route of the mountain passes analyzed.

Table 21. Ranking of Segments Based on EPDO

Rank	Section Number	Highway Section	Route Name	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length (Miles)	EPDO
1	52	ML2000B	WY-22	Decreasing	11.08	5.35	5.73	1683
2	44	ML37B	US-14	Increasing	68.7	71.9	3.2	589
3	7	ML23B	US-287	Decreasing	419.48	419.2	0.28	559
4	19	ML 36B	US-16	Decreasing	67.0	65.5	1.5	544
5	11	ML14B	WY-28	Increasing	34.39	35.04	0.65	543
6	47	ML35B	US-14 Alt.	Decreasing	74.08	77.55	3.47	86
7	46	ML35B	US-14 Alt.	Decreasing	68.44	73.59	5.15	79
8	15	ML14B	W-Y28	Increasing	58.38	62.34	3.96	55
9	41	ML37B	US-14	Decreasing	25.94	21.56	4.38	36
10	48	ML37B	US-14	Increasing	72.88	75.17	2.29	36

Table 22. Ranking of Segments Based on EPDO Normalized by Length

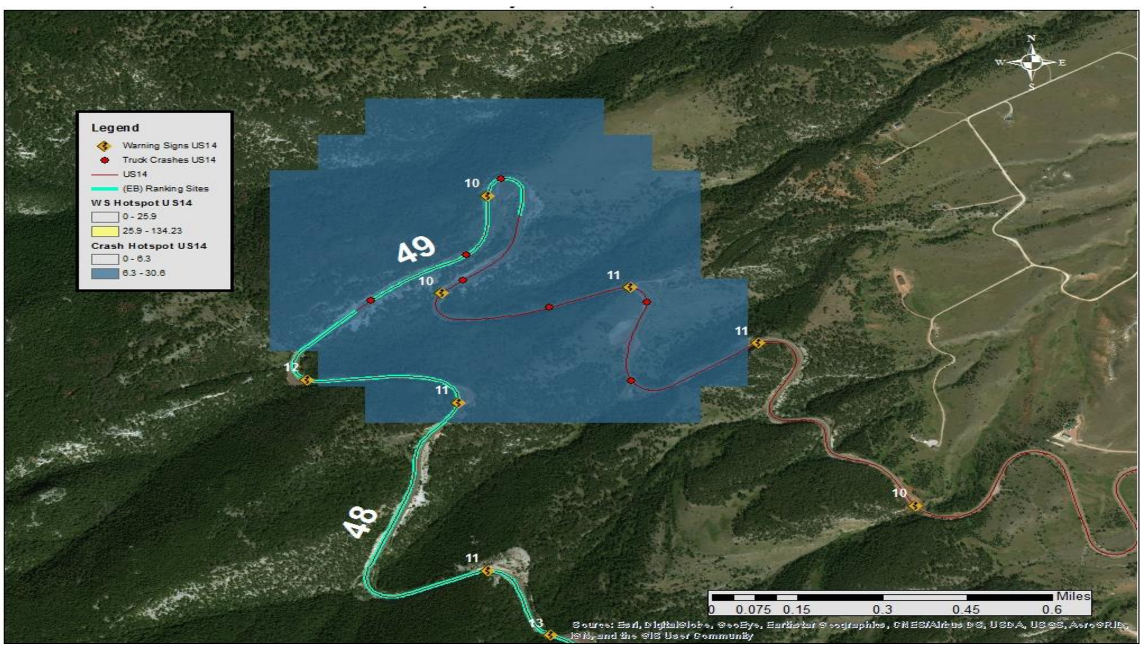
Rank	Section Number	Highway Section	Route Name	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length (Miles)	EPDO	EPDO /Mile
1	7	ML23B	US-287	Decreasing	419.48	419.2	0.28	559	1996
2	11	ML14B	WY-28	Increasing	34.39	35.04	0.65	543	835
3	19	ML 36B	US-16	Decreasing	67.0	65.5	1.5	544	363
4	52	ML2000B	WY-22	Decreasing	11.08	5.35	5.73	1683	294
5	44	ML37B	US-14	Increasing	68.7	71.9	3.2	589	184
6	49	ML37B	US-14	Increasing	75.2	75.7	0.5	27	54
7	47	ML35B	US-14 Alt.	Decreasing	74.08	77.55	3.47	86	25
8	12	ML14B	WY-28	Increasing	45.6	46.6	1	24	24
9	42	ML37B	US-14	Increasing	58.69	59.24	0.55	11	20
10	14	ML14B	WY-28	Increasing	56.15	57.31	1.16	23	20

Table 23. Ranking of Routes Based on EPDO Scores Normalized by Length

Route Name	Rank Score
WY-22	5.67
US-14	2.64
US-16	1.63
WY-28	0.73
US-287	0.29

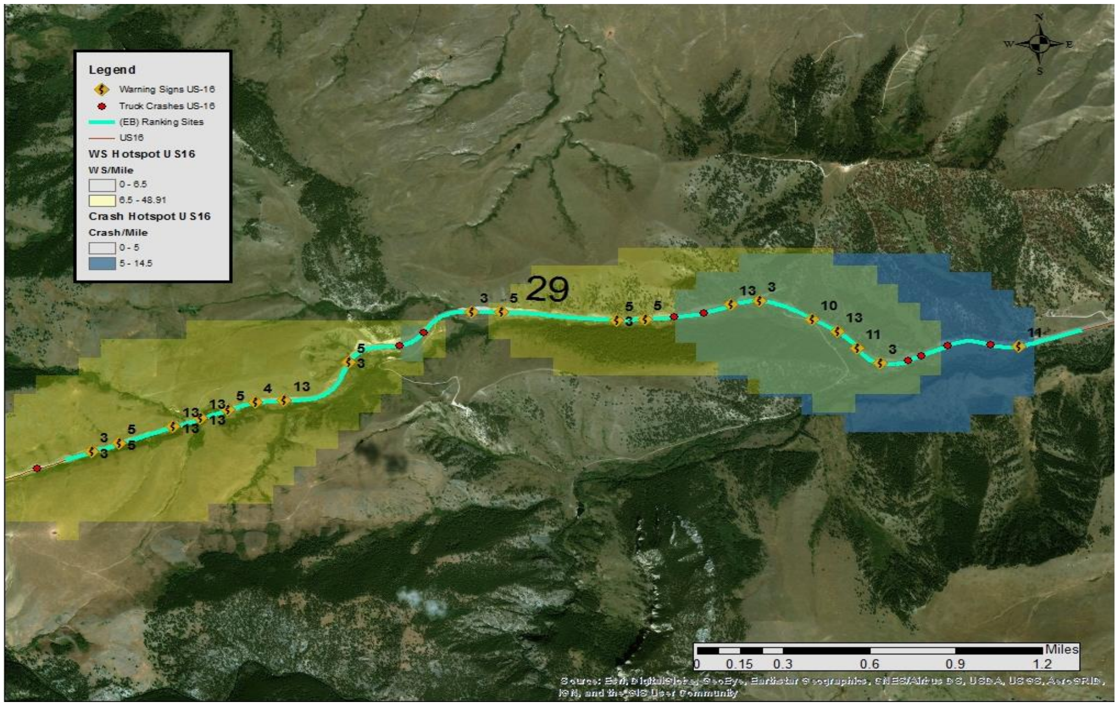
HOTSPOT ANALYSIS

A hotspot spatial analysis was conducted on study areas in the selected mountain passes to assess the relationship between locations with high truck crash frequency and warning sign density. This was done to assess the overlap of warning sign and truck crash densities. The hot spot analysis was carried out for only sections with a final year expected crash frequency with EB adjustment equal or greater than the average for the sections evaluated as was shown on Table 18. The procedure was carried out using the kernel density spatial analysis function of the ArcGIS software. Crash densities on segments were mapped out along with warning sign densities. The hotspots were generated based on threshold values found from the average rates of crash/mile and warning signs/mile for each of the sections. (Erdogan et al., 2008). The hotspot analysis highlighted the placement of warning signs in relation to hazardous sections within the segments identified from the ranking assessment. This analysis aimed to assess if warning signs have been properly placed with regards to hazardous locations. As an example, a segment of US-14 (site 49) shown in Figure 56 Original Photo: © 2018 ArcGIS® (see Acknowledgements section). Figure 56was found to be one of the hazardous segments in the studies, yet lacked a strong presence of warning signs when compared to a similar well treated segment on US-16 (site 29) in Figure 57.



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 56. Diagram. US-14 (Site: 49) Hotspot Map (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 57. Diagram. US-16 (Site: 29) Hotspot Map (ESRI, 2018).

US-16

The hotspot analysis for hazardous locations with high truck crashes on US-16 generally showed a good intersection between truck crash and warning sign density. This can be seen on hotspot maps shown in Appendix 6 for US-16. For example, on site 29, located within the downgrade section within mileposts 83.1 to 86.9, it can be seen that the location of truck crashes and placement of warning signs intersect. This good intersection can again be observed for site 22 located within mileposts 42.0 to 39.03, where downgrade warning signs were installed at dangerous truck crash locations.

US-14

From the hotspot analysis, for sites with high truck frequencies evaluated for US-14, it was found that the warning sign density did not generally intersect with truck crash densities. This may indicate that warning signs are not placed at locations of truck crashes. A typical example is on site 49, located within mileposts 72.9 to 75.2 (Appendix 6). Some locations on this section where truck crashes were relatively high did not have downgrade warning signs. Other signs such as directional and speed warning signs were limited in the numbers installed. Other locations had a good presence of downgrade warning signs but were installed away from locations of high truck crashes. This can be observed on site 41 located within milepost 25.9 to 21.6. An analysis of the installation locations of downgrade warning signs on sections analyzed for this route also showed that most downgrade warning signs were installed at the beginning of the downgrades, with few or none installed within the downgrade section. Chevron warning signs were also found not to be consistently installed on some curved sections of this route.

WY-28

The results of the hotspot analysis showed that a proper number of downgrade warning signs were installed on some hazardous locations while others did not have such signs. Some hazardous locations that had recorded truck crashes had no downgrade warning signs installed. This can clearly be seen on sites 12, and 13 located within sections within mileposts 45.6 to 46.6, and 55.2 to 53.6. Other locations such as sites 14 and 15 located on sections with mileposts 56.1 to 57.3, and 58.38 to 62.34, had a good presence of downgrade warning signs.

US-287

Only one section of US-287 was flagged as a hazardous location from the ranking based on the expected average crash frequency with EB adjustment (MP 419.5 to 419.2). This section is about 0.3 miles. The section includes the beginning of the divided highway in the decreasing milepost direction. The analysis of this section showed that no downgrade warning signs were installed despite the presence of truck crashes.

WY-22

The hotspot analysis of hazardous sites found on WY-22 indicated that there was a good presence of downgrade warning signs. There was also a good intersection between warning sign and truck crash density. This can be seen on site 53, located within mileposts 11.1 to 13.7, where the warning sign densities intersect truck crash densities. The results of this analysis was observed on the field. WY-22 has a lot of advance downgrade warning signs in both downgrade directions.

Summary of Hotspot Analysis

The hotspot analysis for hazardous downgrades showed that the geometric characteristics, and crash locations of the mountain passes were in most cases not taken into account when the warning signs were installed. The MUTCD provides recommendations for warning sign placement based on criteria, such as radius and lengths of curve, speed, and other characteristics. The recommendations provided by the MUTCD were compared with the present warning sign system in each of the hazardous locations. The analysis suggests that downgrade truck warning signs should be placed more frequently and consistently in hazardous areas to warn and guide drivers.

The hotspot analysis also indicated that warning signs are sparsely installed on some downgrades. There were sections characterized by steep downgrades and curves with only a few downgrade signs. An example of this was found on WY-28 has some long downgrades without downgrade signs. Critical warning signs such as Chevron and directional signs combined with supplementary speed signs were sometimes not installed at dangerous locations characterized by sharp curves. Other downgrades had only a few warning signs to notify drivers of the continuous nature of the grade. Examples were found on several downgrades on US-14.

The hotspot analysis also suggests that on some downgrades, a lot of warning signs are installed up the grade with few or none installed within the downgrade section. Again, US-14 had such characteristics. The end downgrades tend to be the locations of brake fade and runaway events. However, there were sometimes no warning signs installed. Additional hotspot maps for other sites listed in the ranking procedure are located in Appendix 6.

DATA ANALYSIS SUMMARY

This chapter discussed the results for the various analyses conducted for the study. Warning sign effectiveness on these routes was measured using two methods. First, a propensity score matching analysis was used to evaluate the safety effectiveness of advance warning signs on mountainous downgrades for trucks. A propensity score model was first calibrated. Matching of sites with and without the warning signs was carried out. Binary logistic models were then calibrated each for the matched treated and untreated observations. A risk ratio computed from the logistic regression models indicated that downgrade grade segments without advance warning signs experience 15 percent more crashes compared to segments without warning signs based on a caliper value of 0.5 times the standard deviation of the propensity scores of the treated group.

A negative binomial model was calibrated to evaluate the safety effectiveness of downgrade signs in preventing truck crashes. The analysis indicated that directional and speed, hill sign combination with distance plaques and truck escape ramp signs were effective in reducing downgrade truck crashes.

Ranking analyses were undertaken using the expected average crash frequency with EB adjustment and EPDO to assess the safety of the mountain routes. WY-22, US-14 and WY-28 were identified as having the most truck crashes and economic losses of the mountain pass routes analyzed. On the other hand, US-287 was found to have the best safety ranking which may be attributed to the system of warning signs installed on it.

Finally, a hotspot analysis was conducted with the results being used to assess the relationship between warning sign placement and truck crash locations. GIS maps were produced as part of this analysis. It was concluded that the warning sign placement on some downgrades was sparse. The analysis also showed that warning signs on some routes were installed away from locations of high crash density.

CHAPTER 6: POTENTIAL AND CURRENT USE OF ITS TECHNOLOGIES IN PREVENTING DOWNGRADE TRUCK CRASHES

This chapter discusses the use of Intelligent Transportation Systems (ITS) in reducing the incidence of truck crashes on downgrades. Potential and current applications of ITS are discussed.

INTELLIGENT TRANSPORTATION SYSTEMS

The ever-increasing need to efficiently move people, goods and services has meant a greater reliance on the transportation infrastructure. The result has been that the transportation infrastructure in most developed countries is burdened. Despite an increase in spending, new road facilities in major cities have been confronted with growing traffic congestion, accompanied by unpredicted emergencies, crashes, pollution and rapidly deteriorating infrastructure. Such inefficiencies cause enormous loss of time, degradation in the quality of life, huge waste of non-renewable fossil fuel with attendant release of carbon dioxide, and an increased safety risk for both vehicles and pedestrians. (Steger-Vonmetz, 2005). It has been clear for some time that these problems have not been solved by building more roads or relying on other traditional approaches. Innovative efforts are required on a broader front to tackle the issues highlighted above. Among such initiatives is a concept known as Intelligent Transportation System (ITS). ITS applies information, communications, and control technologies to improve the operation of transportation network. (PIARC Committee on Intelligent Transportation, 1999).

In the field of traffic safety, ITS helps reduce crashes by employing technologies to warn drivers of impending hazards, speed advisories, in-vehicle systems to avoid, prevent crashes and as an enforcement tool. Current and potential infrastructure as well as vehicle-based ITS solutions to truck crashes on mountain passes are reviewed as part of this study.

POTENTIAL ITS APPLICATIONS TO REDUCE THE INCIDENCE OF TRUCK CRASHES ON DOWNGRADES

Potential use of ITS applications to reduce the incidence of downgrade truck crashes are discussed in this section. This is discussed under infrastructure- and vehicle-based systems.

Infrastructure-Based ITS applications

Infrastructure-based ITS technologies refer to the use of infrastructure with ITS applications. These include virtual weigh-in-motion technology, downhill warning systems, curve and truck rollover warning systems and infrastructure-based thermal imaging of brakes.

Virtual Weigh-in-Motion Technology

Overloaded trucks on mountain passes are more likely to be involved in crashes with greater consequences compared to legally loaded trucks. Heavier loaded vehicles have higher kinetic energy, resulting in greater impact forces and damage to other vehicles or infrastructure when a crash occurs. (Jacob and Beaumelle, 2010). Due to the threats posed by overloaded trucks to road safety, enforcement agencies strive to enforce and monitor weight limits of trucks. The traditional approach to enforcing weight limits is static weighing. Static weigh bridges are constructed at different locations to measure gross vehicle weight and wheel or axle loads. There are three types of static weighing devices: fixed, semi-portable and portable systems. (Jacob and

Beaumelle, 2010). Over the past decades, an increased movement of freight has caused the demand of weigh stations to increase beyond the capacity of traditional weight stations, which affects the efficient movement of trucks through these stations. This may also result in queueing of trucks onto mainlines posing safety risks. Such situations are also known to force stations to clear queues, which may allow overloaded trucks to pass without notice. Advances in technology has allowed the development and growth of weigh-in-motion (WIM) systems to augment static weigh stations. A virtual WIM is an enforcement system that does not require continuous staffing and is monitored from another location. A virtual WIM is a non-intrusive, unmanned, automated data collection from a distance. This technology, which collects real time data, is meant to complement fixed scale stations but not to replace them. (Rivera et al., 2006). Virtual WIM systems integrate wireless communications, remote cameras, electronic transponders, optical character recognition (OCR) cameras, license plate reader (LPR) technology to support enforcement by screening targets and focusing on vehicles in violation. (Rivera et al., 2006).

Virtual WIM systems can be used as tools to prevent downgrade truck crashes by enforcing load limits. The minimum requirement for a virtual weigh system to be functional requires the deployment of (Capecci et al., 2009):

- WIM scales or sensors;
- Camera (digital imaging) system;
- Screening software;
- Communication infrastructure, which makes the data from the WIM system available to authorized users (e.g. mobile enforcement).

The basic layout of the virtual weigh station is shown in Figure 58. The basic operational procedure for the virtual WIM proceeds by weighing trucks on the WIM scale. A picture of the vehicle is taken and aggregated with the weight data and then sent to a mobile enforcement officer downstream of the system. Overweight or heavy vehicles noncompliant with safety are flagged by a mobile office downstream the WIM scale. The vehicle may be further inspected and/or weighed. Additional benefits from the virtual WIM includes the ability to collate weather data from trucks that is sent to system operators for real-time traffic management. Also, localized and real-time traveler information may be sent to the truck for integration with on-board systems designed to display information safely to the driver. Data from a virtual weigh station can also be very useful for planning and reporting purposes. The data can also be utilized by motor carriers for tracking of the company's assets and their performance. (Capecci et al., 2009).

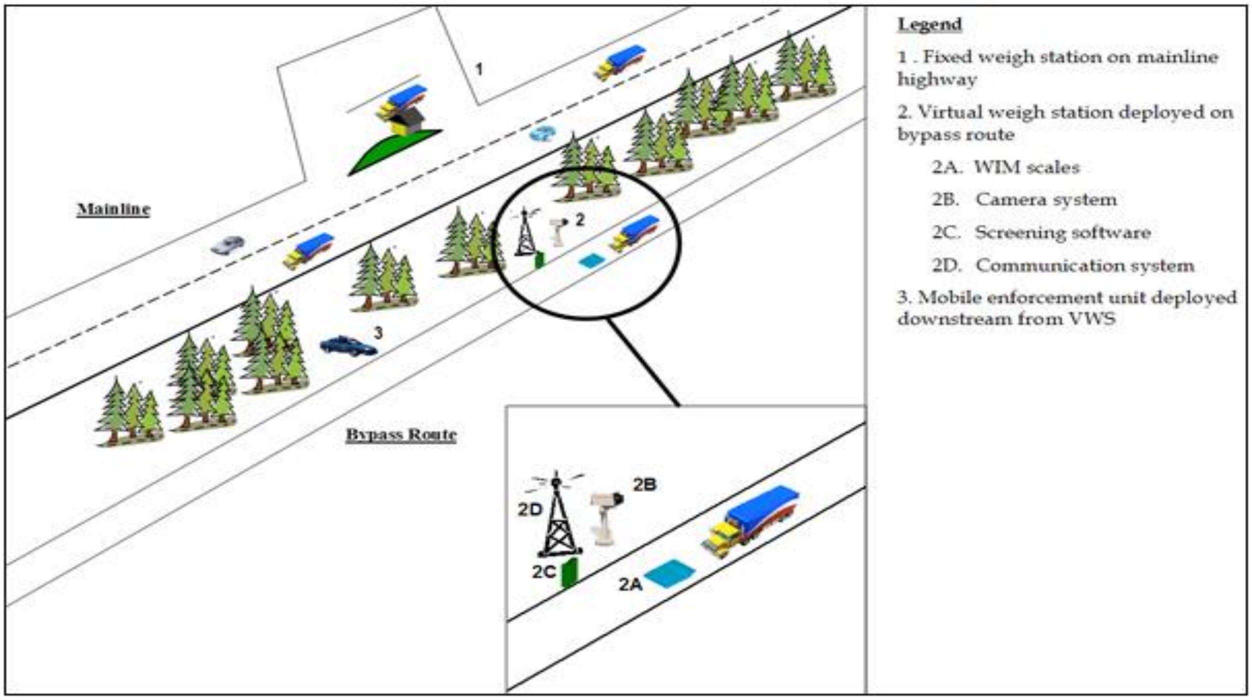


Figure 58. Diagram. Basic Virtual Weigh Station Physical Layout (Capecci et al., 2009).

Automatic Truck Rollover Warning Systems

Truck rollover crashes are prevalent in the United States on mountain passes which are predominantly characterized by sharp horizontal curves. Truck rollovers are associated with severe injury and fatalities in highway crashes. In 2015, about 15 percent of fatal single truck crashes were rollovers. Single truck rollovers accounted for 28 percent of injury crashes and 5 percent of property damage only crashes. (Federal Motor Carrier Safety Administration, 2017).

A host of factors are known to contribute to truck rollover crashes. These include driver inexperience, non-compliance with advisory conditions, driver impairment (fatigue, alcohol, and drugs), environmental effects (wind, blinding sunlight), high center of gravity, load shift, poor brake performance, collapsed suspension and under-inflated tires. (Donnelly, 2008). The most critical measure of the potential of rollover is the static rollover threshold which is expressed as lateral acceleration in gravitational units *(g).* Passenger vehicles predominantly have a threshold greater than 1 g, while light trucks, vans and SUVs have values ranging from 0.8 to 1.2 g. (Winkler et al., 2000). The typical five-axle semi-trailer combination popular on United States roads has a rollover threshold only as high as 0.5g with an optimal high-density, low center-of-gravity load when loaded to legal gross weight. (Winkler et al., 2000). Thus, it is quite clear that trucks are more susceptible to rollover crashes than light vehicles because trucks are more likely to inadvertently be operated beyond the rollover threshold.

Static warning signs that depict a tipping truck with an advisory speed are usually installed to alert drivers about rollover hazards. Generally, highway users become desensitized to static warning signs leading to reduced compliance. This is due to the fact that such signs convey the same message to all users regardless of actual risk. (Donnelly, 2008). The rollover warning signs can go undetected by drivers or ignored in cases where the need for low apparent speed is not obvious. Strategies adopted to improve the attention-grabbing value of these warning signs have included adding flashing beacons and manually activating speed actuated lights when speeds have exceeded predetermined maximum speeds. (McGee et al., 1992).

Automated Truck Rollover Warning Systems (ATRWS) have been in development for some time. These use ITS technologies to provide an automatic assessment of rollover risks to approaching vehicles. A warning message is activated once the risk is identified. The message may be displayed on a VMS or by activating a flashing light which alerts drivers to the potential risk.

ATRWS consider various factors that contribute to rollover conditions, such as vehicle type, speed, weight and height and determines if an approaching vehicle is exceeding the estimated rollover threshold. (Donnelly, 2008). Recent ATRWS algorithms incorporate additional vehicle parameters such as live load, non-live load, and vehicle configuration into the rollover threshold equation. This significantly improves the accuracy and effectiveness of the rollover warning system. (Baker et al., 2001). Such an algorithm has been developed by The University of Michigan Transportation Research Institute (UMTRI). (McGee et al., 1992; Strickland and McGee, 1997). The basic detection and classification system includes (Donnelly, 2008):

- A vehicle classification detection to identify approaching trucks. In-pavement WIM detectors may be installed to determine vehicle classification and weight.
- Speed detection using in-pavement piezo-electric or radar devices.
- A radar based height detection.
- Overhead VMS displaying both a static truck rollover warning sign with an advisory speed and flashing a set of warning signs when an unsafe condition is detected.

The in-pavement piezo-electric device detects vibrations caused by passing tires and produces an output signal that enables an identification of the size of the vehicle. The WIM detectors analyze the signals to determine the axle weights, spacing between axles, axle group weights, and gross vehicle weight and vehicle classification. Combined with height information from the radar detection device, a safe speed can be computed for each truck to negotiate the curve based on the curve geometry. Other systems enable the inclusion of road geometry into the algorithm for calculation of a safe speed. (Bergan et al., 1997). Figure 59 shows a basic outlay of an ATRWS while Figure 60 shows a simple working ATRWS.

Thermal Imaging of Truck Brakes

Trucks with brake defects are known to increase the risk of a crash. Performing heavy vehicle brake inspections and compliance screening is an effective way to decrease the number of large vehicle crashes. An analysis of the Large Truck Crash Causation Study (LTCCS) revealed that 29 percent of large vehicles involved in crashes had brake defects. (Federal Motor Carrier Safety Administration, 2007). Another study conducted using an Infrared Inspection System (IRISystem) placed 59 percent of vehicles surveyed out of service due to brake issues. (Christiaen and Shaffer, Steve, 2000).

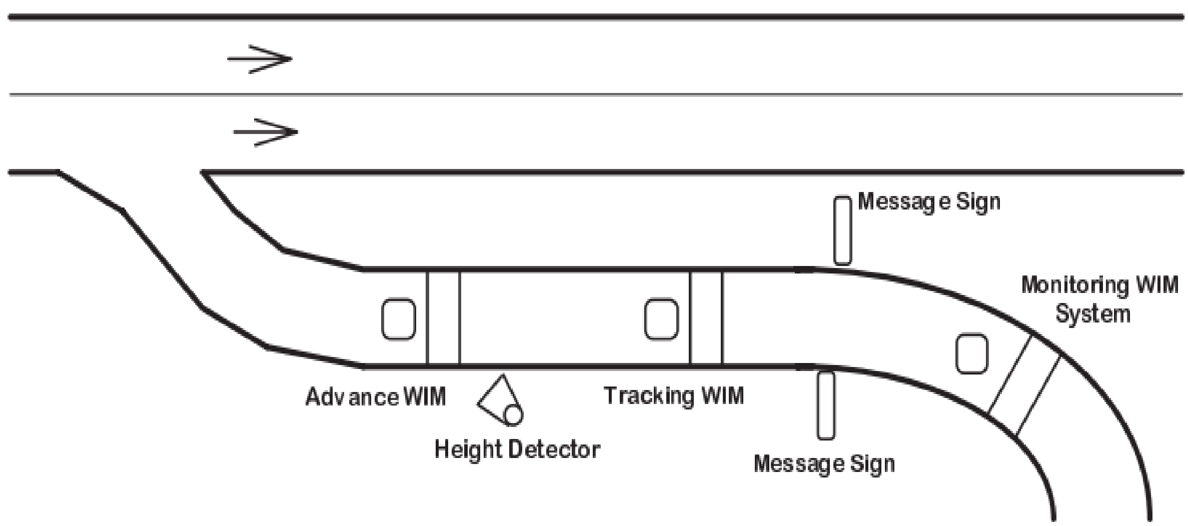


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Figure 59. Diagram. Basic Layout of ATRWS (Bergan et al., 1997).

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Figure 60. Photo. An Activated ATRWS in Canada (Sentinel Staff, 2016).

A possible approach to examining the condition of heavy vehicle brakes is the use of infrared brake screening technology. Abnormally high or low brake temperatures can give an indication of brake systems malfunctioning or having undergone heavy use, which might lead to brake fade. (Eady et al., 2015). The IRISystem, which consists of the brake screening technology integrated into a minivan equipped with an infrared camera and an interior screen display makes road-side screening of large vehicles possible (Figure 61). (Federal Highway Administration, 2003). A screen in the minivan displays thermal images of the wheels, showing their relative temperatures. Functional brakes create heat, so that wheels that are warm appear bright white in the infrared image while the wheels with inoperative (cold) brakes appear dark. The color image helps in the identification of vehicles with functional or inoperative brakes. To achieve effective results, the IRISystem should be placed at sites where trucks must apply their brakes to enter. (Federal Highway Administration, 2003). This makes the system ideal for downgrades where vehicles normally slow down before they start their descent. Vehicles can be screened at speeds less than 10 mph but experienced operators can screen at speeds up to 40 mph.

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Figure 61. Photo. An Infrared Inspection System with an External Infrared Camera (Federal Highway Administration, 2003).

An inspection of heavy vehicle brakes conducted in the year 2000, using the IRISystem placed vehicles out of service by an increase of a factor of 2.5 times compared to conventional screening systems. (Christiaen and Shaffer, Steve, 2000).

The Electronic Machines Corporation (IEM) in conjunction with the United States Department of Transportation, Federal Motor Carrier Safety Administration (FMCSA) and the New York State Energy Research and Development Authority in 2006 began the development of a technology to thermally screen heavy motor vehicle brakes known as the Smart Infrared Inspection System (SIRIS). SIRIS is a roadside tool that assists inspectors in determining if heavy vehicles passing through the screening system are in need of further inspection.

(Siekmann et al., 2014). The temperatures of the brakes, tires and wheel bearing on both wheel ends of a heavy vehicle in motion. The data is analyzed internally by SIRIS before being presented to enforcement personnel on a user-friendly interface inside the inspection station. The enforcement personnel can then carry additional inspection. The roadside components of SIRIS consist of two thermal infrared cameras, a visible camera, a vehicle presence detection sensor, wheel triggers, roadside electronics system control and power management, cross-lane cabling for remote camera system, fiber cable from roadside to a computer, computer system and monitor, and SIRIS software. (Siekmann et al., 2014). The SIRIS roadside components are shown in Figure 62.

SIRIS evaluated 4,373 heavy vehicles in 2009, during the period of August and July on a field operational test. Approximately 63 percent of vehicles flagged by the system were placed out of service. (Siekmann et al., 2014). The impressive results from SIRIS makes it a viable screening tool for use in low-speed applications. However, the overall value of the current SIRIS as an enforcement tool is limited due to operational issues caused by power fluctuation, inclement weather, and unreliability of results at high speeds. (Siekmann et al., 2014).

Other studies have found that handheld infrared cameras can adequately measure temperatures of heavy vehicles. (Green, 2009; Salonen, 2012). This can be achieved by scanning a moving vehicle with one camera on either side of the vehicle to identify brake conditions. In order to achieve reliable results, handheld infrared measurements of wheels on the same axle must be performed in the same way, with the targeted area at the same angle and distance. Measurements must be taken on all axles simultaneously, and as soon as the vehicle has stopped. (Salonen, 2012). It has been noted that the use of infrared cameras is well suited for the control of the brakes of large trucks. However, the use of handheld infrared cameras requires experience and knowledge of the functioning of different brake systems. (Salonen, 2012).

Figure 62. Photo. Driver and Passenger Side Components of SIRIS System (Siekmann et al., 2014).

Vehicle-Based ITS Applications

Vehicle control, safety and navigation systems have advanced over the past decades. Vehicle-based ITS takes advantage of these advancement to reduce downgrade truck crashes. Examples are on-board rollover prevention systems, advance braking systems, and speed alerting and limiting systems.

On-Board Rollover Prevention Systems

On-board rollover prevention systems are installed to reduce the incidence of truck rollovers. Some rollover detection systems from third party vendors can be fitted into trucks. One of such common devices is the LG Alert Rollover Warning System. This product was developed by Stability Dynamics Limited in Ontario, Canada and uses lateral acceleration measured at different locations on the vehicle as the input to determine a rollover threshold. The device has been successful in reducing the incidence of rollovers in aircraft rescue and fighting (ARFF) vehicles. The device has a display module which is mounted within the driver's field of vision and provides visual and audible alarms in response to lateral acceleration increases during cornering maneuvers and operations on side slopes (Figure 63). (Connor, 2007). The sensitivity of the rollover alert system is adjustable to suit many vehicle configurations. The vehicle's safe operating parameters must be identified so that the rollover system can be adjusted to reflect the maximum operating limits under which the vehicle is to be operated. The system helps drivers to stay within safe speed, grade and turning parameters. (Connor, 2007).

Figure 63. Photo. LG Rollover Alert Display Module (Connor, 2007).

In recent years, some truck companies have built electronic stability and anti-rollover devices. These devices concentrate on center of gravity and gravitational forces caused by hard braking and sudden lateral movements. The electronic stability control devices also have sensors to measure steering input and yaw, or side-to-side rotation. (Berg, 2009). The devices are linked to electronic controls and sensors already used by anti-lock braking systems which are now standard on air-braked trucks, tractors and semitrailers. When the electronic controls detect an impending rollover, the devices cut the engine's throttle and apply brakes to slow and recover the vehicle in a matter of milliseconds before the driver even realizes what is happening. (Berg, 2009). Examples of these electronic devices are Electronic Stability Program (ESP) from Bendix, Roll Stability Control (RSC) for trucks and tractors from Meritor Wabco and Trailer Roll Stability (TRS) from Haldex Commercial Vehicle Systems. (Berg, 2009). Figure 64 shows the DAF Vehicle Control Stability System.

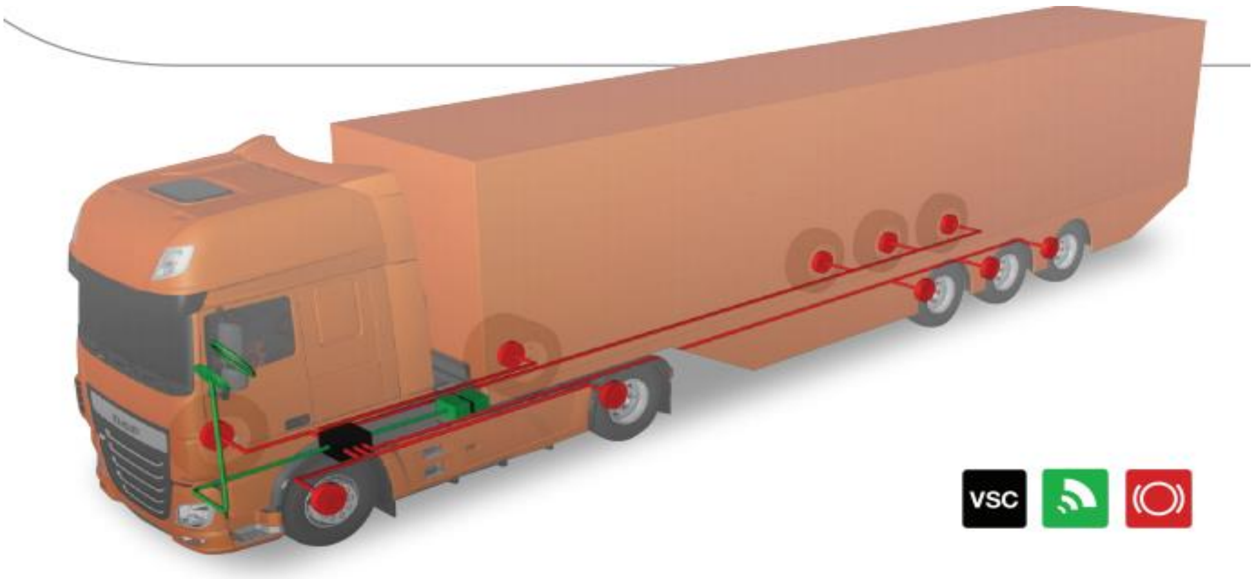

Figure 64. Diagram. DAF Vehicle Stability Control System (DAF, 2015).

Advanced Braking Systems

Heavy vehicles require additional braking effort much different from passenger cars. Addressing this difference entails extra braking interventions. An example of such an intervention is the Electronic Braking System (EBS). The EBS combines the anti-lock braking system (ABS) and traction control into one braking system. ABS ensures braking effort of the vehicle during an emergency maneuver is just below the limit where the wheels begin to lock. If wheel locking begins to occur, the ABS releases the braking force to prevent skidding so that greater control can be maintained resulting in shorter stopping distances. (Eady et al., 2015). EBS replaces air with electronic signals sent by the brake pedal to activate the brakes due to the inherent lag present in air signals, thereby improving stopping distances and braking system performance because of the reduced response time. (Eady et al., 2015). Additionally, the EBS software and hardware are integrated with the Roll Stability System to prevent rollover crashes.

Another form of advance braking assistance is the Advanced Emergency Braking Systems (AEBS) which was mandated in 2015 by the European Union for all new vehicles. (Andersson, 2016). The AEBS warns drivers with an audio alarm when a collision is imminent. If the driver does not respond immediately, the system engages the brakes fully to avoid the crash. AEBS provides brake assist when it detects insufficient force to avoid a collision. This is done by calculating the extra braking force required and the distance to collision with an obstacle ahead. Trucks with AEBS will decelerate as much as possible to prevent a collision or to minimize the impact if one does occur. (DAF, 2015). The AEBS is equipped with both camera and radar sensors mounted on the front of the vehicle to scan for objects ahead. By combining cameras and radars, the system harnesses the strengths of each sensor to gain a more precise environment model. Radar sensors are adept at determining an object's range, relative velocity and solidity but are unable to discern an objects shape or lateral position. Cameras complement the radar sensors by their ability to pinpoint an object's size and lateral position. (Andersson, 2016). Figure 65 shows an overview of AEBS.

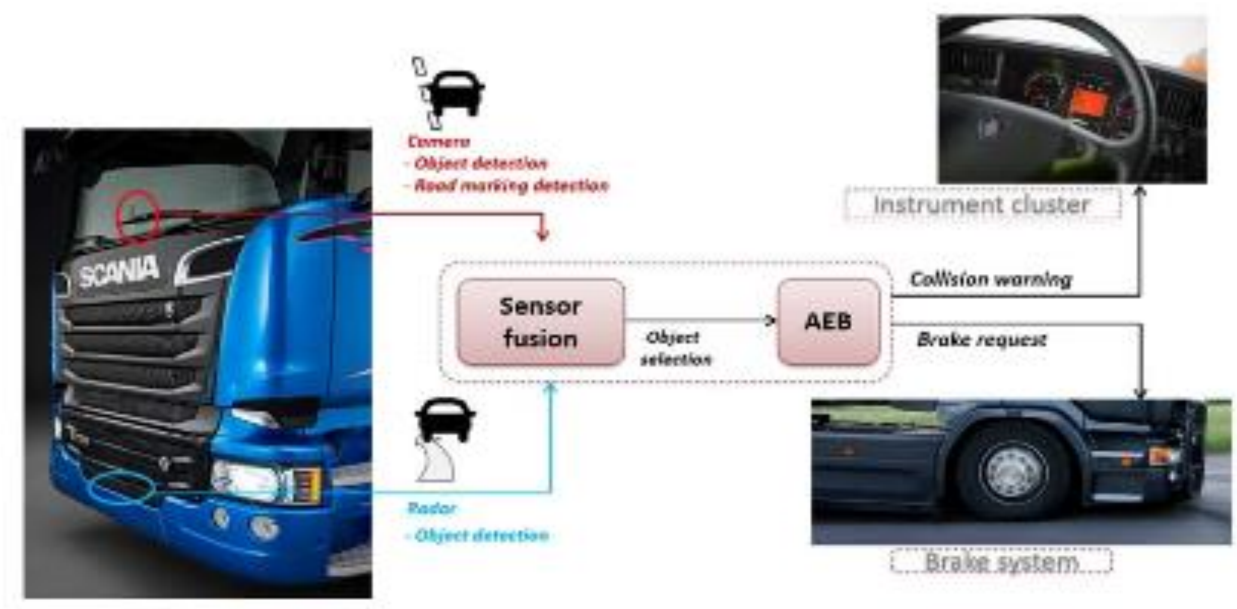

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Figure 65. Diagram. AEBS Overview (Andersson, 2016).

Dedicated Short Range Communication and Connected Vehicle Technology

Dedicated Short Range Communication (DSRC) allows for short to medium range, real-time, low latency wireless communication between vehicles, and between vehicles and infrastructure over the 5.9 GHz frequency channels and is the technology connected vehicles are based on. (Eady et al., 2015). The DSRC technology which is similar to Wi-Fi is fast, secure, reliable, and unlikely to be vulnerable to interference. (United States Department of Transportation, 2010). DSRC unlike Wi-Fi is intended for highly secure, high-speed wireless communication.

A lot of research is being conducted by the NHTSA on the potential benefits of connected vehicles in terms of truck safety. Connected vehicle technology allows cars, trucks, buses and other vehicles to communicate or "talk" to each other over a wireless communication network such as the DSRC. (Hartman, 2009). The technology could also allow for vehicles to wirelessly communicate with transportation infrastructure such as toll booths, traffic signals, and work zones among others. These connected vehicles could automatically alert drivers of potential hazards such as when another vehicle is too close or when a steep downgrade is being approached giving the driver time to react to avoid a potential crash. (Hartman, 2009). The USDOT as part of its research drive initiated the Integrated Truck Safety Program and the Commercial Vehicle Retrofit Safety Device Program to incorporate DSRC technology into a heavy vehicle platform to determine potential applications such as crash avoidance on heavy vehicles. (Hartman, 2009). The applications developed will be interoperable with other vehicle platforms especially light vehicles so that all vehicles will be more aware of each other as they share highways. Some potential benefits of connected vehicle technology include (Eady et al., 2015):

- Intersection collision warning,
- Road condition warning,
- Work zone warning,
- Emergency vehicle pre-emption,
- Curve speed warning.

Current ITS Applications on Downgrades

ITS has been applied on some downgrades in different states with some success at reducing downgrade truck crashes. This section of the report discusses some of these applications.

Downhill Truck-Warning System, Colorado

The Colorado Downhill Truck Warning System was installed in 1998 inside the west-end of the Eisenhower Tunnel. A long downgrade of about ten miles with grades 5 percent to 7 percent follows the tunnel. 125 truck-related crashes were recorded over nine years from 1990 to 1998 on this downgrade. (Janson, 2001). This necessitated instituting measures to prevent or at least reduce the crashes. A first system had been installed 0.3 miles west of the Eisenhower tunnel in 1995 but was relocated because trucks often changed lanes before they could be detected by the sensors causing a large percentage of missed trucks. This system was eventually dismantled and replaced with the current warning scheme. The objectives of the system are to (Robinson et al., 2002):

- Identify vehicle-specific safe operating speeds for long downgrades
- Reduce the incidence runaway truck crashes through real-time driver information
- Modify driver behavior in downgrade descents.

The primary system is made up of inductive loop detectors, a piezoelectric WIM system, and variable message sign. As the vehicle passes over the detectors, its mass is measured using the WIM system, which sends a signal to a primary programmable controller that determines the characteristics of the truck and its passage over the system. These include a time stamp, lane number, vehicle speed, number of axles, axle weights, axle spacing, gross combination mass, and its axle configuration. A safe speed calculated from these characteristics and the downgrade slope is displayed to the driver on a VMS. The VMS is located 250 feet from the loops and WIM sensors. This layout of the system gives the truck drivers 4.2 seconds to read the advised speed before they commence descending the downgrade. (Eady et al., 2015). Figure 66 shows the downhill truck warning system in Colorado.

An evaluation was carried out in 1999 to gauge the effectiveness of the warning system. (Janson, 2001). The research indicated that the system had not been installed long enough to assess if it reduced downgrade truck crashes but examined driver awareness and compliance with the system. The study concluded that overall, the warning system appears to have significantly reduced truck descent speed based on statistical analyses comparing mean truck speeds on days the system is in use versus days the system is off. It was also noted from the study results that the mean speed of the trucks for each weight range was still above the advised speed for that vehicle, a possible indication ‘that the majority of truck drivers considered the advised speed to be too conservative'. (Janson, 2001). Similar downhill warning systems have been installed in Oregon, West Virginia and British Columbia. (Robinson et al., 2002).

Figure 66. Diagram. Downhill Truck Warning System, Colorado (Sisiopiku, 2001).

Signal Pre-emption System, Pennsylvania

A runaway truck signal control system was installed in 1999 by the Pennsylvania Department of Transportation. Trucks pass over a WIM system made up of loops and piezoelectric sensors. Parameters like vehicle speed, weight and classification are measured which help determine if the vehicle 'is exceeding its critical speed threshold for its location on the downgrade'. (Baker et al., 2001). Vehicles which are exceeding the critical speed trigger a signal transmitted to traffic lights further down the road on an intersection. The lights facing the truck driver will remain green or change to green until the runaway truck has passed through the intersection. (Eady et al., 2015). This intersection is between State Route 0031 and State Route 0982 at the bottom of an 8 percent steep grade. No formal safety effectiveness study has been undertaken on this system but officials from the Pennsylvania DOT have indicated their satisfaction with the system. (Baker et al., 2001).

Dynamic Curve Warning Systems, California

Five speed-based curve warning systems were installed along I-5 near the Sacramento River Canyon by California DOT (CALTRANS) to warn drivers of alignment changes and provide speed advisories in the Sacramento River Canyon. (Tribbett et al., 2000). The five sites where the system was installed were along Sidehill Viaduct, O'Brien, Salt Creek, La Moine, and Sims Road. The components of the curve warning system at each site include a VMS, a radar speed-measuring device, and a control/communication equipment. Speed advisories are displayed on the VMS and can be changed every 3 to 4 seconds. A safety effectiveness study was carried out by a comparison of speed data before and after the installation of the curve warning system. The speed data was collected 9 months before the system was installed and 2, 5, and 10 months after installation. The results indicate a reduction in truck operating speeds in 3 out of the 5 installation sites in the data collected after installation of the warning system. A preliminary analysis also showed a reduction in truck crashes in 2 out of the 5 sites which had downgrades greater than 5 percent. (Tribbett et al., 2000). Figure 67 shows some dynamic warning signs in the Sacramento River Canyon area.

Figure 67. Photo. Dynamic Curve Warning Signs in the Sacramento River Canyon (Tribbett et al., 2000).

Automatic Truck Rollover Warning Systems, Virginia and Maryland

A truck rollover warning system incorporating multiple vehicle parameters to assess the risk of rollover was installed at three location in Virginia and Maryland. The installation locations are in Springfield-Virginia, McLean-Virginia, and Beltsville, Maryland. (Strickland and McGee, 1998). The ATRWS installed can identify a truck whose speed on a curve is likely to be close or exceeding the rollover threshold speed as determined by its weight, rollover threshold factor and the geometrics of the curve or ramp. The system warns the driver to reduce speed if the truck is at the critical rollover threshold speed prior to reaching the curve. The ATRWS is made of two sets of WIM for each lane to measure the weight and speed of trucks by class, loop magnetic detectors for each lane to measure the speed of trucks, a radar sensing device which determines whether a truck has exceeded a pre-set height value, a VMS which displays the message “TRUCKS REDUCE SPEED” when activated, and a controller that operates the system by processing data from all the sensors and detectors. (Strickland and McGee, 1998). An evaluation was carried out by analyzing both speed and crash data. The analysis showed that the installation of the system at the three locations caused truck drivers to reduce their speeds. The before and after crash analysis showed that 10 reported crash rollovers in the before period across all 3 locations reduced to 0 rollover crashes in the 3-year after period. (Strickland and McGee, 1998).

Potential and Current ITS Application Summary

This chapter explored potential and current applications of ITS in reducing the incidence of truck crashes on mountain downgrades. The safety effectiveness of most infrastructure-based ITS that have been adopted by agencies are known but vehicle-based systems show great promise. Admittedly, a lot of research must be conducted on practical applications of vehicle-based ITS; efforts which are currently on-going with technologies such as connected vehicles, on-board mass monitoring, in-vehicle telematics, rollover prevention systems, among many others. ITS and autonomous vehicle technology development will soon allow in-vehicle systems to automatically communicate with infrastructure-based systems with vehicles acting on their own to avoid crashes not only on mountain passes, but also on other crash prone locations.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the summary of the study. A brief introduction of the research is given and specific research findings are discussed. The chapter then proceeds to discuss recommendations based on the findings of the study and concludes with suggestions for future studies.

SUMMARY OF THE RESEARCH

Mountain passes have difficult terrain which increases the risk of truck crashes due to brake heating, fade and runaway events. WYDOT in an effort to counter truck crash events on mountain passes has installed steep grade advance warning signs on various mountain passes throughout the state. However, truck crashes on mountainous downgrades still occur. This study was undertaken to evaluate the safety effectiveness of the current advance downgrade warning signs installed on mountain passes and to recommend the best system to communicate downgrade information to truck drivers.

Hazardous downgrades were identified based on criteria set out in the MUTCD for the installation of downgrade warning signs. Grade profiles were plotted for all downgrades on mountain pass routes in Wyoming. Grades which met the MUTCD criteria were identified for further analysis. A total of 157 downgrades were identified as hazardous to trucks and were used for the analyses. Five mountain pass routes with the highest truck crash frequency were also identified for a detailed field analysis of their warning systems and geometric features.

Several analyses were conducted to evaluate effectiveness of advance warning signs in reducing the incidence of downgrade truck crashes. The safety effectiveness of warning signs was first evaluated using propensity score matching. This was followed by an assessment of the warning sign types using the negative binomial model. Five mountain pass routes with the highest truck crash frequency were ranked using the expected average crash frequency with EB adjustment and EPDO. A hotspot analysis was conducted to evaluate the relationship between the locations of warning signs and hazardous downgrades.

Findings of the study

Safety Effectiveness Analysis using Propensity Score Matching

The safety effectiveness of advance warning signs was analyzed using propensity score matching. All the 157 downgrades identified were included in the analysis. The use of propensity scores was appropriate because the methodology allows observational studies to mimic randomization. Important findings from the propensity score matching were:

- A good overlap was found to exist between the treated (downgrades with downgrade warning signs installed at least 0.5 miles in advance of the downgrade) and untreated (downgrades without downgrade warning signs installed at least 0.5 miles in advance of the downgrade) downgrade sections. This validated the use of propensity score matching in evaluating the safety effectiveness of downgrade warning signs.
- The results of the propensity score analysis indicates that the current advance downgrade warning signs are effective in reducing truck crashes. The estimated probability of a truck crash occurring on a downgrade segment with an advance warning sign was 0.072 (i.e., one in every 14 crashes on segments with advance downgrade signs). For downgrades without advance warning signs, the estimated probability was found to be 0.082 (i.e., one

in every 12 crashes on segments without advance downgrade signs). The estimated risk ratio of 0.082/0.071=1.15 indicates that truck crash risks on downgrades without advance downgrade warning signs are 15 percent higher than those with downgrade warning signs installed.

- A 90 percent bootstrap confidence interval was computed for the mean risk ratio of the caliper width of 0.064 by repeatedly drawing samples a hundred times with replacement from the original sample. The 90 percent bootstrap confidence interval was 1.04 to 1.53. The absence of 1 within the confidence interval indicated a high reliability of the treatment effect estimated using propensity score matching.
- A sensitivity analysis was conducted to assess the sensitivity of the treatment effect with respect to sample size. Binary logistic models were calibrated for matched treated and untreated sections using caliper widths of 0.1 to 1 times the standard deviation of the propensity scores of the treated entities. The analysis did not show a wide variation in the treatment effect when different caliper widths were used.

Safety Effectiveness of Current Warning Sign Types

These analyses were conducted to evaluate the safety effectiveness of individual warning signs in preventing downgrade truck crashes. Two crash prediction models were calibrated for trucks and other vehicular crashes using the negative binomial (NB) model. The analysis included data from all the 157 downgrades identified as part of the study. The safety effectiveness was estimated from the estimates and elasticity of significant variables of the NB model.

- For truck crashes, the analysis suggests that the combination of hill signs and distance advisory signs are effective in decreasing truck crash frequency. An increase in this type of sign was found to result in a 36 percent decrease in truck crash frequency. The elasticity analysis indicates a one percent increase in the frequency of downgrade and advisory speed signs were found to be associated with an 11 percent decrease in truck crash frequency.
- Directional and speed advisory sign combination was found to be associated with a 32 percent decrease in the frequency of truck crashes while holding all the variables in the model constant. In terms of elasticity, a one percent increase in this sign type is associated with a 16.8 percent decrease in truck crashes.
- Truck escape ramp signs were found to be associated with a decrease in truck crashes. The NB analysis suggests that a unit increase in the number of truck escape ramp signs will lead to a 36 percent decrease in truck crashes. The elasticity analysis shows a one percent increase in this type of warning sign will lead to a 5.7 percent reduction in truck crashes.
- The presence of a passing lane was also found to decrease truck crashes. The parameter estimate of passing lane from the NB model indicates the presence of a passing lane will lead to a decrease of truck crashes by 47 percent. The elasticity analysis indicates the presence of a passing lane results in a 47 percent decrease in truck crashes.
- The presence of a downgrade warning sign was found to decrease the crash frequency of non-truck crashes. The analysis indicates the installation of a downgrade warning sign results in about a 28 percent decrease in non-truck crashes. The associated decrease in non-truck crashes for a one percent increase in downgrade warning signs was found to be 28 percent.

- Some warning signs were also found to be effective in preventing other vehicular crashes. The analysis suggests hill signs, directional and speed combination advisory signs, and Chevron warning signs are associated with a decrease in truck crash frequency. A unit increase in these signs was found to result in a 43 percent, 8 percent and 11 percent decrease respectively for hill, directional and speed advisory, and Chevron warning signs respectively in non-truck crashes. The corresponding elasticity analysis indicates a one percent increase in these signs leads to a 9 percent, 10 percent and 2 percent decrease in non-truck crashes respectively.

Ranking of Routes by Expected Average Crash Frequency with EB Adjustment and EPDO Methods

Mountain pass routes with the highest truck crash frequency were ranked using the expected average crash frequency with EB adjustment and EPDO methods. A total of 51 sections were used for this analysis. A safety performance function (SPF) was calibrated for the EB adjustment method using the NB model. The final year adjusted average crash frequency were normalized with segment lengths after which the ranking was done. For the EPDO, ranking was done using crash severity costs and weights. Again, normalized ranking was done with segment lengths.

- US-14 was found to have multiple segments with expected adjusted crashes greater than 0.52; the average score for all the segments analyzed. This suggests US-14 may be a high-risk route.
- The results suggest that WY-22 has the highest EB adjusted average crash frequency of the five routes analyzed. WY-22 was followed in ranking by WY-28, US-14, US-16, and US-287. This indicates that US-16 and US-287 were the safest routes in terms of truck crashes. This may be attributed to the system of warning signs installed on the route.
- The results of the EPDO analysis suggests that WY-22 has the highest rank score of the routes. The ranking indicates WY-22 is followed in ranking by US-14, WY-28, US-16 and US-287. The analysis shows that US-16 and US-287 are less hazardous than US-14, WY-28, and WY-22. The two routes have the least potential for improvement and are thus the safest of the routes.

Hotspot Analysis and Warning Sign

A hotspot analysis was conducted to assess the relationship between locations of high truck crash frequency and warning signs. Using the ArcGIS kernel density spatial analysis tool, estimation was applied to identify locations of high truck crash and warning sign density within the segments. The hotspots generated in ArcGIS highlighted areas within the ranked sites that are hazardous and related warning sign installation to these hotspots. The main conclusions drawn from this analysis were:

- The overlap between hotspot areas of warning signs and areas of high truck crash density may indicate sufficient advanced warning sign placement. As an example, US-16 (Section 29) shows a good overlap between warning sign placement and crash densities.
- The hotspot analyses show that when the warning signs are sparsely installed, the system may not be as effective. The analysis found some sections to be characterized by curves accompanied by steep downgrades, yet only a few downgrade warning signs were

installed before (i.e. priming) and within such segments. On some long downgrades, only a few warning signs were installed to remind the driver of the continuous downgrade. US-14 (Section 48) is a good example and is identified as a very hazardous section in the study.

- A disproportionate number of warning signs installed further up the downgrade with few signs installed within the section may result in drivers losing attention at critical moments while driving toward the bottom of a steep downgrade. Hotspots tended to appear at the bottom of downgrades and are most prone to brake fade. More attention should be placed on segments at the end downgrades due to the likelihood of runaway events. US-14 (site: 41) is an example with a crash hotspot at the end of the downgrade and a disproportionate number of signs located further up the downgrade.
- All locations which are listed as severely hazardous sections based on the ranking conducted in the study should have downgrade warning signs installed. Several sites, on WY-28 (MP 45.6 – 46.6) and US-287 (MP 419.48 – 419.20), experienced truck crashes, but did not have downgrade warning signs on several sections.

RECOMMENDATIONS

The findings of this study are needed to address the incidence of truck crashes on downgrades in Wyoming. The objective of the study is to evaluate the warning system on Wyoming mountain passes with regards to their effectiveness in preventing downgrade truck crashes. The output from this study is a recommendation of the best means of communicating downgrade information to truck drivers to reduce the probability of truck crashes on mountain passes in the state. The results of the study will be useful not only to WYDOT, but other policy makers and road users.

The following are recommendations based on the analysis and conclusions drawn from the study. These are listed in the numbered section below:

- The results of the expected average crash frequency with EB adjustment and EPDO show that sections with higher rank scores are consistently found on routes with steeper grades. This result is intuitive and is an indication that more attention and resources should be channeled on such routes to improve downgrade safety.
- The analysis on warning sign safety effectiveness suggests that the hill sign with downgrade percent and distance plaque combination (W7-1 + W7-3aP) sign is effective in preventing downgrade truck crashes. These signs should be placed intermittently at one-mile intervals on long grades to inform drivers of the downgrade length remaining. This will aid truck drivers in saving their brakes during long descents. In conjunction with the downgrade percent and distance plaque combination sign, route layout signs with downgrade information should be installed at the beginning of downgrades. This has been done on some downgrades, but the practice should be consistently adopted along all grades meeting the MUTCD criteria of downgrade warning sign installation. Evidence suggests these signs are effective in reducing truck crashes though an analysis could not be conducted to validate this due to data limitations.
- Speed has been known to be a critical factor in most truck runaway incidents on downgrades. Crashes on mountain passes are also known to be exacerbated by curves

which characterize mountain highways. The frequent use of directional warning signs in combination with supplementary speed signs will not only provide safe advisory speeds for truck operation, but caution and guide drivers on hazardous grades.

- Past studies and empirical evidence have indicated that Chevron warning signs are effective in preventing all vehicular crashes. (Agent and Creasley, 1986; Zador et al., 1987). For this study, Chevron warning signs were found to be effective in preventing non-truck crashes. It is recommended that Chevron signs should be installed on curved sections of downgrades as specified by section 2C.06 of the MUTCD. Chevron signs provide additional emphasis and guidance on highways with a lot of curves.
- Results from the propensity score matching analysis suggests the current warning systems on the mountain passes are generally effective to some degree. Downgrade truck safety may be improved by incorporating ITS technologies. Infrastructure-based ITS technologies seem to have the highest potential for short-term implementation. A viable infrastructure-based candidate capable of being easily installed is the virtual weigh-in-motion technology. This could be installed on long downgrades such as those found on WY-22, US-14 and US-16. Other technologies such as the ATRWS and infrared brake inspection systems may also be adopted. The downhill truck warning systems which have been successfully implemented in Colorado, Oregon and West Virginia may be considered in the long term.
- Installation of weight specific speed (WSS) signs from an updated and validated GSRS will greatly enhance truck safety on mountain passes. GSRS provides advisory grade descent speeds based on truck weights and downgrade characteristics. The GSRS concept is a major step forward for downgrade safety because it tells the driver directly what to do, instead of giving him information which requires evaluation under different loading and downgrade conditions.
- Though the analyses conducted for this study show that warning signs generally reduce the incidence of truck crashes on downgrades, a lot of thought should go into the location and number of warning signs installed. Indiscriminate installation of warning signs may result in drivers losing respect for them and disregarding pertinent information in the process.

FUTURE RESEARCH

Evaluating the safety effectiveness of warning signs should continue as new and improved warning systems are developed and new technologies enter the transportation industry. One such development is the emerging technology of autonomous and connected vehicles, where vehicles can communicate with each other and roadway infrastructure. This provides ample opportunity to conduct research on the effect of current and innovative warning systems on downgrade safety.

Before-after studies using sound methods such as the EB approach could be conducted on roadway segments as data becomes available. WY-28 may be a candidate for this type of study as it was found not to have a sufficient number of downgrade warning signs.

Recent data collection efforts on traffic safety have focused on naturalistic driving. Naturalistic driving studies record details of the driver, vehicle and surroundings through unobtrusive data gathering equipment with minimal experimental control. This provides a huge amount of data to analyze driver behavior under different conditions and has the potential to contribute to the understanding of crashes and near-crash events. As more data from naturalistic driving studies become available, future studies may consider the impact of warning signs may have on driver behavior at the individual level. Also, the response of drivers to warning signs could be assessed under different environmental, and vehicle conditions which lead to safety enhancements or otherwise.

Finally, the safety evaluation of warning signs should be linked to the importance drivers place on them. This may need a comprehensive psychological evaluation to understand the preventative impacts of the warning signs on downgrade crashes. Driving simulator experiments may be designed for such studies.

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APPENDICES

APPENDIX 1: DATA COLLECTION SHEET

Highway Section #	Milepost Marker	Increasing MP	Decreasing MP
Downgrade Beginning MP	**Downgrade Ending MP**	**Posted Speed Limit**	
Number of Lanes	**Downgrade Direction**	**Skid Marks**	
		No.	MP

Skid Marks No.	MP
01	
02	
03	
04	
05	
06	
07	
08	
09	
10	
11	
12	
13	
14	
15	

Presence of Passing Lane	
01	Yes
02	No

Presence of Median	
01	Yes
02	No

Road Circumstance	
MP	Description

Rest/Brake Check Area 1	
MP	
01	Before Section
02	Within Section

Rest/Brake Check Area 2	
MP	
01	Before Section
02	Within Section

Rest/Brake Check Area 3	
MP	
01	Before Section
02	Within Section

Rest/Brake Check Area 4	
MP	
01	Before Section
02	Within Section

Rest/Brake Check Area 5	
MP	
01	Before Section
02	Within Section

Weather Condition	
1st Choice	
2nd Choice	
01	Clear
02	Raining
03	Snow
04	Cloudy/ Overcast
05	Severe Wind
06	Cloudy/ Overcast
07	Other

Signs 3 Miles Before Downgrade Section

Type of Sign	MP	Sign Direction	State of Maint.	Last Install. Date

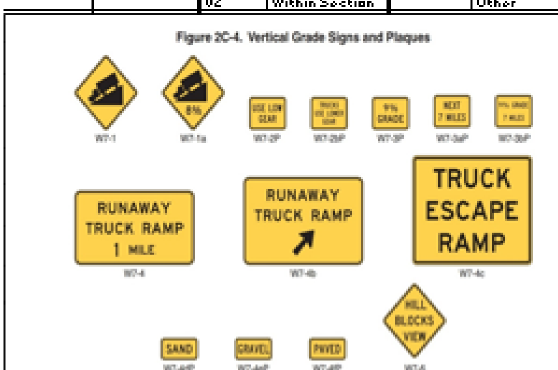
Warning Signs Within Downgrade Section

Type of Sign	MP	Sign Direction	State of Maint.	Last Install. Date

01	W7-1
02	W7-1a
03	W7-2P
04	W7-2bP
05	W7-3P
06	W7-3aP
07	W7-3bP
08	W7-4
09	W7-4b
10	W7-4c
11	Other (VMS etc.)

State of Maintenance	
01	Good Visibility
02	Average Visibility
03	Faded

Road Circumstance	
01	Worn or polished surface
02	Traffic control device obscured
03	Lane markings missing or faded
04	Reduced road width
05	Ruts, Holes, Bumps
06	Near
07	Other



COMMENTS

Figure 68. Data Collection Sheet.

APPENDIX 2: LIST OF ROADWAY SEGMENTS IN STUDY AREA

Table 24. US-16 Roadway Segments

Highway Section	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length	Fatal	Injury	PDO	Total Crashes	Number of Warning signs
ML36B	Decreasing	75.9	75.2	0.7	0	0	0	0	7
ML36B	Decreasing	67.0	65.5	1.5	1	0	2	3	7
ML36B	Decreasing	51.49	50.6	0.9	0	0	1	1	5
ML36B	Decreasing	42.01	39.03	3.0	0	2	4	6	22
ML36B	Decreasing	38.35	33.70	4.7	0	2	3	5	29
ML36B	Increasing	55.63	58.99	3.4	0	2	0	3	11
ML36B	Increasing	69.86	72.7	2.8	0	2	0	2	10
ML36B	Increasing	74.89	75.8	0.9	0	0	0	0	8
ML36B	Increasing	77.23	78.66	1.4	0	0	2	2	12
ML36B	Increasing	78.91	79.97	1.1	0	0	1	1	10
ML36B	Increasing	81.96	82.65	0.7	0	0	0	0	12
ML36B	Increasing	83.1	86.93	3.8	0	0	1	1	28
ML36B	Increasing	90.07	90.72	0.7	0	0	0	0	7
			∑	25.5	1	8	14	24	168

Table 25. WY-28 Roadway Segments

Highway Section	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length	Fatal	Injury	PDO	Total Crashes	Number of Warning signs
ML14B	Decreasing	31.77	30.9	0.87	0	0	0	0	3
ML14B	Increasing	34.39	35.04	0.65	1	0	1	2	2
ML14B	Increasing	45.6	46.61	1.01	0	2	2	4	1
ML14B	Increasing	53.55	55.24	1.69	0	1	5	6	0
ML14B	Increasing	56.15	57.31	1.16	0	2	1	3	5
ML14B	Increasing	58.38	62.34	3.96	0	4	11	15	15
ML14B	Increasing	66.53	67.49	0.96	0	0	1	1	2
ML14B	Decreasing	67.61	66.89	0.72	0	0	0	0	1
			∑	11.0	1.0	9.0	21.0	31.0	29.0

Table 26. US-14 Roadway Segments

Highway Section	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length	Fatal	Injury	PDO	Total Crashes	Number of Warning signs
ML607B	Decreasing	185.16	184.15	1.01	0	0	0	0	5
ML607B	Decreasing	169.08	168.15	0.93	0	0	0	0	4
ML607B	Increasing	169.56	170.37	0.81	0	0	3	3	6
ML607B	Increasing	189.86	190.63	0.77	0	0	1	1	6
ML607B	Increasing	196.83	197.71	0.88	0	0	1	1	9
ML37B	Decreasing	36.96	35.43	1.53	0	0	1	1	5
ML37B	Decreasing	34.18	33.4	0.78	0	0	0	0	8
ML37B	Decreasing	31.39	30.26	1.13	0	0	1	1	13
ML37B	Decreasing	29.95	28.82	1.13	0	0	0	0	11
ML37B	Decreasing	27.89	26.48	1.41	0	0	0	0	14
ML37B	Decreasing	25.94	21.56	4.38	0	3	3	6	24
ML37B	Increasing	58.69	59.24	0.55	0	1	0	1	0
ML37B	Increasing	66.22	68.71	2.49	0	0	0	0	0
ML37B	Increasing	68.7	71.9	3.2	1	4	3	8	24
ML37B	Increasing	72.88	75.17	2.29	0	3	3	6	16
ML37B	Increasing	75.2	75.7	0.5	0	2	5	7	9
ML37B	Increasing	79.45	80.45	1	0	0	0	0	4
ML37B	Increasing	80.5	83.7	3.2	0	0	2	2	4
			∑	25.5	1	13	18	32	132

Table 27. WY-22 Roadway Segments

Highway Section	Downgrade (Inc/Dec MP)	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Length	Fatal	Injury	PDO	Total Crashes	Number of Warning signs
ML2000B	Decreasing	11.08	5.35	5.73	4	3	3	10	52
ML2000B	Increasing	11.08	13.68	2.6	0	1	4	5	19
			∑	8.3	4.0	4.0	7.0	15.0	71.0

Table 28. US-287 Roadway Segments

Highway Section	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length	Fatal	Injury	PDO	Total Crashes	Number of Warning signs
ML30B	Decreasing	24.4	23.26	1.14	0	0	2	2	8
ML30B	Decreasing	13.92	12.43	1.49	0	1	0	1	0
ML30B	Decreasing	10.89	9.99	0.9	0	1	2	3	13
ML30B	Decreasing	8.78	7.97	0.81	0	0	0	0	10
ML21B	Increasing	14.58	15.11	0.53	0	0	2	2	0
ML23B	Decreasing	419.84	419.2	0.64	1	1	6	8	0
ML30B	Increasing	27.62	28.59	0.97	0	0	3	3	8
ML15B	Increasing	29.73	30.88	1.15	0	0	0	0	0
ML23B	Increasing	245.68	250.47	4.79	0	0	2	2	1
ML20B	Increasing	49.76	52.5	2.74	0	0	1	1	0
			∑	15.2	1.0	3.0	18.0	22.0	40.0

APPENDIX 3: EB AND EPDO RANKING RESULTS

Table 29. Road Segment Ranking Based on the Expected Av. Crash Frequency with EB Adjustment

Rank	Section Number	Route Name	Highway Section	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length	Final Year EB-Adjusted Expected Average Crash Frequency
1	48	US-14	ML37B	Increasing	72.88	75.17	2.29	2.92
2	49	US-14	ML37B	Increasing	75.20	75.70	0.50	2.23
3	44	US-14	ML37B	Increasing	68.70	71.90	3.20	2.05
4	14	WY-28	ML14B	Increasing	56.15	57.31	1.16	1.63
5	41	US-14	ML37B	Decreasing	25.94	21.56	4.38	1.41
6	15	WY-28	ML14B	Increasing	58.38	62.34	3.96	1.32
7	52	WY-22	ML2000B	Decreasing	11.08	5.35	5.73	1.23
8	29	US-16	ML36B	Increasing	83.10	86.93	3.83	1.13
9	22	US-16	ML36B	Decreasing	38.35	33.70	4.65	1.09
10	46	US-14	ML35B	Decreasing	68.44	73.59	5.15	0.78
11	53	WY-22	ML2000B	Increasing	11.08	13.68	2.60	0.77
12	21	US-16	ML36B	Decreasing	42.01	39.03	2.98	0.56
13	12	WY-28	ML14B	Increasing	45.60	46.60	1.00	0.54
14	23	US-16	ML36B	Increasing	55.63	58.99	3.36	0.52
15	7	US-287	ML23B	Decreasing	419.48	419.20	0.28	0.52
16	13	WY-28	ML14B	Increasing	53.55	55.24	1.69	0.52

Table 30. Ranking of Road Segments Based on EPDO Scores

Rank	Section Number	Highway Section	Route Name	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length	EPDO
1	52	ML2000B	WY-22	Decreasing	11.08	5.35	5.73	1683
2	44	ML37B	US-14	Increasing	68.7	71.9	3.2	589
3	7	ML23B	US-287	Decreasing	419.48	419.2	0.28	559
4	19	ML 36B	US-16	Decreasing	67.0	65.5	1.5	544
5	11	ML14B	WY-28	Increasing	34.39	35.04	0.65	543
6	47	ML35B	US-14 Alt.	Decreasing	74.08	77.55	3.47	86
7	46	ML35B	US-14 Alt.	Decreasing	68.44	73.59	5.15	79
8	15	ML14B	WY-28	Increasing	58.38	62.34	3.96	55
9	41	ML37B	US-14	Decreasing	25.94	21.56	4.38	36
10	48	ML37B	US-14	Increasing	72.88	75.17	2.29	36
11	49	ML37B	US-14	Increasing	75.2	75.7	0.5	27
12	21	ML36B	US-16	Decreasing	42.01	39.03	2.98	26
13	22	ML36B	US-16	Decreasing	38.35	33.7	4.65	25
14	12	ML14B	WY-28	Increasing	45.6	46.6	1	24
15	14	ML14B	WY-28	Increasing	56.15	57.31	1.16	23
16	23	ML36B	US-16	Increasing	55.63	58.99	3.36	22
17	24	ML36B	US-16	Increasing	69.86	72.7	2.84	22
18	13	ML14B	WY-28	Increasing	53.55	55.24	1.69	16
19	53	ML2000B	WY-22	Increasing	11.08	13.68	2.6	15
20	3	ML30B	US-287	Decreasing	10.89	9.99	0.9	13
21	2	ML30B	US-287	Decreasing	13.92	12.43	1.49	11
22	42	ML37B	US-14	Increasing	58.69	59.24	0.55	11
23	45	ML35B	US-14 Alt.	Decreasing	65.73	68.58	2.85	11

Table 31. Ranking of Segments Based on Normalized EPDO Scores

Rank	Section Number	Highway Section	Route Name	Downgrade (Inc/Dec MP)	Downgrade Beginning MP	Downgrade Ending MP	Length	EPDO	EPDO/Mile
1	7	ML23B	US-287	Decreasing	419.48	419.2	0.28	559	1996
2	11	ML14B	WY-28	Increasing	34.39	35.04	0.65	543	835
3	19	ML 36B	US-16	Decreasing	67.0	65.5	1.5	544	363
4	52	ML2000B	WY-22	Decreasing	11.08	5.35	5.73	1683	294
5	44	ML37B	US-14	Increasing	68.7	71.9	3.2	589	184
6	49	ML37B	US-14	Increasing	75.2	75.7	0.5	27	54
7	47	ML35B	US-14 Alt.	Decreasing	74.08	77.55	3.47	86	25
8	12	ML14B	WY2-8	Increasing	45.6	46.6	1	24	24
9	42	ML37B	US-14	Increasing	58.69	59.24	0.55	11	20
10	14	ML14B	WY-28	Increasing	56.15	57.31	1.16	23	20
11	48	ML37B	US-14	Increasing	72.88	75.17	2.29	36	16
12	46	ML35B	US-14 Alt.	Decreasing	68.44	73.59	5.15	79	15
13	3	ML30B	US-287	Decreasing	10.89	9.99	0.9	13	14
14	15	ML14B	WY-28	Increasing	58.38	62.34	3.96	55	14
15	13	ML14B	WY-28	Increasing	53.55	55.24	1.69	16	9
16	21	ML36B	US-16	Decreasing	42.01	39.03	2.98	26	9
17	41	ML37B	US-14	Decreasing	25.94	21.56	4.38	36	8
18	24	ML36B	US-16	Increasing	69.86	72.7	2.84	22	8
19	2	ML30B	US-287	Decreasing	13.92	12.43	1.49	11	7
20	23	ML36B	US-16	Increasing	55.63	58.99	3.36	22	7
21	53	ML2000B	WY-22	Increasing	11.08	13.68	2.6	15	6
22	22	ML36B	US-16	Decreasing	38.35	33.7	4.65	25	5
23	45	ML35B	US-14 Alt.	Decreasing	65.73	68.58	2.85	11	4

APPENDIX 4: LOGISTIC MODELS FOR VARIOUS CALIPERS

Table 32. Binary Logit Model for Treated and Untreated Groups (0.1σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-1.856	3.096	-0.599	0.5489	-4.116	2.565	-1.604	0.1086
Downgrade length	-0.061	0.302	-0.201	0.8405	0.287	0.186	1.542	0.1231
Grade	-0.227	0.119	-1.916	0.0554	0.083	0.124	0.666	0.5054
Average curve length	0.564	0.354	1.596	0.1104	-0.657	0.446	-1.475	0.1403
Lane width	0.146	0.156	0.931	0.3518	0.055	0.113	0.483	0.6292
Number of access points	-0.842	0.365	-2.305	0.0211	-0.266	0.142	-1.874	0.0609
Presence of passing lane	0.403	0.683	0.591	0.5545	-0.022	0.669	-0.033	0.9738
Number of lanes	-1.191	0.831	-1.434	0.1517	-0.415	0.735	-0.565	0.5722
Shoulder width	0.133	0.181	0.736	0.4616	0.069	0.072	0.954	0.3402
LN(ADTT)	0.302	0.347	0.872	0.3832	0.489	0.290	1.687	0.0917
Presence of traffic control	-2.795	1.025	-2.728	0.0064	-2.117	0.610	-3.469	0.0005
Speed limit (1 if greater than 50 mph, 0 otherwise)	-0.213	0.665	-0.320	0.7486	0.262	0.515	0.508	0.6115
Number of observations	167				167			
AIC	259.62				321.89			

Table 33. Binary Logit Model for Treated and Untreated Groups (0.2σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	1.760	5.664	0.311	0.7560	-3.083	2.880	-1.070	0.2844
Downgrade length	-0.026	0.296	-0.086	0.9311	0.167	0.180	0.930	0.3524
Grade	-0.221	0.132	-1.679	0.0931	-0.067	0.129	-0.521	0.6023
Average curve length	0.348	0.436	0.798	0.4249	-0.836	0.454	-1.841	0.0656
Lane width	-0.096	0.307	-0.314	0.7538	0.041	0.115	0.357	0.7214
Number of access points	-1.228	0.581	-2.115	0.0345	-0.138	0.133	-1.038	0.2993
Presence of passing lane	-0.191	0.911	-0.210	0.8336	-0.004	0.798	-0.005	0.9963
Number of lanes	-1.362	0.943	-1.445	0.1485	-0.588	0.835	-0.704	0.4814
Shoulder width	0.142	0.192	0.742	0.4581	0.061	0.070	0.868	0.3851
LN(ADTT)	0.347	0.367	0.947	0.3438	0.697	0.298	2.336	0.0195
Presence of traffic control	-3.107	1.032	-3.012	0.0026	-3.297	1.022	-3.226	0.0013
Speed limit (1 if greater than 50 mph, 0 otherwise)	-0.067	0.670	-0.099	0.9208	-0.125	0.516	-0.243	0.8080
Number of observations	617				617			
AIC	261.79				331.03			

Table 34. Binary Logit Model for Treated and Untreated Groups (0.3σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-3.069	3.623	-0.847	0.3969	-4.319	2.401	-1.798	0.0721
Downgrade length	0.482	0.220	2.192	0.0284	0.241	0.167	1.446	0.1481
Grade	-0.198	0.103	-1.925	0.0542	0.135	0.107	1.265	0.2058
Average curve length	0.902	0.366	2.467	0.0136	-0.411	0.379	-1.086	0.2775
Lane width	-0.113	0.217	-0.518	0.6045	0.087	0.115	0.754	0.4506
Number of access points	-0.868	0.316	-2.743	0.0061	-0.138	0.130	-1.061	0.2886
Presence of passing lane	0.485	0.687	0.705	0.4807	-0.395	0.591	-0.668	0.5040
Number of lanes	-0.430	0.773	-0.556	0.5780	-0.562	0.639	-0.880	0.3788
Shoulder width	-0.178	0.169	-1.051	0.2934	0.071	0.066	1.076	0.2820
LN(ADTT)	0.968	0.343	2.824	<0.001	0.441	0.269	1.639	0.1013
Presence of traffic control	-2.689	0.757	-3.552	<0.001	-1.996	0.533	-3.741	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	-0.111	0.600	-0.185	0.8534	-0.346	0.462	-0.748	0.4542
Number of observations	650				650			
AIC	291.22				360.69			

Table 35. Binary Logit Model for Treated and Untreated Groups (0.4σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-4.072	2.514	-1.620	0.1053	-4.391	2.465	-1.782	0.0748
Downgrade length	-0.153	0.229	-0.670	0.5030	0.318	0.157	2.023	0.0430
Grade	-0.160	0.098	-1.635	0.1021	0.128	0.109	1.181	0.2374
Average curve length	0.484	0.323	1.497	0.1343	-0.075	0.348	-0.214	0.8302
Lane width	0.134	0.140	0.952	0.3412	0.108	0.129	0.833	0.4049
Number of access points	-0.571	0.261	-2.189	0.0286	-0.206	0.138	-1.495	0.1349
Presence of passing lane	0.628	0.583	1.078	0.2812	-0.338	0.579	-0.584	0.5590
Number of lanes	-0.552	0.682	-0.809	0.4184	-0.497	0.625	-0.794	0.4271
Shoulder width	0.049	0.145	0.342	0.7327	0.093	0.064	1.461	0.1441
LN(ADTT)	0.519	0.299	1.737	0.0824	0.216	0.264	0.817	0.4138
Presence of traffic control	-3.015	1.021	-2.953	0.0032	-2.568	0.730	-3.519	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	-0.197	0.644	-0.306	0.7598	0.054	0.452	0.119	0.9056
Number of observations	692				692			
AIC	318.08				379.16			

Table 36. Binary Logit Model for Treated and Untreated Groups (0.5σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-4.451	2.449	-1.817	0.0692	-5.075	2.602	-1.950	0.0511
Downgrade length	0.345	0.174	1.986	0.0470	0.272	0.157	1.736	0.0826
Grade	-0.158	0.096	-1.650	0.0989	0.154	0.095	1.627	0.1037
Average curve length	0.825	0.297	2.775	0.0055	-0.164	0.347	-0.474	0.6357
Lane width	0.068	0.128	0.527	0.5980	0.054	0.137	0.397	0.6911
Number of access points	-0.628	0.249	-2.523	0.0116	-0.170	0.121	-1.410	0.1586
Presence of passing lane	0.431	0.572	0.754	0.4508	-0.263	0.632	-0.416	0.6772
Number of lanes	-0.594	0.683	-0.869	0.3849	-0.362	0.693	-0.522	0.6015
Shoulder width	-0.120	0.133	-0.898	0.3691	0.037	0.058	0.636	0.5246
LN(ADTT)	0.813	0.286	2.840	0.0045	0.515	0.256	2.007	0.0447
Presence of traffic control	-3.311	1.021	-3.244	<0.001	-2.097	0.528	-3.973	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	0.059	0.580	0.102	0.9187	0.197	0.414	0.477	0.6335
Number of observations	723				723			
AIC	345.78				416.57			

Table 37. Binary Logit Model for Treated and Untreated Groups (0.6σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-4.867	2.528	-1.925	0.054	-5.120	2.594	-1.973	0.048
Downgrade length	0.103	0.230	0.446	0.656	0.276	0.148	1.867	0.062
Grade	-0.189	0.099	-1.907	0.056	0.113	0.102	1.114	0.265
Average curve length	0.617	0.332	1.862	0.063	-0.335	0.340	-0.984	0.325
Lane width	0.189	0.141	1.335	0.182	0.084	0.126	0.669	0.504
Number of access points	-0.738	0.271	-2.720	0.007	-0.176	0.124	-1.414	0.157
Presence of passing lane	0.412	0.568	0.725	0.469	-0.015	0.661	-0.022	0.982
Number of lanes	-0.683	0.690	-0.990	0.322	-0.180	0.723	-0.248	0.804
Shoulder width	-0.030	0.150	-0.200	0.841	0.016	0.058	0.273	0.785
LN(ADTT)	0.672	0.320	2.102	0.036	0.427	0.241	1.774	0.076
Presence of traffic control	-3.091	1.020	-3.030	0.002	-2.317	0.600	-3.861	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	0.091	0.581	0.156	0.876	-0.083	0.437	-0.191	0.848
Number of observations	746				746			
AIC	334.14				431.67			

Table 38. Binary Logit Model for Treated and Untreated Groups (0.7σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-4.350	2.229	-1.952	0.0510	-4.512	2.493	-1.810	0.0703
Downgrade length	-0.115	0.209	-0.551	0.5818	0.250	0.143	1.750	0.0801
Grade	-0.196	0.095	-2.053	0.0401	0.159	0.093	1.703	0.0885
Average curve length	0.039	0.173	0.227	0.8201	-0.273	0.321	-0.850	0.3951
Lane width	0.067	0.114	0.583	0.5599	0.010	0.132	0.073	0.9414
Number of access points	-0.488	0.237	-2.058	0.0396	-0.321	0.130	-2.463	0.0138
Presence of passing lane	1.227	0.536	2.290	0.0220	-0.149	0.606	-0.246	0.8054
Number of lanes	-0.034	0.661	-0.051	0.9595	-0.359	0.661	-0.543	0.5871
Shoulder width	0.207	0.150	1.384	0.1664	0.009	0.056	0.162	0.8717
LN(ADTT)	0.320	0.305	1.049	0.2942	0.566	0.238	2.375	0.0175
Presence of traffic control	-2.194	0.733	-2.992	0.0028	-2.488	0.600	-4.147	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	-0.651	0.802	-0.811	0.4173	0.305	0.420	0.726	0.4678
Number of observations	772				772			
AIC	347.110				447.650			

Table 39. Binary Logit Model for Treated and Untreated Groups (0.8σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-3.618	2.366	-1.529	0.1262	-4.312	2.532	-1.703	0.0886
Downgrade length	-0.259	0.199	-1.300	0.1937	0.315	0.142	2.219	0.0265
Grade	-0.146	0.092	-1.595	0.1108	0.216	0.089	2.436	0.0149
Average curve length	0.045	0.158	0.283	0.7775	-0.166	0.321	-0.517	0.6049
Lane width	0.076	0.143	0.534	0.5936	0.042	0.139	0.301	0.7636
Number of access points	-0.440	0.216	-2.036	0.0417	-0.217	0.129	-1.683	0.0924
Presence of passing lane	0.672	0.511	1.316	0.1881	-0.410	0.588	-0.697	0.4860
Number of lanes	-0.416	0.633	-0.657	0.5113	-0.558	0.641	-0.870	0.3841
Shoulder width	0.042	0.145	0.292	0.7705	0.020	0.059	0.342	0.7327
LN(ADTT)	0.580	0.303	1.916	0.0554	0.404	0.237	1.705	0.0882
Presence of traffic control	-3.142	1.018	-3.086	0.0020	-2.426	0.600	-4.041	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	0.168	0.597	0.282	0.7780	-0.218	0.459	-0.475	0.6350
Number of observations	794				794			
AIC	365.79				449.44			

Table 40. Binary Logit Model for Treated and Untreated Groups (0.9σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	1.852	3.324	0.557	0.5774	-4.490	2.481	-1.810	0.0703
Downgrade length	-0.299	0.204	-1.469	0.1419	0.302	0.147	2.051	0.0402
Grade	-0.119	0.100	-1.182	0.2371	0.133	0.092	1.440	0.1499
Average curve length	-0.012	0.173	-0.068	0.9457	-0.604	0.383	-1.578	0.1146
Lane width	-0.380	0.222	-1.714	0.0866	0.042	0.147	0.286	0.7746
Number of access points	-0.743	0.304	-2.445	0.0145	-0.240	0.129	-1.862	0.0626
Presence of passing lane	0.103	0.552	0.187	0.8517	-0.362	0.527	-0.686	0.4924
Number of lanes	-0.536	0.663	-0.808	0.4189	-0.861	0.588	-1.464	0.1433
Shoulder width	-0.173	0.150	-1.152	0.2495	0.045	0.059	0.776	0.4375
LN(ADTT)	0.952	0.321	2.965	0.0030	0.828	0.245	3.380	<0.001
Presence of traffic control	-3.461	1.035	-3.344	<0.001	-2.236	0.525	-4.257	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	0.760	0.561	1.355	0.1753	0.045	0.439	0.102	0.9188
Number of observations	808				808			
AIC	361.63				455.85			

Table 41. Binary Logit Model for Treated and Untreated Groups (1.0σ Caliper Width)

	Treated				Untreated			
Variable	**Estimate**	**Std. Error**	**Z**	**p>|Z|**	**Estimate**	**Std. Error**	**Z**	**p>|Z|**
Intercept	-4.895	2.551	-1.919	0.0550	-4.114	2.326	-1.768	0.0770
Downgrade length	-0.345	0.198	-1.741	0.0816	0.197	0.133	1.480	0.1388
Grade	-0.134	0.088	-1.516	0.1296	0.173	0.089	1.958	0.0503
Average curve length	-0.043	0.138	-0.309	0.7572	-0.348	0.328	-1.060	0.2891
Lane width	0.085	0.161	0.526	0.5990	0.027	0.129	0.210	0.8337
Number of access points	-0.387	0.200	-1.936	0.0528	-0.210	0.121	-1.729	0.0839
Presence of passing lane	0.833	0.509	1.637	0.1016	-0.373	0.519	-0.719	0.4720
Number of lanes	-0.043	0.617	-0.069	0.9448	-0.435	0.557	-0.781	0.4349
Shoulder width	0.037	0.139	0.269	0.7881	0.047	0.055	0.840	0.4010
LN(ADTT)	0.657	0.295	2.229	0.0258	0.478	0.221	2.163	0.0306
Presence of traffic control	-3.129	1.024	-3.055	0.0023	-2.597	0.598	-4.344	<0.001
Speed limit (1 if greater than 50 mph, 0 otherwise)	0.246	0.607	0.406	0.6850	-0.001	0.425	-0.003	0.9977
Number of observations	820				820			
AIC	368.86				480.07			

APPENDIX 5: WARNING SIGN DATA COLLECTION CODE

Codes for Warning Sign Data Collection

Two warning sign codes were used for the study and are shown below. The code shown on figure A-6-1 was used in the warning sign maps while codes on table A-6-2 were adopted for the field data collection.

Table 42. Coding for Warning Sign Combinations

Warning Signs (Code)	Sign Type
1	01 & 3
2	01 & 06
3	02 & 03
4	02 & 06
5	08 & 09
6	Truck Turnout/Brake Check Area
7	Trucker Warning/Trucker Speed
8	Misc. Downgrade Signs (01, 01&04, 01&07, 02&04,07,06, Steep Grades Ahead, etc.)
9	Directional Sign
10	Speed sign
11	Directional and Speed Combination Sign
12	Chevron
13	Others (Lane Merges, VMS, Rollover warning, Pass with Care, Sharp Curve etc.)

Table 43. Warning Sign Coding

01	W7-1
02	W7-1a
03	W7-2P
04	W7-2bP
05	W7-3P
06	W7-3aP
07	W7-3bP
08	W7-4
09	W7-4b
10	W7-4c
11	Other (VMS, etc.)

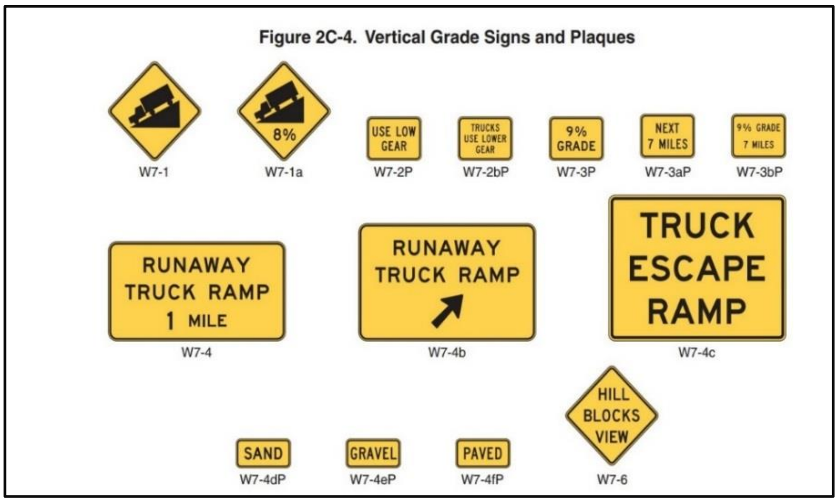
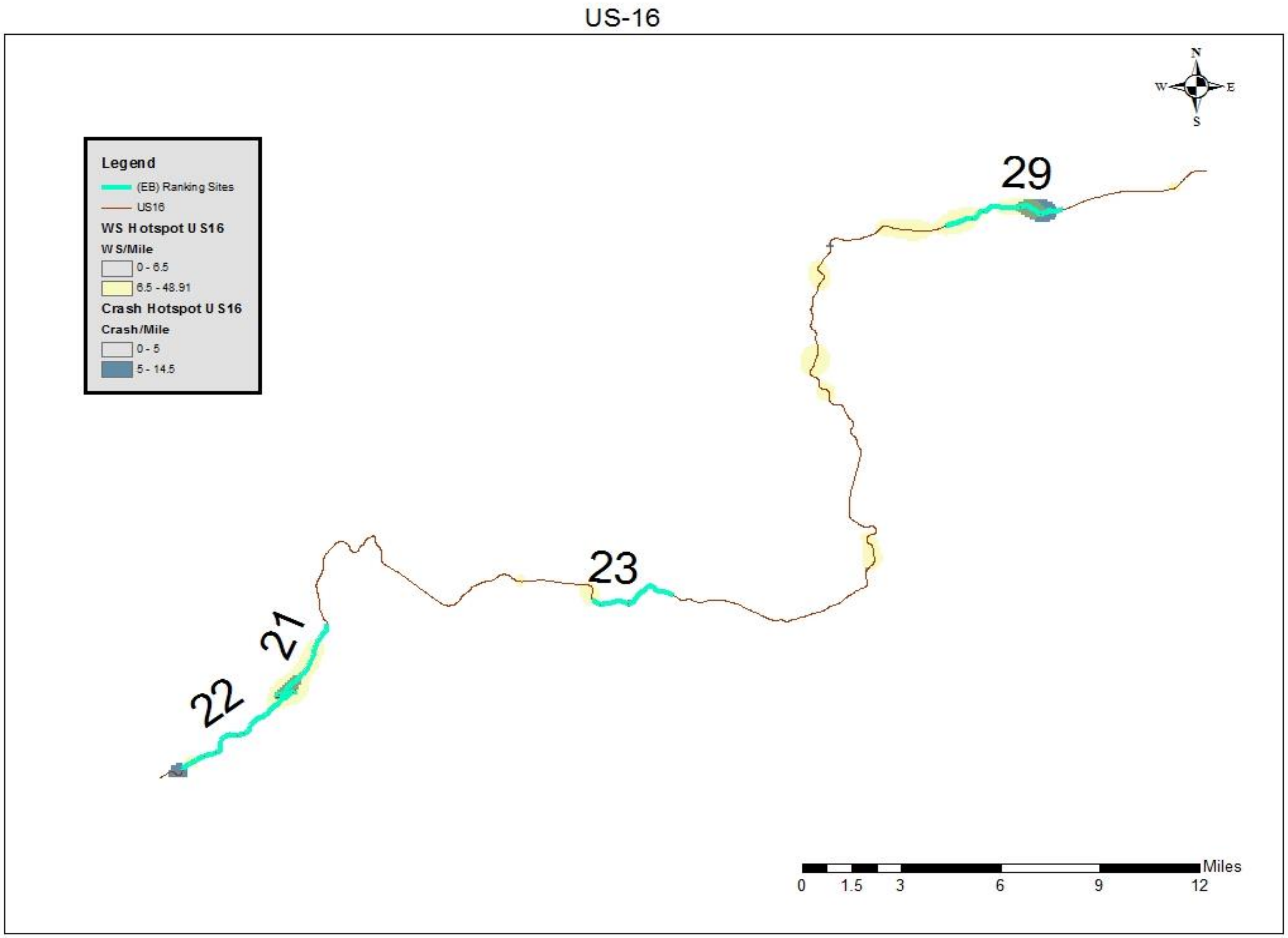


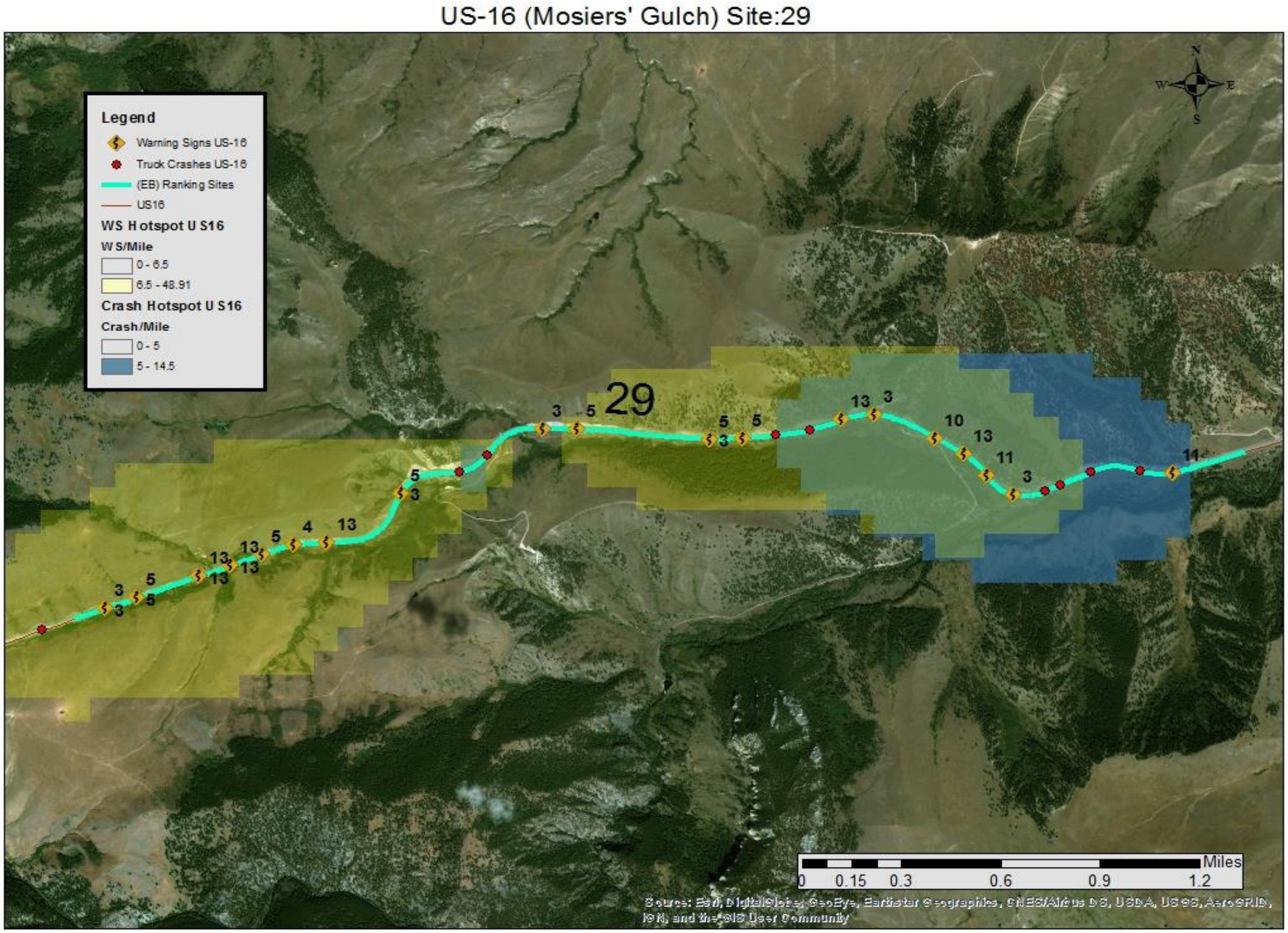
Figure 69. Hill Warning Signs.

APPENDIX 6: HOTSPOT ANALYSIS - WARNING SIGN MAPS



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

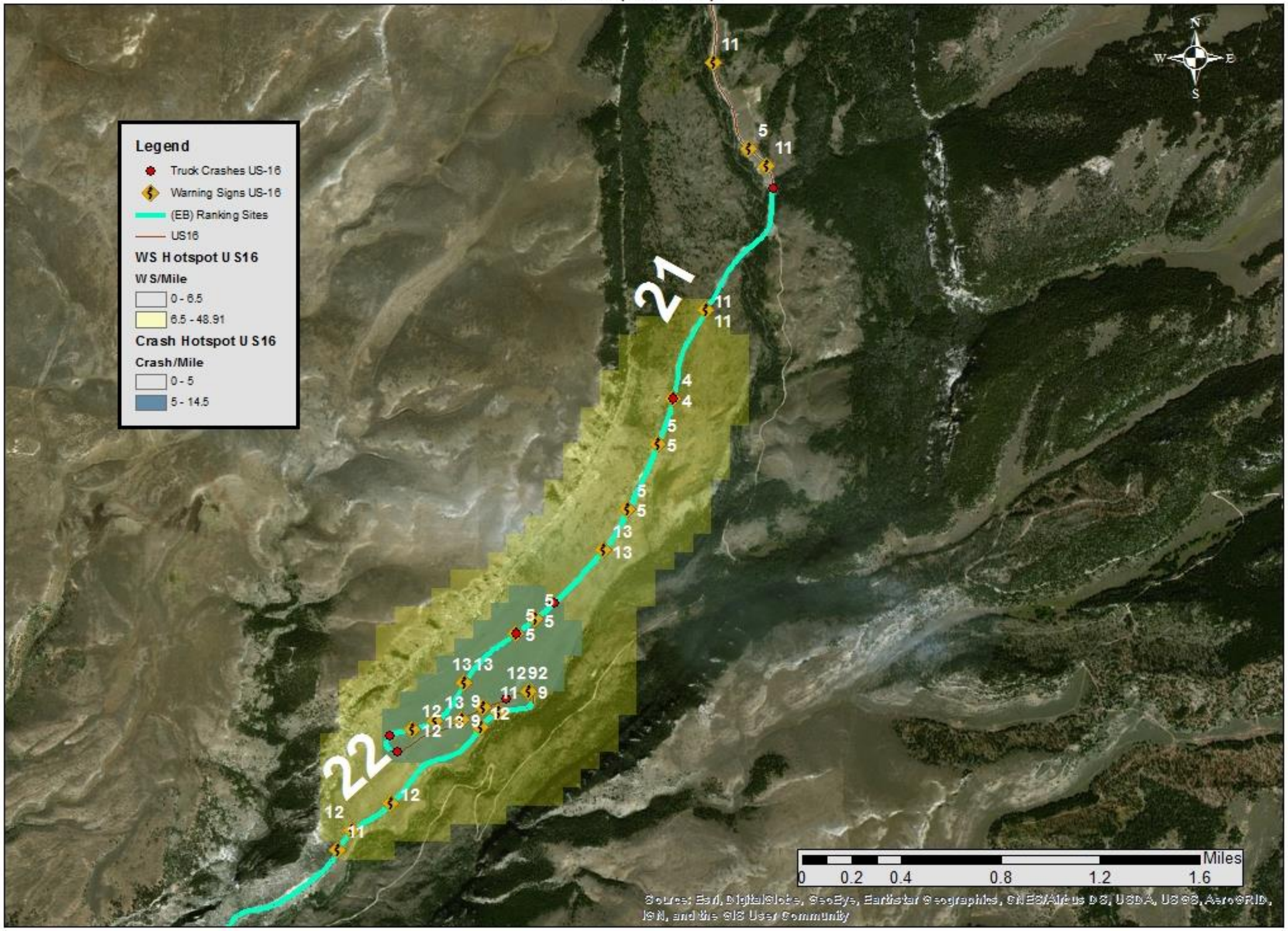
Figure 70. US-16 General Hotspot Map (ESRI, 2018).



Original Photo: © 2018 **ArcGIS®** (see Acknowledgements section).

Figure 71. ML36B (Increasing MP) 83.10 to 86.93 – Downgrade Direction: East (ESRI, 2018).

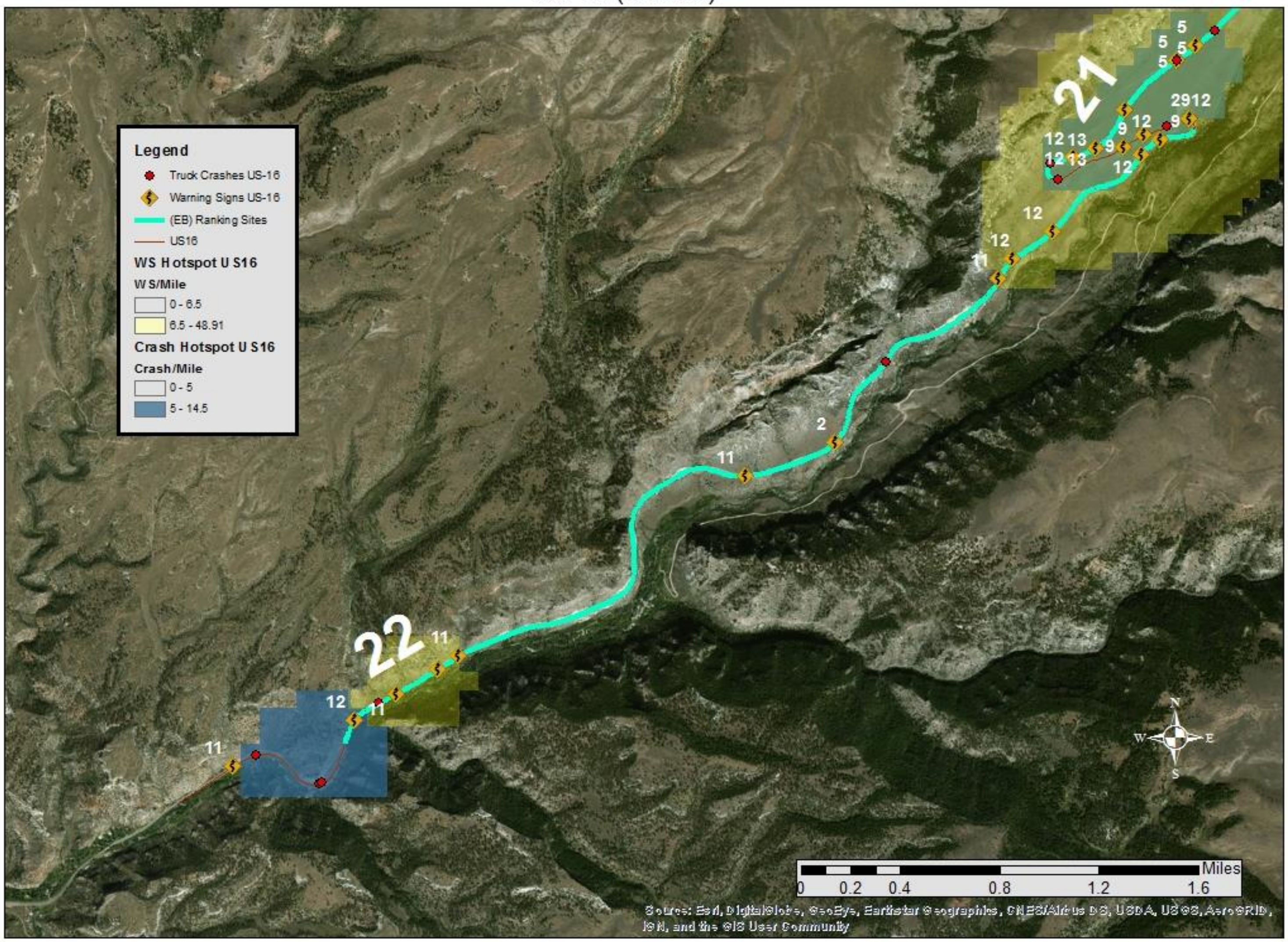
US-16 (Site:21)



Original Photo: © 2018 **ArcGIS®** (see Acknowledgements section).

Figure 72. ML36B (Decreasing MP) 42.01 to 39.03 – Downgrade Direction: South West (ESRI, 2018).

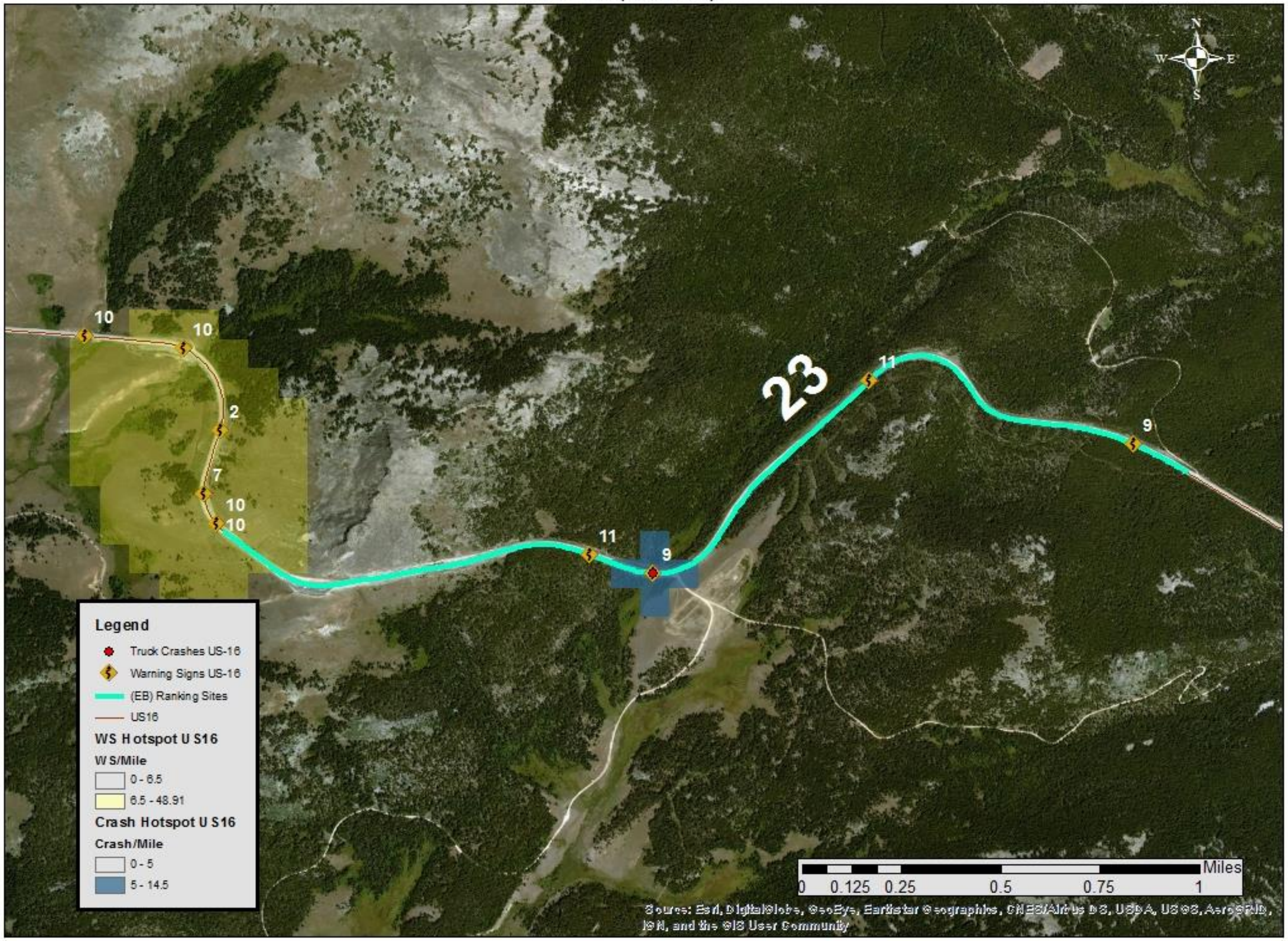
US-16 (Site:22)



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

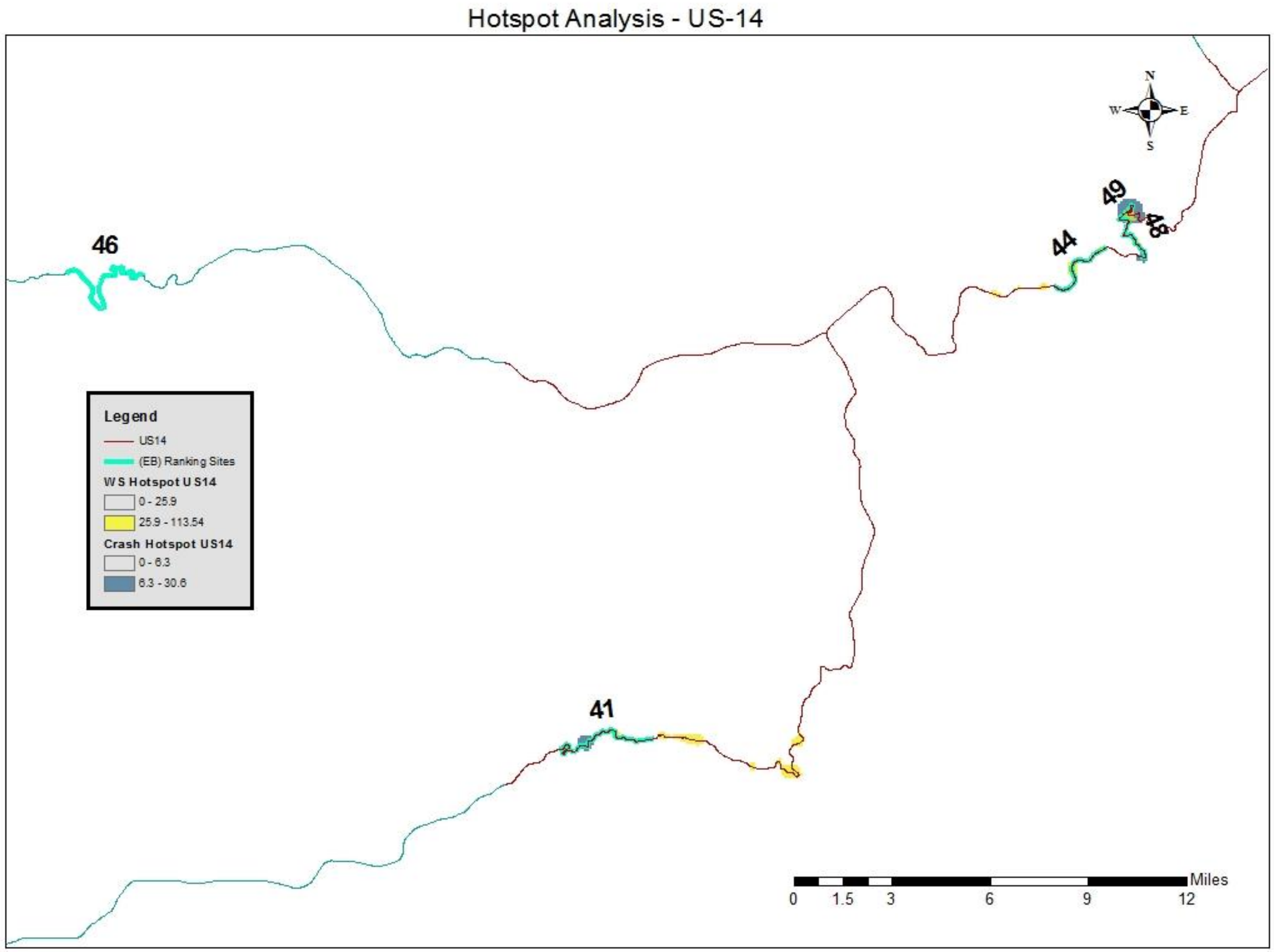
Figure 73. ML36B (Decreasing MP) 42.01 to 39.03 – Downgrade Direction: South West (ESRI, 2018).

US-16 (Site:23)



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

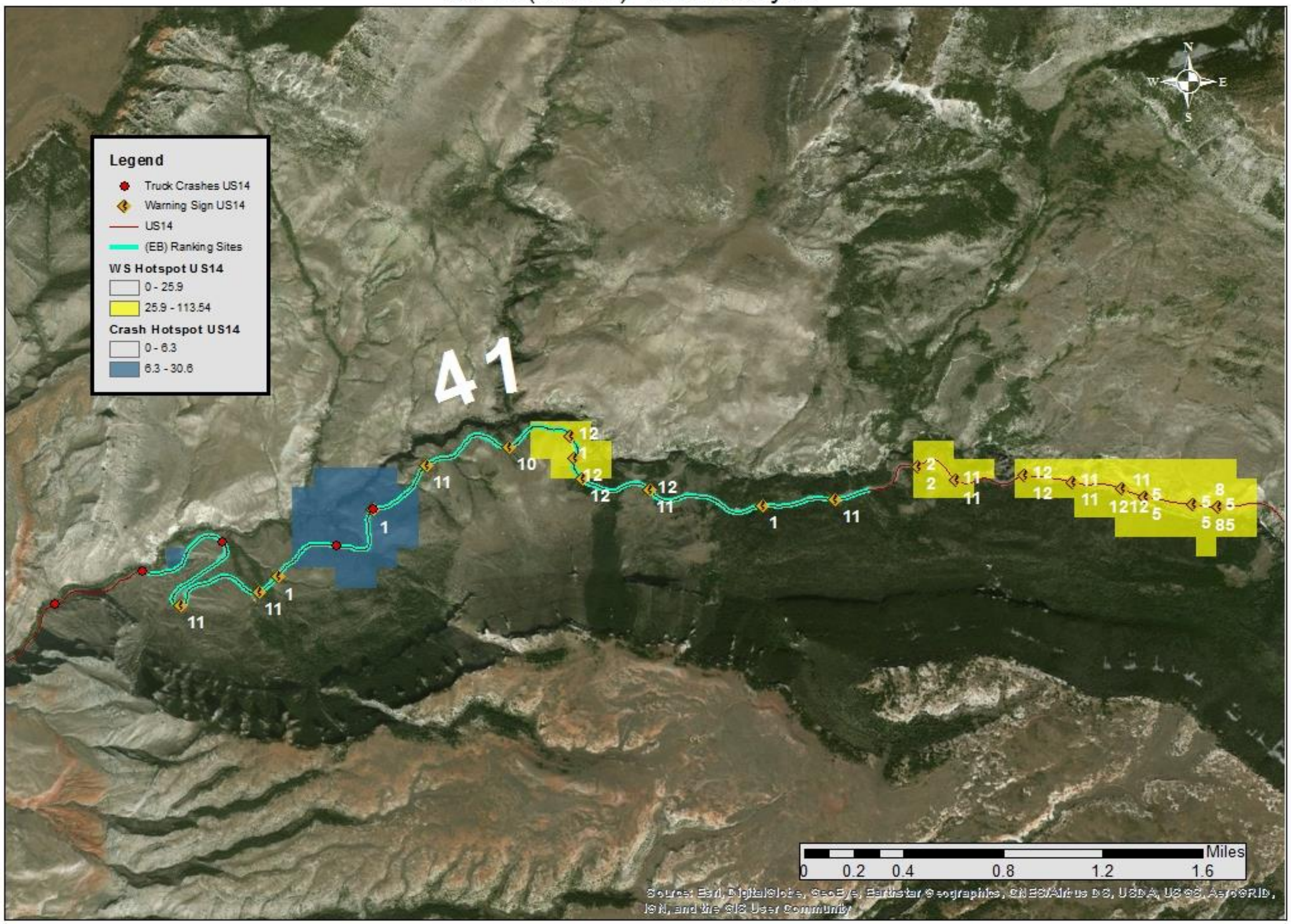
Figure 74. ML36B (Increasing MP) 55.63 to 58.99 – Downgrade Direction: West (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

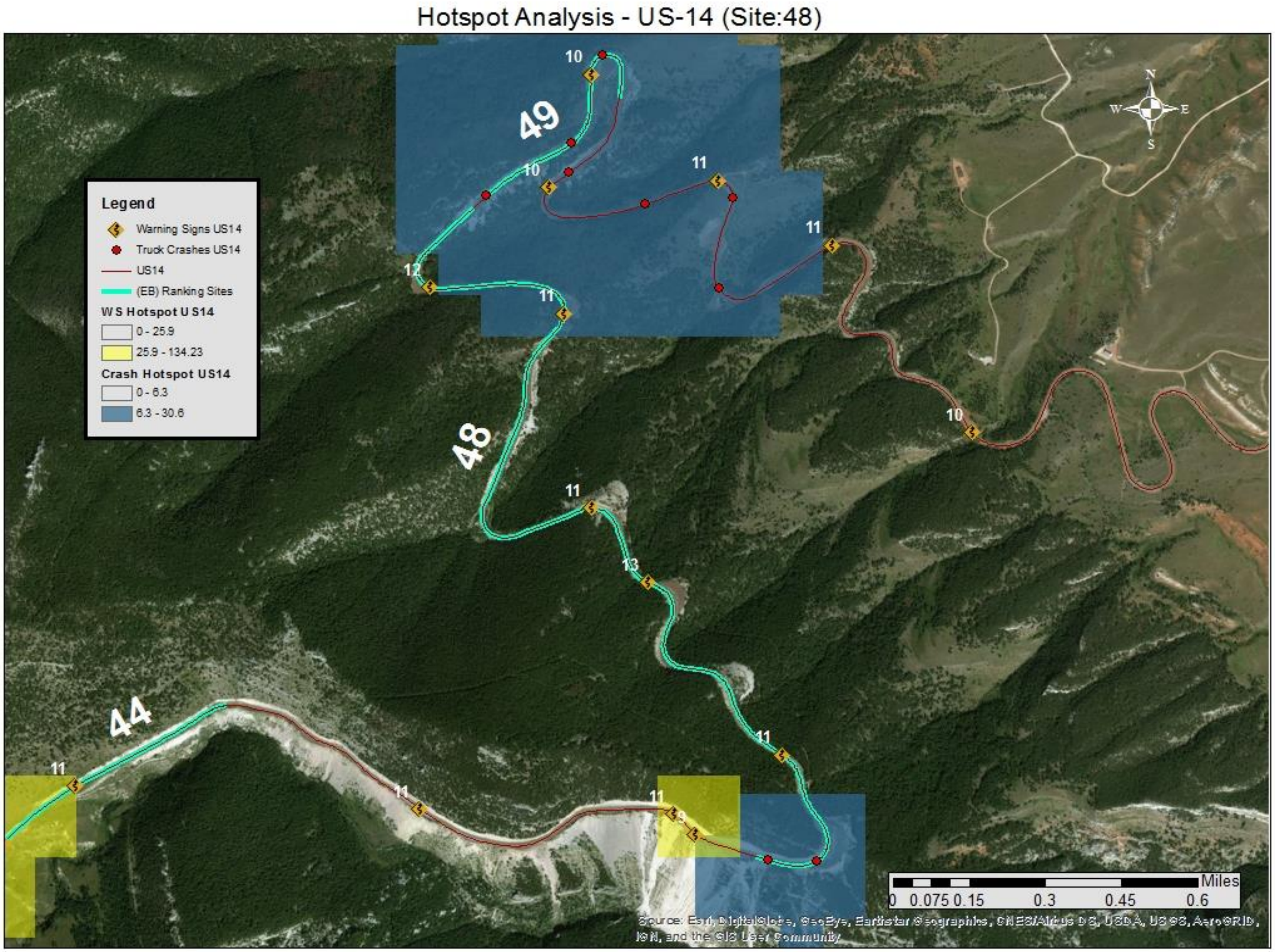
Figure 75. US-14 General Hotspot Map (ESRI, 2018).

US-14 (Site:41) - Shell Canyon



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

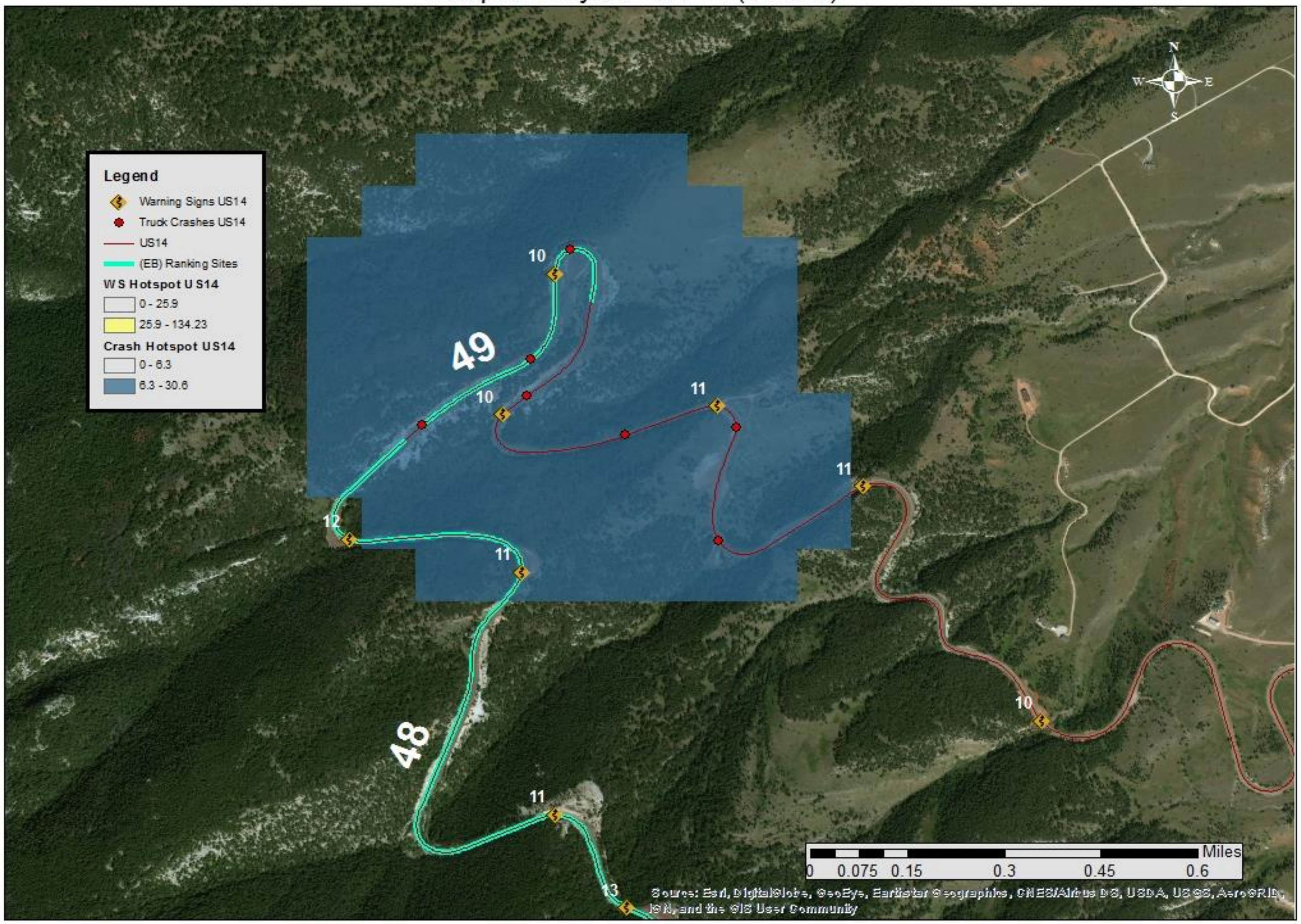
Figure 76. ML37B (Decreasing MP) 25.94 to 21.56 – Downgrade Direction: West (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

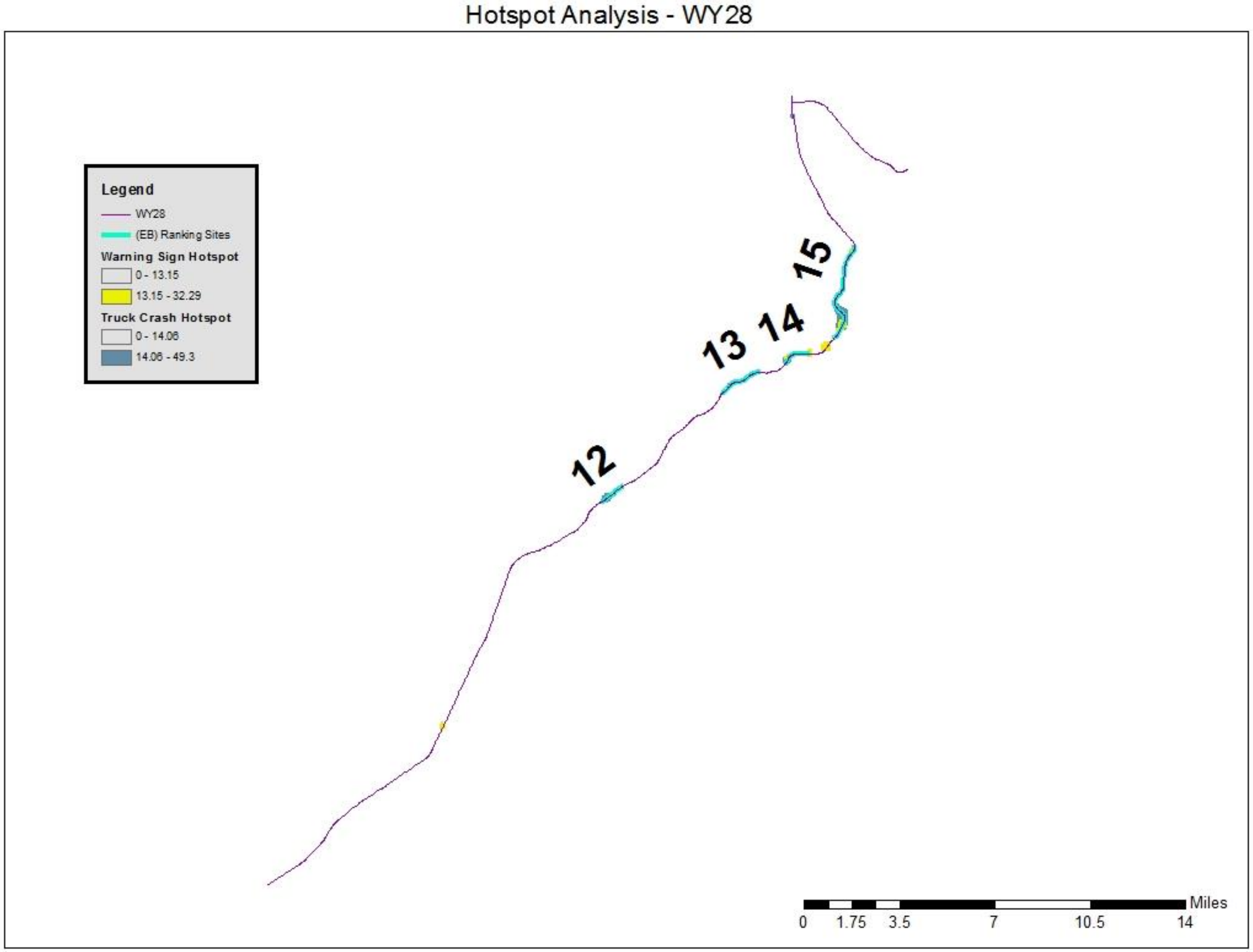
Figure 77. ML37B (Increasing MP) 72.88 to 75.17 – Downgrade Direction: North-East (ESRI, 2018).

Hotspot Analysis - US-14 (Site:49)



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

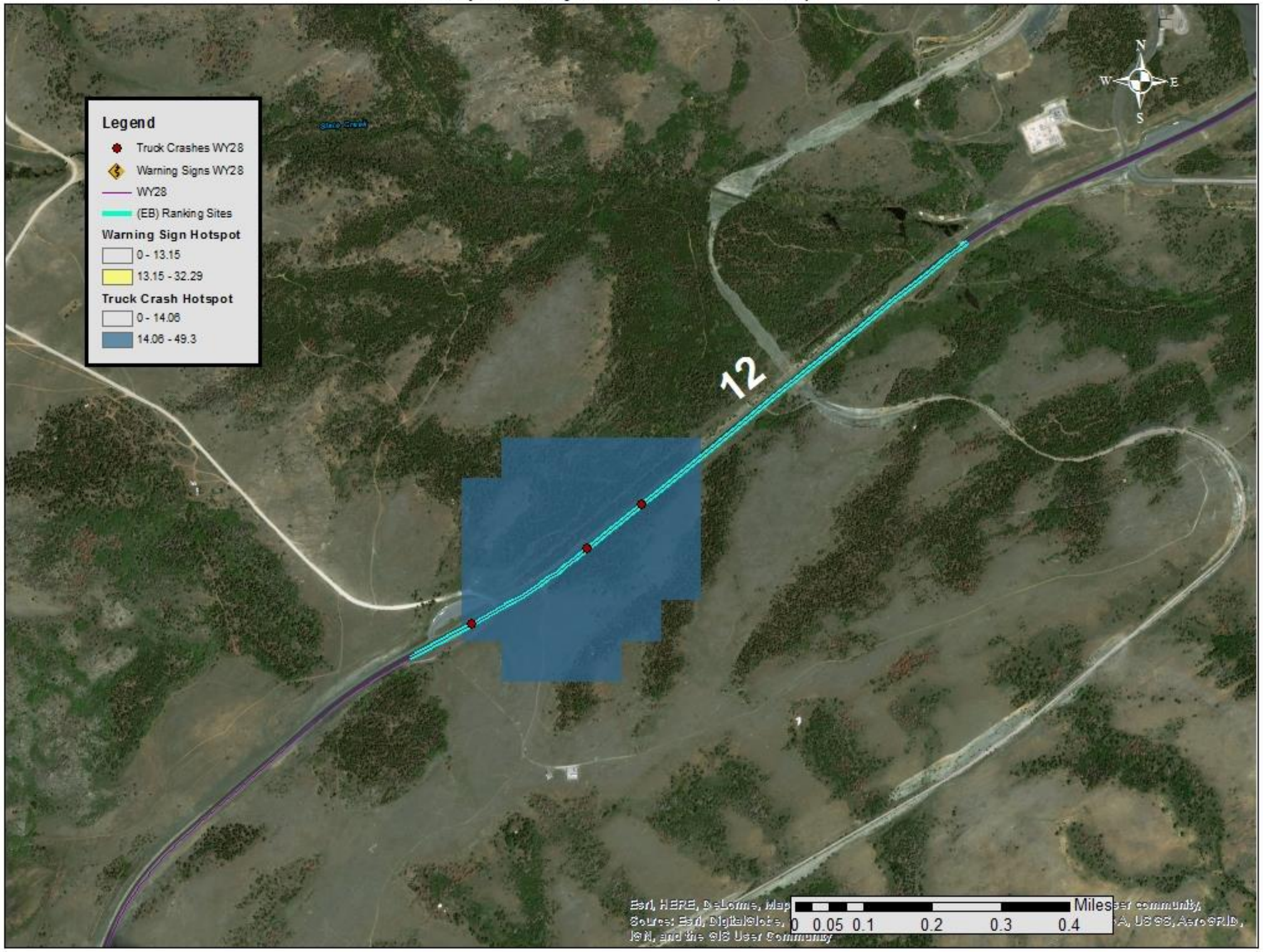
Figure 78. ML37B (Increasing MP) 75.2 to 75.7 Downgrade Direction: East (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

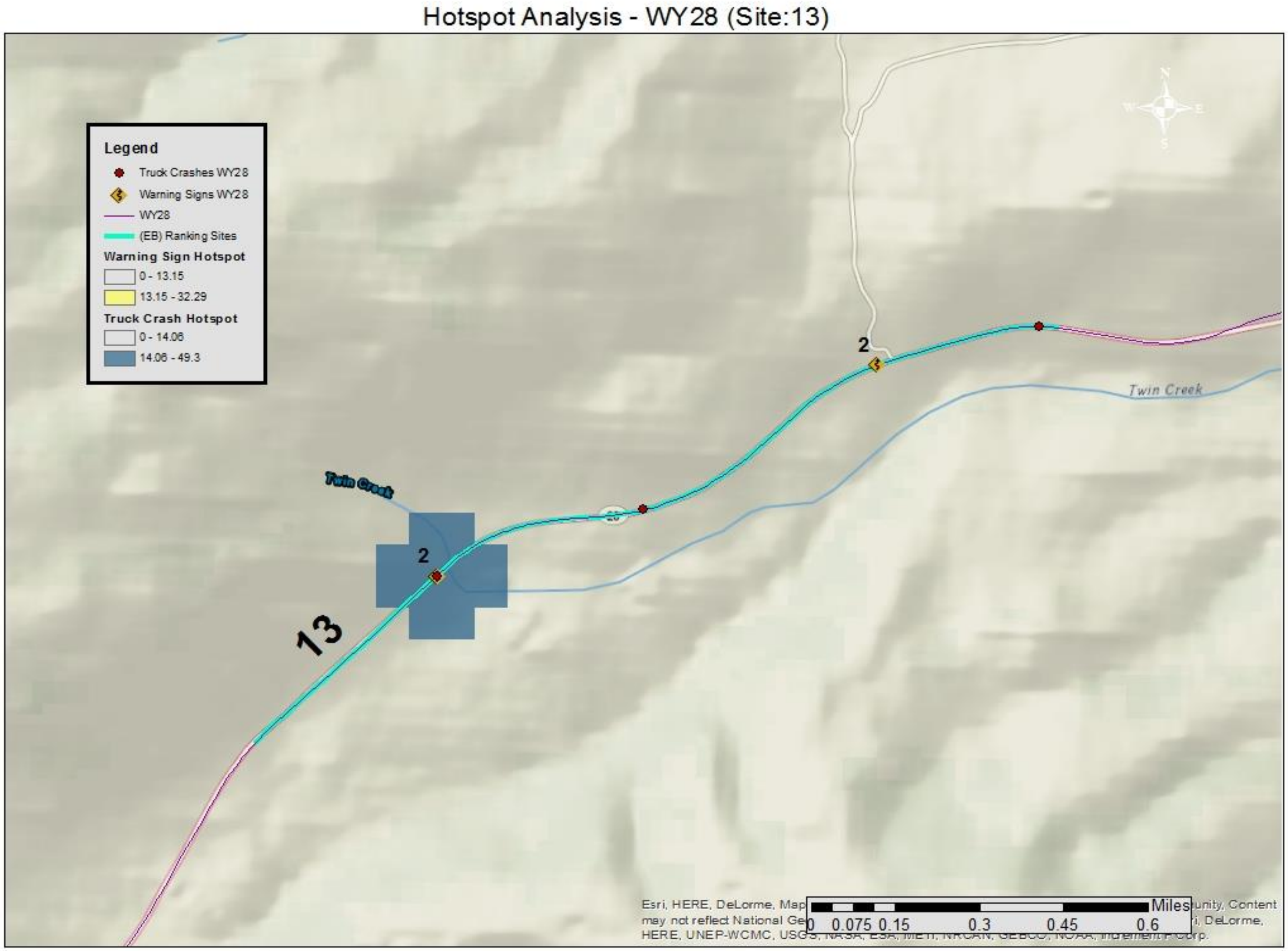
Figure 79. WY-28 General Hotspot Map (ESRI, 2018).

Hotspot Analysis - WY28 (Site:12)



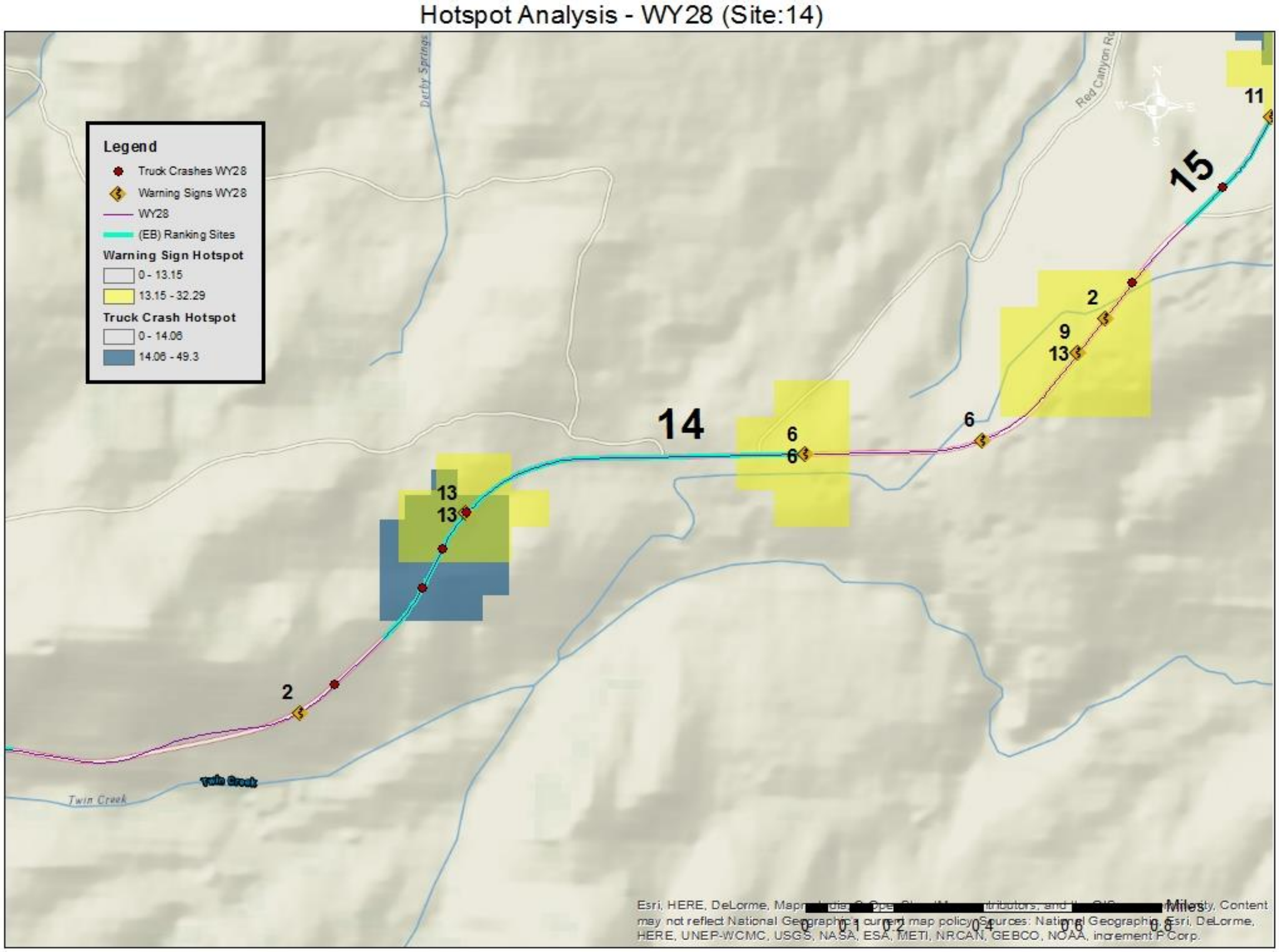
Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 80. ML14B (Increasing MP) 45.6 to 46.6 – Downgrade Direction: North-East (ESRI, 2018).



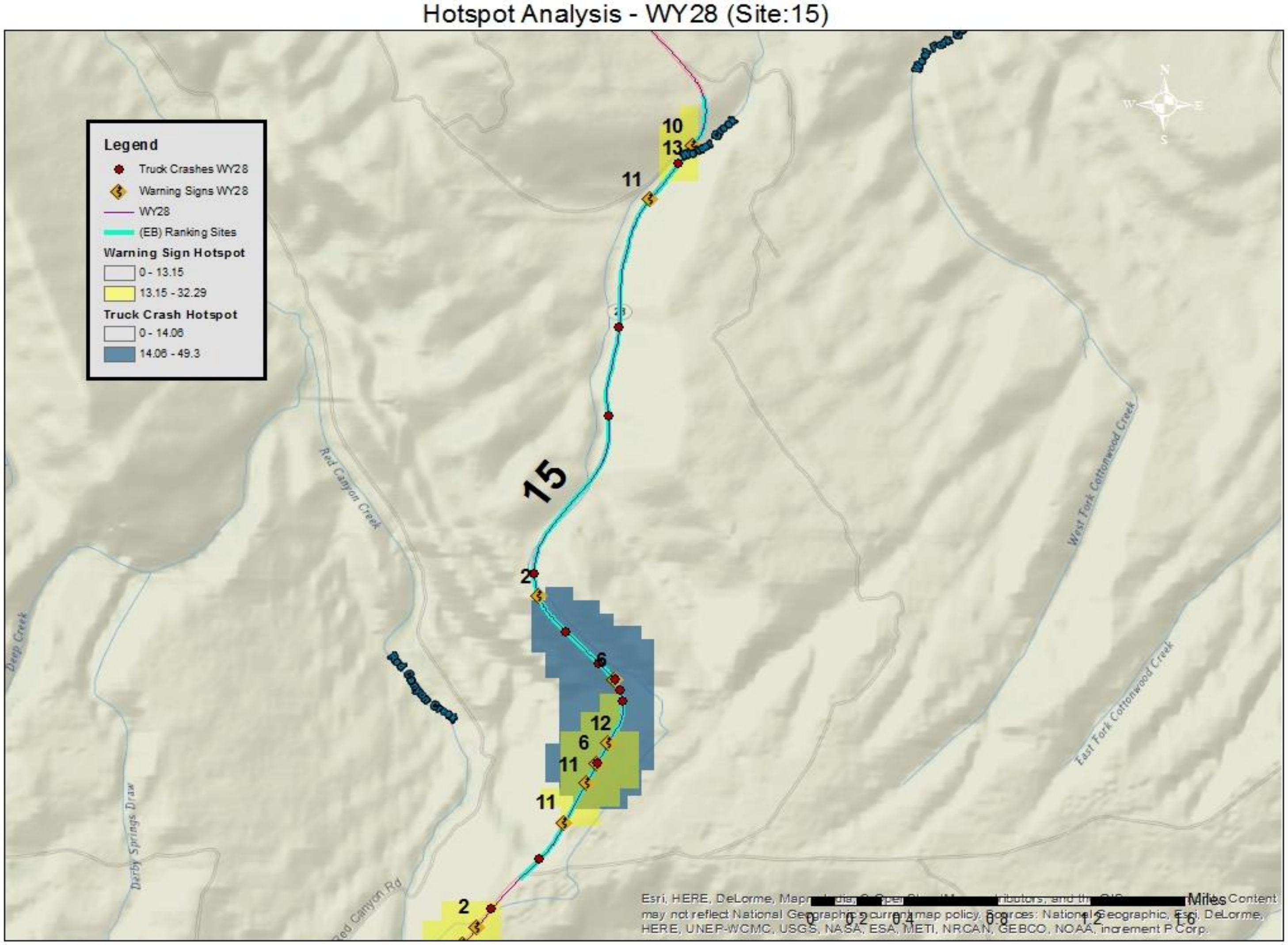
Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 81. ML14B (Increasing MP) 53.55 to 55.24 – Downgrade Direction: North-East (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

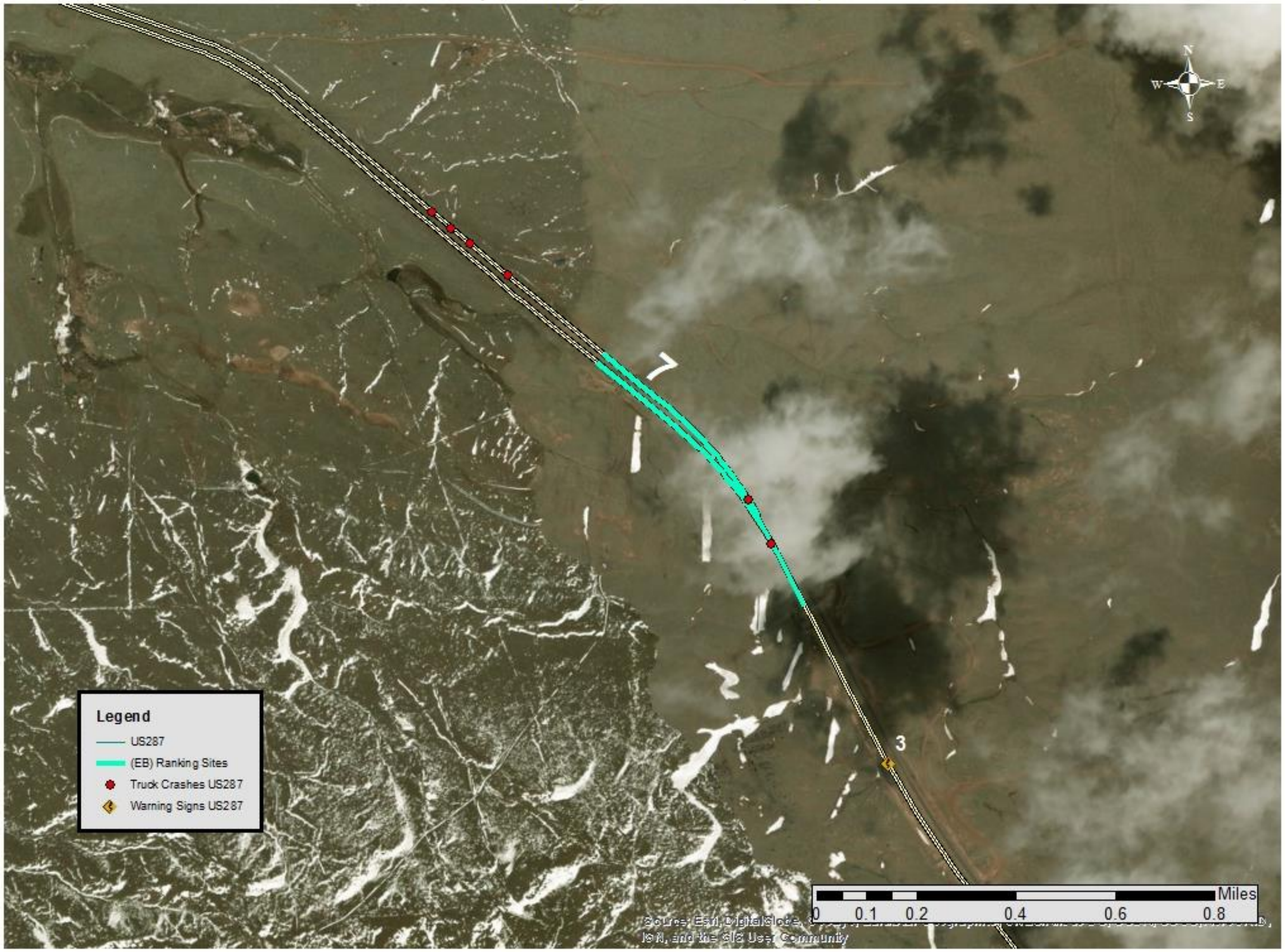
Figure 82. ML14B (Increasing MP) 56.15 to 57.31 – Downgrade Direction: North-East (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 83. ML14B (Increasing MP) 58.38 to 62.34 – Downgrade Direction: East (ESRI, 2018).

Hotspot Analysis - US287 (Site:7)



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 84. ML23B (Decreasing MP) 419.48 to 419.2 – Downgrade Direction: North-West (ESRI, 2018).

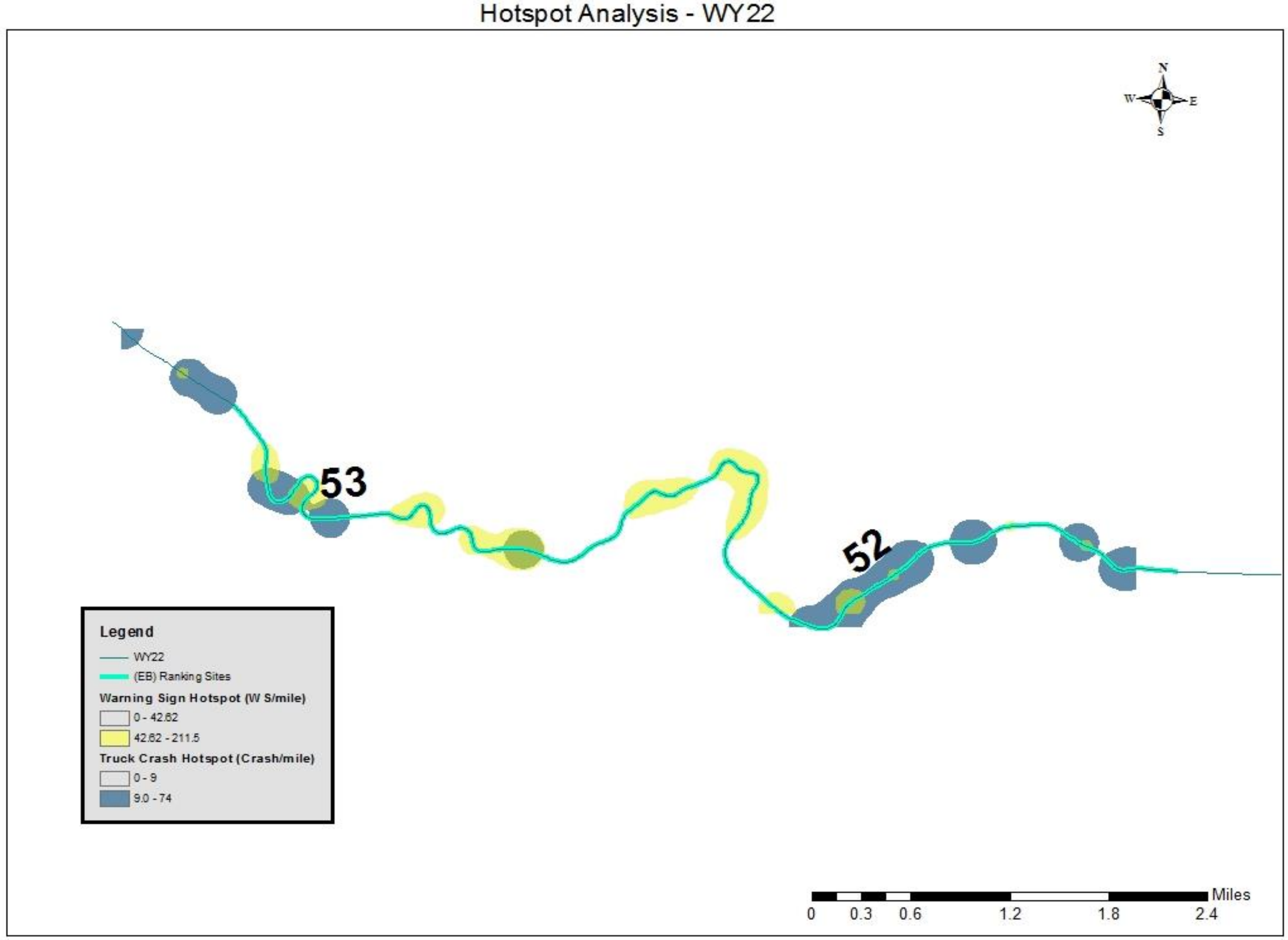
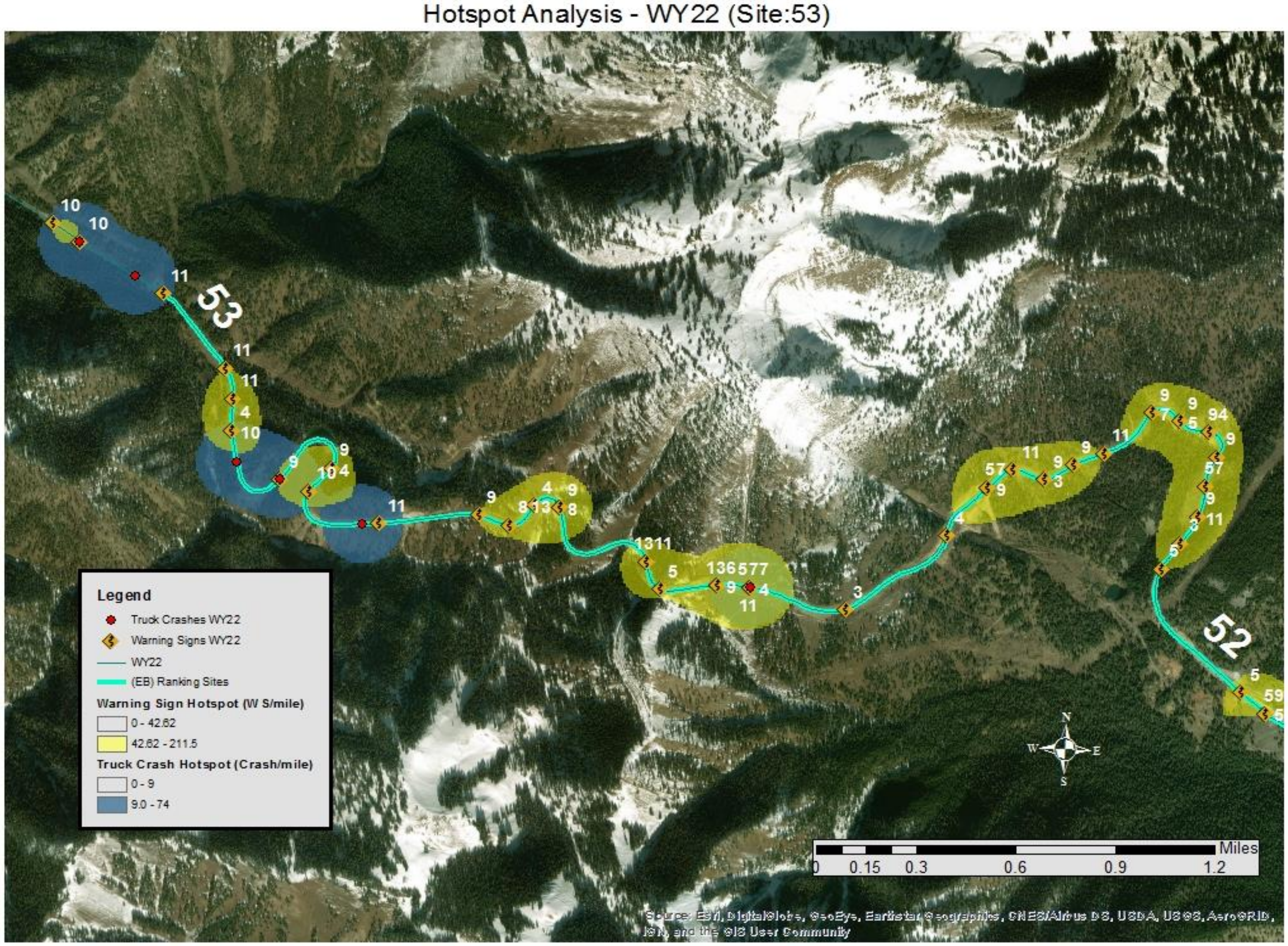
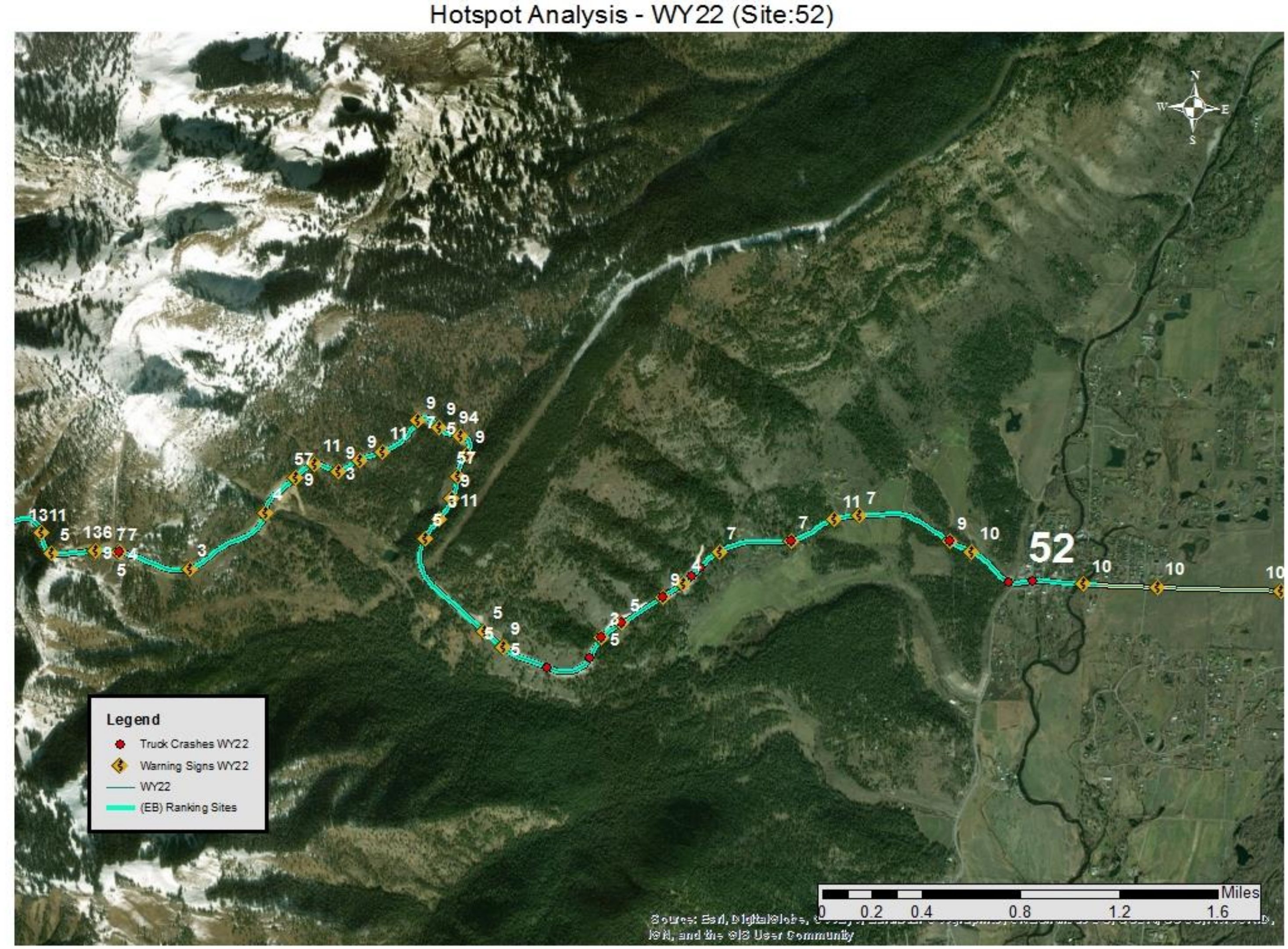


Figure 85. WY-22 General hotspot Map (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 86. ML2000B (Increasing MP) 11.08 to 13.68 – Downgrade Direction: North-West (ESRI, 2018).



Original Photo: © 2018 ArcGIS® (see Acknowledgements section).

Figure 87. ML 2000B (Decreasing MP) 11.08 to 5.35 – Downgrade Direction: East (ESRI, 2018).

APPENDIX 7: DOWNGRADE-RELATED WARNING SIGNS

Downgrade Route Layout

Downgrade route layout maps were installed on US-14 and US-16. They outline the horizontal curves, number of grades, grade percent, locations of runaway truck ramps and brake check areas. Figure 88 shows route layout signs on US-14 and US-16.

(A) – Route Layout Sign at Burgess Junction (US-14).

(B) – Route Layout Signs at Pole Creek and Hospital Hill Respectively (US-16).

Figure 88. Downgrade Route Layout Signs.

Cable Catch-Net System and Truck Escape Ramps

Several truck escape ramps were found installed on the study area. Cable catch-net systems were also found on WY-22 and US-16. These systems retained their traditional gravel escape ramps located not more than half a mile in either direction (Figure 89). Other traditional gravel truck escape ramps including the two in the vicinity of the catch-net system are found on US-22 (Teton Pass), US-16 (Tensleep canyon and Mosier Gulch) and US-14 (Shell Creek Canyon) (figure A-8-1).

(A) Cable Catch-Net System at Teton Pass (WY-22).

(B) Cable Catch-Net System at Mosier Gulch (US-16).

Figure 89. Cable Catch-Net Systems

Traditional escape ramps were found on most of the hazardous mountain passes identified. Below are the locations of escape ramps found in the study areas (Figure 90). Ideally, the escape ramps should be located on the right shoulder. However, due to the landscape, cross traffic escape ramps on the left shoulder was found to exist on WY-22, endangering oncoming traffic. On Teton Pass and Mosier's Gulch, the newly installed catch-net system and the traditional escape ramps were located within the same segments.

(C) Escape Ramps at Teton Pass (WY-22) and Shell Creek (US-14) Respectively.

(D) Escape Ramps at Ten Sleep Canyon and Mosier Gulch (US-16) Respectively.

Figure 90. Traditional Gravel Escape Ramps.

Truck Escape Ramp Signs

Two types of truck escape ramp signs were found during the data collection. These signs signaled the presence of a traditional gravel escape ramp sign and cable catch-net systems. Variations of these signs were found and examples can be seen on Figure 91 below.

(A) Runaway Truck Signs (US-16).

(B) Truck Escape Ramp Caution Sign (US-14).

Figure 91. Truck Escape Ramp Signs on US-16 and US-14.

Special Truck Signs

Signs cautioning drivers to the presence of hazardous grades and the need to drive at advisory speeds were found on some routes. Some of these truck signs were equipped with flashers, to alert the drivers in adverse conditions. The majority of these signs were found on US-14 and WY-22. Examples of such special truck signs are shown in Figure 92.

(A) Truck Speed Sign (WY-22).

(B) Truck Warning Sign with flasher and Curve Warning Sign (US-14).

(C) Trucker Steep Grade Warning and Turnout Signs (US-16).

Figure 92. Special Truck Signs.

Turnout/Brake Check Signs

Truck turnout and brake check areas are usually one of the two signs below. One has words and arrow while the other type has a symbol (Figure 93). Both of these signs below were found on US-287.

Figure 93. Truck Turnout Signs.

Downgrade Warning Signs

Below are examples of downgrade signs found during the field assessment (Figure 94). In Wyoming, the signs are usually a combination of the truck symbol and grade with either a “Next Mile” sign or use lower gear sign or both.

(A) Grade and Distance Combination Sign (US-287).

(B) Grade and Distance Combination (US-16).

Figure 94. Hill Signs with Advisory Plaques.

Speed and Directional Signs

A variety of speed and direction signs are used for speed and directional guidance on mountain passes. Some signs use text with others being symbol combinations, while other signs were VMS (Figure 95).

(A) Speed and Direction Warning Sign (US-16).

(B) Speed and Direction Warning Sign (US-16).

Figure 95. Speed and Directional Warning Signs.

Weight Limit Signs

On WY-22, signs warning truck drivers not to exceed a specific weight were found. The VMS sign displaying the same information was placed at the approach of the mountain pass. The following signs were installed at the approach from the Idaho side of WY-22 (Figure 96). A weigh station is located at the Wyoming side of the border to ensure compliance of the weight limits.

(A) Weight Limit Signs on WY-22.

(B) GSRS Weight Limit Sign (WY-22).

Figure 96. Weight Limit Sign.

APPENDIX 8: ROAD SIGN CONSTRUCTION

This section shows pictures from the WYDOT sign shop located at the agency's headquarters in Cheyenne, Wyoming. The shop produces 20,000 sign per year which makes it the largest sign shop in Wyoming. The signs produced are made up of either a special plywood (Figure 97) material or aluminum (Figure 98).

Figure 97. Plywood Used in Sign Construction.

Figure 98. Aluminum Used in Sign Construction.

After the materials are cut or snipped to the desired size and shape, they are coated with an electrochromic (EC) material, which is the white or colored reflective material found on signs. Below is the machine used to apply the reflective material onto the precut sign shapes (Figure 99 and Figure 100). The signs are printed with a computer programmed with a sign production software.

Figure 99. Machine used to Apply EC Material to Signs.

Figure 100. Sign About to be applied with Reflective EC Material.

Below are some of the standard sizes and shapes of signs that can be found on roadways, such as octagonal and diamond shaped warning signs (Figure 101). Sign-making is a multi-stage process. After the sign is cut out and applied with the base EC coat. The desired sign is printed out and applied to on top of the reflective material often in layers of more than print.

Figure 101. Different Shapes and Sizes of Signs.

As described above, a sign often consists of multiple layers which can be seen below in Figure 102. For instance, to create a "No- U Turn" sign, the aluminum plate is first coated with an EC base. After that, the crossed-out circle is applied and finally the U-Turn symbol along with the black border are pressed onto the plate.

Figure 102. Layers of Sheets Applied to Sign.

There are different types of EC material, with various colors, quality and reflectiveness (Figure 103). Yellow is the most expensive as well as the most visible. The signs are designed on CAD programs with a printer cutting the material to the desired shape using a very thin blade. The printer is shown in Figure 104.

Figure 103. Reflective Material for Warning Signs.

Figure 104. Printer for Warning Signs.

ACKNOWLEDGEMENTS

Maps throughout this report were created using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and can be accessed from https://www.esri.com/en-us/arcgis/products/index. The maps have been modified to show routes, crash locations, crash densities and warning sign densities.

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