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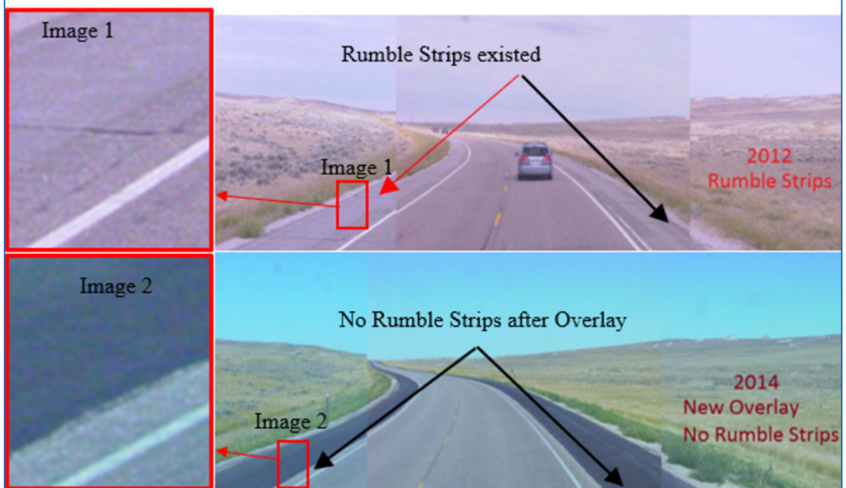

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Highway Safety Manual Part D: Validation and Application in Wyoming

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ABSTRACT

This study is considered a first step toward validating applicability of the Highway Safety Manual (HSM) Part D to Wyoming conditions. The HSM Part D provides a quantitative measure of safety for various countermeasures known as crash modification factors (CMF). These CMFs are provided for four distinct groups of treatments: roadway segments (e.g., rumble strips, passing lanes, etc.), intersections (e.g., flashing yellow arrows), special facilities (e.g., Highway-rail crossings, and interchanges), and road networks. CMFs provided in the HSM Part D are calibrated based on data collected from a few states in the United States**,** which may not represent the same safety efficacy of countermeasures implemented in Wyoming. The objectives of this study are to (1) validate applicability of the HSM Part D to Wyoming conditions, (2) calibrate CMFs for various countermeasures in Wyoming, and (3) provide recommendations in terms of data requirements, how to mitigate data shortcoming, and applicability of alternative analytical methodologies to evaluate the safety effectiveness of specific countermeasures.

Depending on data availability, various observational before-after and cross-sectional techniques were adopted in this study to calibrate CMFs for six countermeasures applied to roadway segments, intersections, and special facilities. Results indicated that the majority of these countermeasures are statistically significant in reducing crash frequency and severity. Moreover, CMFs from the HSM and Clearinghouse should not be implemented in Wyoming without proper calibration and validation. Wyoming conditions are unique and therefore, site-specific Safety Performance Functions (SPFs) and Crash Modification Factors (CMFs) must be calibrated and updated every five years.

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1. INTRODUCTION

The Highway Safety Manual (HSM), published in 2010 by the American Association of State Highway and Transportation Officials (AASHTO) is considered the sole national source to scientifically quantify safety performance of roadway facilities and evaluate safety effectiveness of countermeasures. Highway agencies and safety practitioners can carry out safety analyses efficiently with the help of the HSM. The HSM consists of four main parts: 1) Part A – Introduction, Human Factors, and Fundamentals of Safety, 2) Part B – Roadway Safety Management Process, 3) Part C – Predictive Methods; and, 4) Part D – Crash Modification Factors. It provides methodologies to evaluate the current safety performance of roadway facilities as well as evaluating the effectiveness of the implemented roadway treatments.

To advance implementation of the HSM in the United States, the National Cooperative Highway Research Program (NCHRP 17-50) conducted the "Lead State Initiative for Implementing the Highway Safety Manual" project and published the Implementation Guide for Managers in 2011 [1]. Twenty-one states participated in the NCHRP 17-50 project, with 13 lead states and eight supporting states as shown in Figure 1.1.

Figure 1.1 Lead states and support states in the "NCHRP 17-50 HSM Lead State Initiative Project"

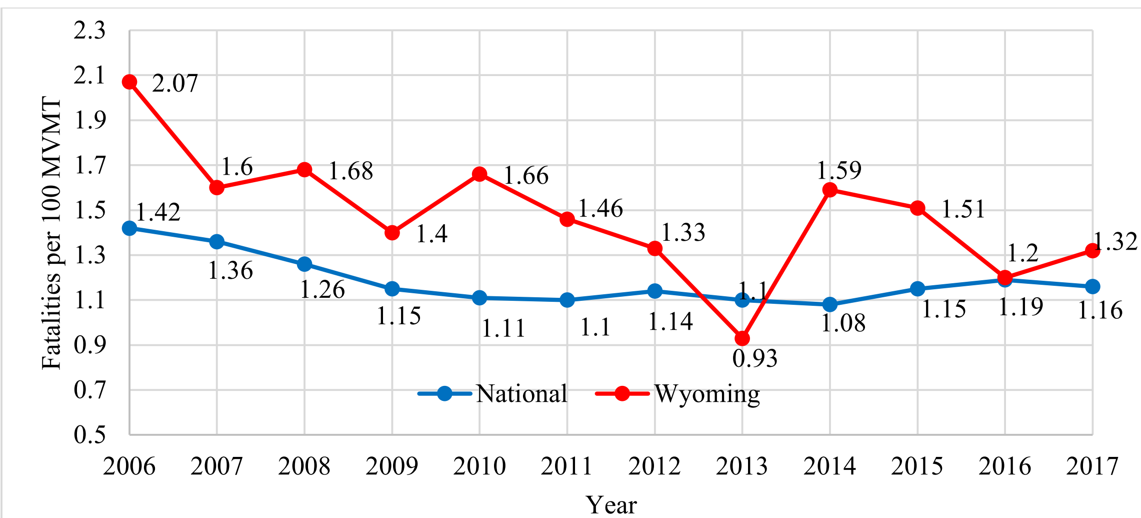
As an additional effort to widely use the HSM to evaluate and enhance the safety performance of roadway networks in the United States, the Federal Highway Administration (FHWA) provided a guide to incorporate the HSM into the different highway project development processes [2]. The guide contains examples and ideas for integrating safety performance measures into the project development process.

The HSM includes several Safety Performance Functions (SPFs) for different roadway facilities and intersections. However, a debate between adopting the provided SPF in the HSM with applying calibrating factors versus developing new site specific SPFs to account for the local conditions of the road network is initiated. This argument is introduced as the SPF provided in the HSM are developed using data from few states not representative for the characteristics of the United States.

Many states, which include Florida [3], [4], and [5], Utah [6], Kansas [7], and Oregon [8], have already worked on calibrating their own site-specific SPFs rather than adopting the HSM developed SPFs. Comparing characteristics of the states used to develop the SPFs in the HSM to Wyoming, it was found that Wyoming is completely different in many aspects. In Wyoming weather conditions are more severe, it is characterized by a rural and remote nature, and the traffic volumes and mix are unique. Therefore, it could be said that the SPFs and Crash Modification Factors (CMFs) provided in the HSM are not transferable to Wyoming specific conditions. Hence, it is necessary to develop accurate CMFs representing Wyoming-specific conditions, which will help in prioritizing and selecting the most appropriate and cost-effective countermeasures.

1.1 Transferability and Limitations of the HSM

According to the National Highway Traffic Safety Administration (NHTSA), the comparison of crash fatality rates between Wyoming and the national average shows that the fatality rates in Wyoming were always higher than the national average (Figure 1.2). This could be due to the extreme weather conditions, challenging roadway geometry, and the rural nature of Wyoming. The highest surge in fatality rate in the last 10 years was observed in 2014 where Wyoming had 72 percent increase in fatality rates (Figure 1.3).



Source: Traffic Safety Facts 2006 to 2017

Figure 1.1 Fatality rates in Wyoming and U.S. from 2006 to 2017

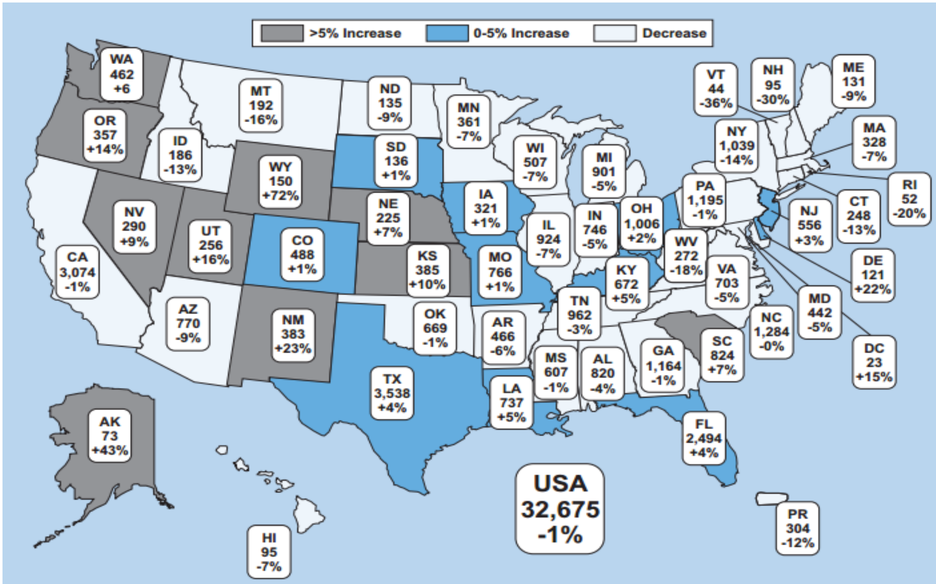


Figure 1.2 Percentage increase in fatality rates from 2013 to 2014 in the U.S.
Source (Traffic Safety Facts 2014) [9]

High crash fatality rates in Wyoming initiated the need of a state-wide implementation of the HSM to evaluate the safety performance of Wyoming's roadway network and to quantify the safety effectiveness of different countermeasures on different roadway types and intersections. This would help to identify the most cost-effective strategies and countermeasures to reduce and mitigate crashes. The first step to carry out the safety analyses is to calibrate SPFs to Wyoming conditions, since the SPFs presented in the HSM cannot be transferred to provide reliable results. One of the main limitations in the first edition of the HSM is that the SPFs for roadway facilities are developed using observed crash data collected from six states (California, Minnesota, Michigan, New York, Texas, and Washington) as shown in Figure 1.4. These states do not adequately represent the Rocky Mountains and Plain Regions, which has unique weather characteristics. Figure 1.5 shows the different climate regions, as defined by the National Oceanic and Atmospheric Administration (NOAA) [10].

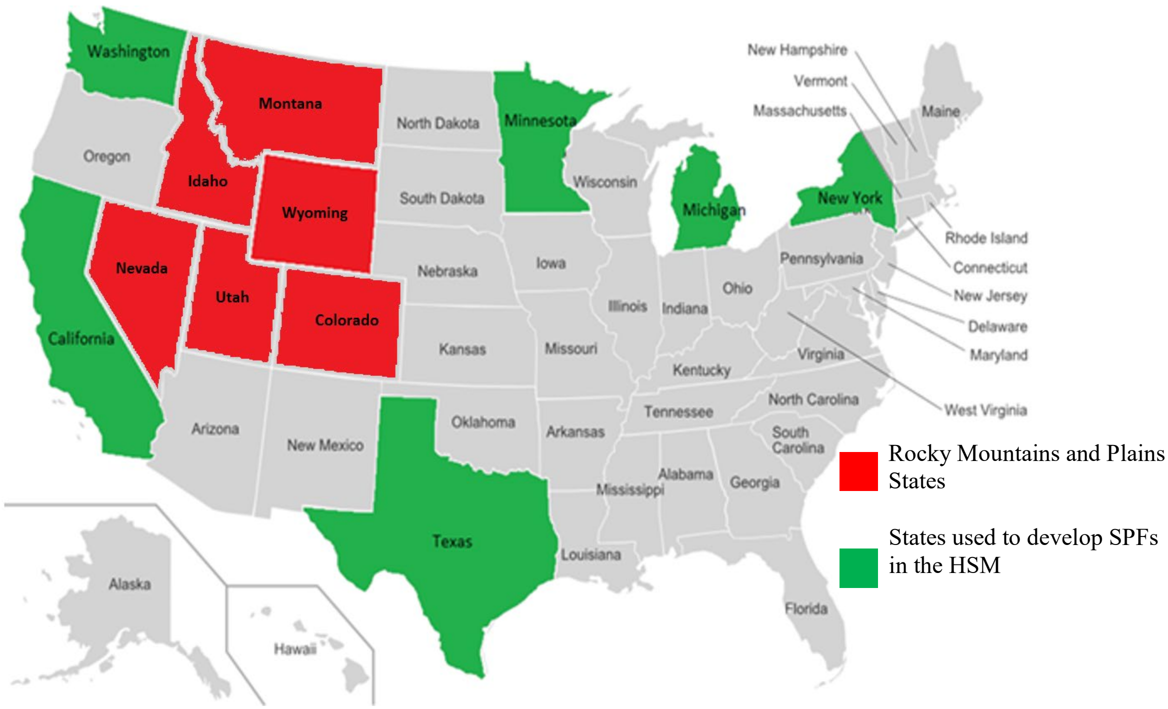


Figure 1.3 Crash data collected from the states to develop SPFs in the HSM

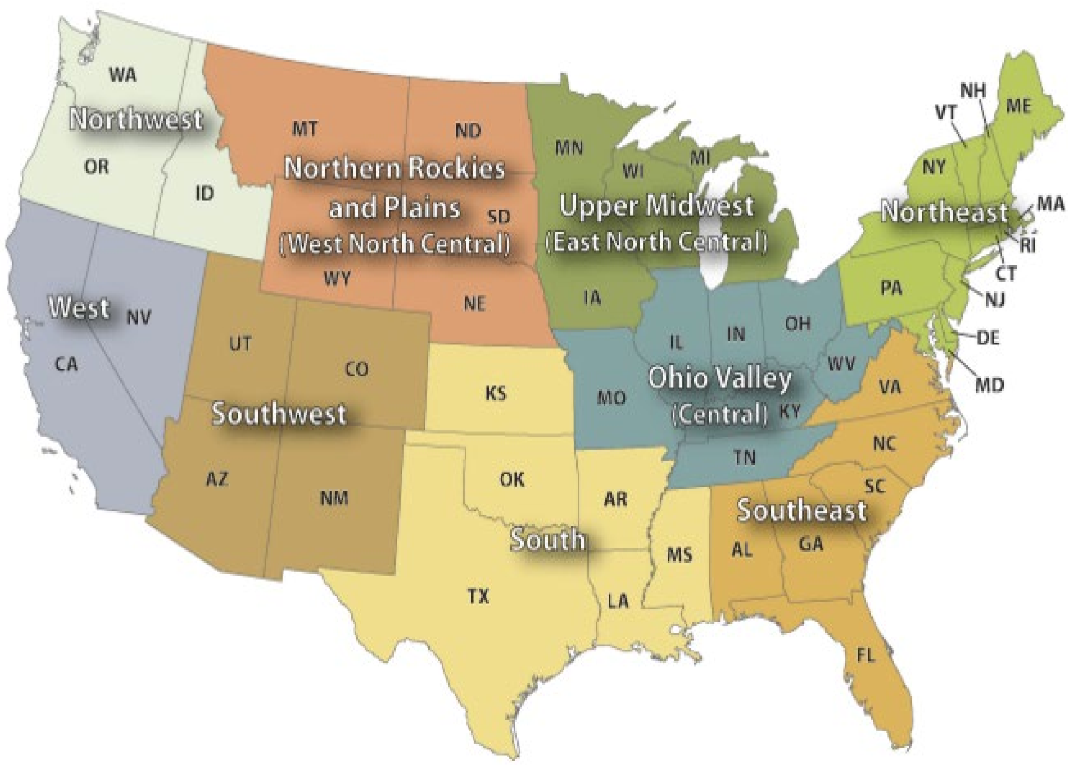


Figure 1.4 U.S. climate regions identified by NOAA
Source: National Centers for Environmental Information

Specific issues that hinder adopting the SPFs provided in the HSM to Wyoming-specific conditions are:

- Certain facility types are not accounted for such as rural roadways with low traffic volumes, challenging roadway geometry, and high percentage of heavy trucks.
- Each state has different crash reporting thresholds and use different reporting forms.
- Driving behavior and regulations in the mountain plains region are different from the states whose crash data were used to calibrate SPFs in the HSM.
- Adverse weather conditions in the region are not considered.
- The effect of specific activities in some areas (e.g., energy-related activities) are not addressed.

It was necessary to resolve these issues to obtain more accurate crash prediction by crash type and severity for roadways in Wyoming. This is because the CMFs in the HSM apply only to certain collision types or crashes at certain severity levels. Furthermore, HSM safety management methodology includes economic evaluation of the expected crash outcomes of road improvement scenarios. Fully accounting for all factors associated with crash severities will result in better prediction of crash counts by severity, and thus, more accurate economic evaluations.

2. METHODOLOGIES

The methodologies used in this study — calibrate Wyoming-specific Safety Performance Functions (SPFs) and develop Crash Modification Factors (CMFs) — included spatial geographical analyses, regression models with various distributions, observational before-after studies, and cross-sectional analyses are provided in this section.

2.1 Kernel Density Estimation

Chainey et al. [11] and Sabel [12] pointed out that Kernel Density Estimation (KDE) was the most promising tool among the various spatial techniques to assist in producing a smooth density surface of spatial point events.

"Kernel density estimation involves placing a symmetrical surface over each point, evaluating the distance from the point to a reference location based on a mathematical function, and then summing the value for all the surfaces for that reference location. This procedure is repeated for all reference locations" [13]. This allows us to place a kernel over each crash observation, and summing these individual kernels gives the density estimate for the distribution of crash points by Equation 2.1 [13].

$$\mathbf{f(x,y) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right)} \qquad \text{Equation 2.1}$$

Where,

f (x, y): density estimate at the location (x, y);
n: number of observations,
h: bandwidth or kernel size,
K: kernel function, and
Di: distance between the location (x, y) and the location of the ith observation.

The kernel density method divides the entire study area into predetermined number of cells. Rather than considering a circular neighborhood around each cell (the point density method), the kernel method draws a circular neighborhood around each feature point (the crash) and then a mathematical equation is applied that goes from one at the position of the feature point to zero at the neighborhood boundary [14].

2.2 Safety Performance Functions

Safety Performance Functions (SPFs) are mathematical models used to predict average crash frequencies per year as a function of exposure and roadway characteristics. The SPFs provided in the HSM are to be used for certain base conditions. The base conditions for roadway segments on rural two-lane two-way roads as provided in the HSM are [15]:

- Lane width = 12 feet
- Shoulder width = six feet
- Shoulder type = paved
- Roadside hazard rating (RHR) = 3
- Driveway density (DD) = five driveways per mile
- Horizontal curvature = None
- Vertical curvature = None
- Centerline rumble strips = None
- Passing Lanes = none

- Two-way left-turn lanes = none
- Lighting = none
- Automated speed enforcement = none
- Grade level = 0 %

The HSM provides 18 steps, as shown in Figure 2.1, to estimate the number of crashes by developing site-specific SPF. These steps are combined in the general form provided in Equation 2.2 [15]:

$$(N_{predicted}) = N_{spf}\ x(CMF_1\ x\ CMF_2\ x \ldots \ldots x\ CMF_{yz})\ x\ C_x \qquad \text{Equation 2.2}$$

Where,

$N_{predicted}$: predicted average crash frequency for a specific year for site type x;
$N_{spf:}$ predicted average crash frequency determined for base conditions of the SPF developed for site type x;
CMF_{nx}: crash modification factors specific to SPF for site type x; and
C_x: calibration factor to adjust SPF for local conditions for site type x.

Each predictive model is specific to a facility or site type and a specific year. It should be noted that the predictive method can be used to predict crashes for past years based on observed AADT or for future years based on forecasted AADT.

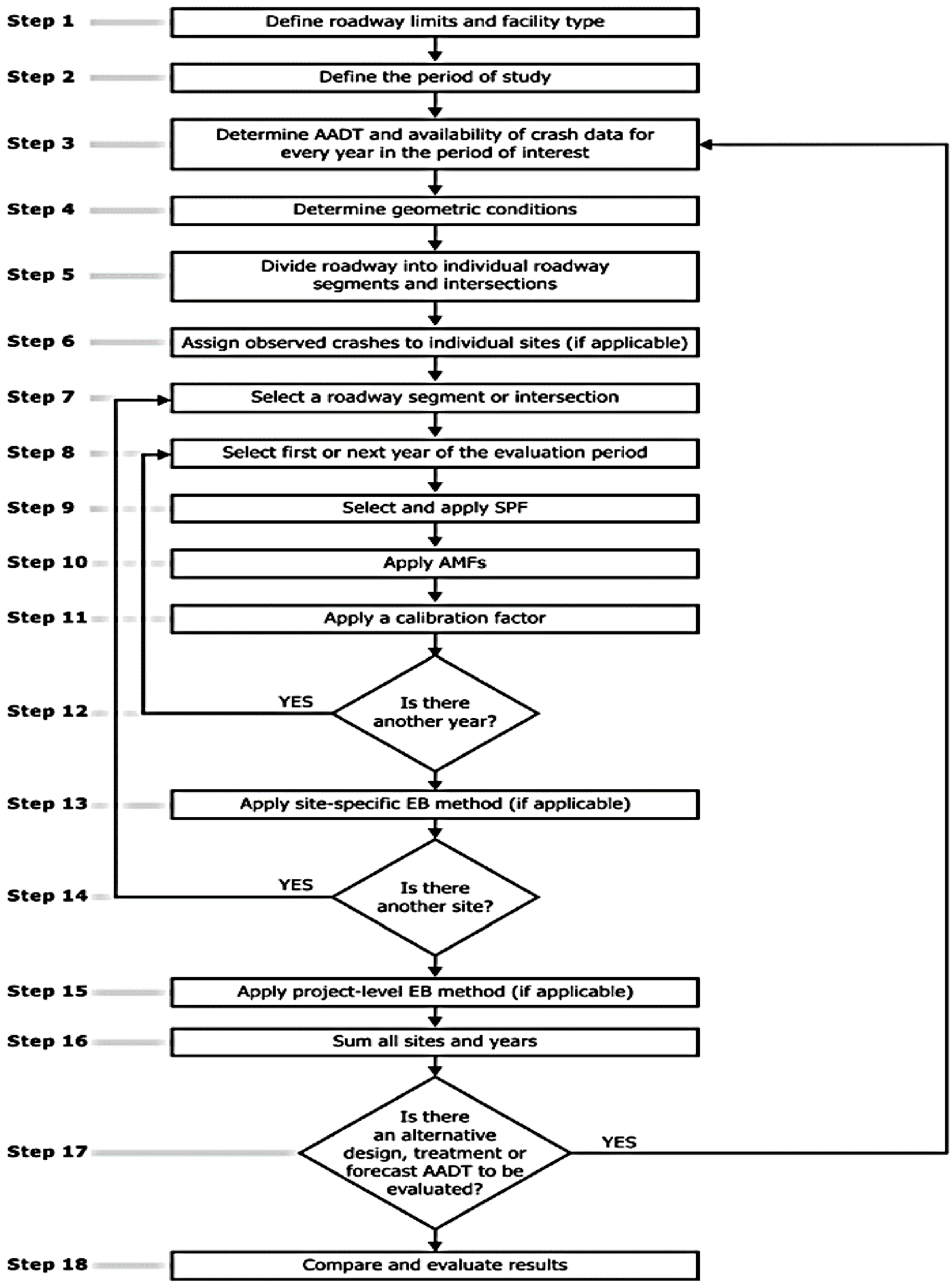


Figure 2.5 HSM predictive methods (Source: HSM 2010)

SPFs in the HSM are developed using the Negative Binomial regression model. In this study, various approaches such as the Poisson model, Negative Binomial (NB) model, Log-normal (LN) model, Zero Inflated Poisson (ZIP) model, and Zero Inflated Negative Binomial (ZINB) models were used. Among these models, Log-Normal (LN), and Negative Binomial (NB) models were superior in predicting crashes for roadway segments and intersections, respectively.

2.2.1 Poisson Model

The Poisson distribution is commonly used to model discrete, nonnegative, and random count data. Let Y_i denotes the number of crashes at site i, where (i=1…n) assuming that crashes at the n sites are independent. Poisson distribution is given by Equation 2.3.

$$Y_i|\theta_i \sim \text{Poisson}\ (\theta_i)$$ Equation 2.1

Where,

θ_i is the Poisson parameter. The probability of a site i having y_i collisions is given by Equation 2.4.

$$P_r\left\{Y_i = y_{i|\theta_i}\right\} = \frac{e^{-\theta_i}\theta_i y_i}{y_i!}$$ Equation 2.2

The Poisson parameter θ_i is commonly specified as an exponential function of site-specific attributes such as exposure, traffic and geometric characteristics [16]. The Poisson's parameter usually expressed as given in Equation 2.5.

$$\theta_i = e^{(X_i^{'}\alpha)}$$ Equation 2.3

Where X_i ' is a row vector of covariates representing site-specific attributes and α is a vector of regression parameters. In the Poisson regression model, the mean and variance of the count variable are constrained to be equal as shown in Equation 2.6.

$$E(Y_i)Var\ (\theta_i) = \theta_i$$ Equation 2.4

Kulmala (1995) showed that crash data has an over-dispersed characteristic, which is not applicable with Poisson regression models [17]. Poisson regression cannot handle overdispersion.

2.2.2 Negative Binomial Model (NB)

Poisson model assumes that the mean is equal to the variance, but the negative binomial distribution compensates for situations where the variance is greater than the mean, or when the data is overdispersed. Overdispersion for unobserved or unmeasured heterogeneity is addressed, as shown in Equation 2.7.

$$\theta_i = \mu_i e^{(\mu_i)}, \mu_i = e^{(X_i^{'}\alpha)}$$ Equation 2.5

Where the term $e^{(\mu_i)}$ represents a multiplicative random effect. The negative binomial (Poisson-Gamma) model is obtained by the assumption given in Equation 2.8.

$$e^{(\mu_i)|\kappa} \sim \text{Gamma}(\kappa, \kappa)$$ Equation 2.6

Where κ is the inverse dispersion parameter. The dispersion (or over-dispersion) parameter is usually referred to as β = 1/κ. The probability density function of the NB model is given by Equation 2.9 [18].

$$Pr(Y_i = y_i | \mu_i, \kappa) = \frac{\Gamma(y_i + \kappa)}{y_i! \, \Gamma(\kappa)} (\frac{\kappa}{\kappa + \mu_i})^{\kappa} (\frac{\mu_i}{\kappa + \mu_i})^{y_i} \qquad \text{Equation 2.7}$$

Under the NB model, the mean and variance are given by Equation 2.10.

$$E(Y_i) = \mu_i, \qquad Var(Y_i) = \mu_i + \mu_i^2/\kappa \qquad \text{Equation 2.8}$$

When mean will be equal to variance, β will go to zero and NB model would be transformed into a Poisson model. The Negative Binomial regression model has been widely applied in the road safety analysis in the literature.

2.2.3 Log-Normal Regression Model

Negative binomial model addresses the discrete response variables, while the log-normal model can accommodate continuous response variable [19]. Log-Normal model has a continuous probability distribution of a random variable whose logarithm is normally distributed. The general form of the log normal model is given by Equation 2.11 [19]:

$$\ln(Y) = intercept + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_n X_n \qquad \text{Equation 2.9}$$

Where,

Y: Observed crash count during a period for site i

X_1, X_2… X_n: A series of variables, such as shoulder width, truck percentage, number of snowy days per year etc.

$\alpha_1, \alpha_2, \ldots \alpha_n$: Coefficients to be estimated.

2.2.4 Zero Inflated Models

Zero crash counts can be observed on some roadway segments, especially on low volume rural roadways. This could lead to a higher variance for the observed data than the obtained theoretical model, which is known as overdispersion. The issue becomes serious when the observed zero counts exceeds the tolerable zero counts by simple Poisson regression and simple Negative Binomial models. With the excess zero counts, the data set becomes a distribution with low sample mean. Zero Inflated Poisson (ZINP) and Zero Inflated Negative Binomial (ZINB) models can accommodate the low sample mean issue and provide a better estimation of crash prediction [18].

2.2.5 Selection of Variables

Regression models are accurate in predicting expected crashes but have not been satisfactory in identifying the underlying geometric or traffic control factors affecting the crashes [20]. Therefore, it is not possible to include all relevant independent variables that could potentially have an impact on safety [21]. Variables were selected considering Wyoming-specific characteristics such as traffic and weather-related components.

2.2.6 Model Evaluation

Models were evaluated by the significance of the estimates and their signs. Significance of estimates are generally done with t-test. Signs should be relevant with the response. For example, logarithm of AADT estimates should be positive in signs explaining increase in crash frequencies or crash rates with the increase in exposure to more traffic volumes. The model goodness of fit is also examined using Akaike Information Criterion (AIC) and log likelihood values. The general equation of AIC is given by Equation 2.12 [22].

$$AIC = 2K - 2\log(likelihood) \qquad \text{Equation 2.10}$$

Where, K is the number of estimable parameters (degrees of freedom).

2.3 Crash Modification Factors

The methodologies adopted to develop crash modification factors for the selected countermeasures in this study are:

1. Odds, Odds Ratio (OR), and Ratio of Odds Ratio (ROR).
2. Naïve Before-After.
3. Before-After with Empirical Bayes.
4. Cross-Sectional Analysis.

Observational before-after with Empirical Bayes (EB) accounts for regression-to-the-mean bias (RTM) and this provides an advantage over the other methods. This methodology requires implementation dates of the countermeasures in addition to before-after data. The safety effectiveness of roadway segment countermeasures were evaluated using before-after with EB in this study. Conversely, intersection safety evaluation was estimated using cross-sectional method due to unavailability of implementation dates and before period data necessary to perform before-after study.

2.3.1 Odds, Odds Ratio (OR), and Ratio of Odds Ratio (ROR)

Odds ratio indicates the increased/decreased likelihood of a crash occurring when a treatment is present. It indicates the probability of event occurrence over the non-occurrence probability [23]. Case-controlled data should be selected to conduct the analysis to control for confounding factors, which could affect the real impact of the investigated countermeasure. An odds ratio of less than 1.0 indicates a reduction in crashes, which implies a positive safety effect of the treatment and vice versa. Ratio of odds ratios has a stronger ability to control for possible confounding factor than the simple odd ratio. Ratio of odds ratio would provide a more reliable results [24].

Several studies used the odds ratio to assess safety effectiveness of using different safety treatments [25], [26] and [27]. Equation 2.13 can be used to calculate the odds ratio [28]. Equation 2.14 and Equation 2.15 provide the confidence intervals for 95 percent confidence level for the odds ratio.

$$OR = \frac{\pi_{11}/\pi_{12}}{\pi_{21}/\pi_{22}}$$ Equation 2.11

$$CI_{upper} = e^{[\ln(OR)+Z_{0.05}*\sqrt{SE}]}$$ Equation 2.12

$$CI_{lower} = e^{[\ln(OR)-Z_{0.05}*\sqrt{SE}]}$$ Equation 2.13

Where,

OR: The odds ratio

π: The odds for each group category

$Z_{0.05}$: The Z-score for 95 percent confidence level = 1.96

SE: Standard Error and is obtained by Equation 2.16

$$\frac{1}{\pi_{11}} + \frac{1}{\pi_{12}} + \frac{1}{\pi_{21}} + \frac{1}{\pi_{22}}$$ Equation 2.14

2.3.1 Naïve Before-after Analysis

The simple, or naïve, before-after analysis is a straightforward method of comparison which allows for the crashes that were observed during the before and after periods of the study to be compared. CMF is determined by using crash frequencies accumulated during their respective periods. Naïve before-after analyses do not include additional roadway and environmental variables. They act as a basic and preliminary safety effectiveness evaluation method. However, they can allow for the effects of various additional variables to be observed regarding safety effectiveness.

2.3.3 Before-after with Empirical Bayes

The before-after with Empirical Bayes (EB) method was introduced by Hauer (1997) [29]. This method is considered a reliable method as it accounts for the RTM bias. Assumptions underlying this method include Poisson distribution of crash frequency, a gamma distribution of means and changes from year to year are similar for all reference sites. This method has 14 steps to calibrate Crash Modification Factors (CMFs). In this study, before-after with EB was used to calibrate CMFs for shoulder rumble strips, passing lanes, and snow fences. The HSM provided the following rigorous method consisting of 14 steps (Figure 2.2) [15].

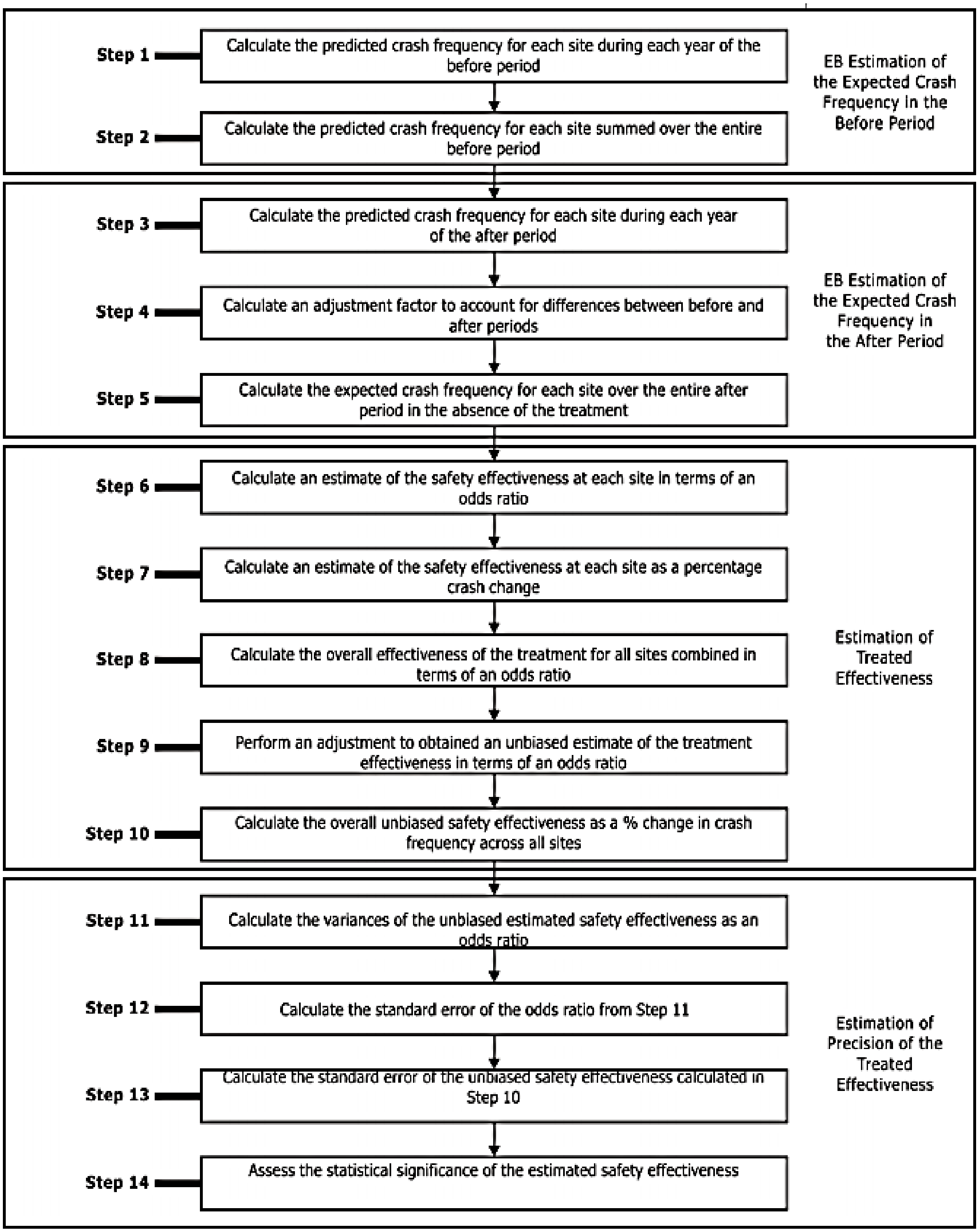


Figure 2.6 Steps of before-after Empirical Bayes (EB) method (Source: HSM 2010)

The estimate of the expected crashes at treatment sites is based on a weighted average of information from treatment and reference sites as given in Equation 2.17 [29]:

$$\hat{E}_i = (\gamma_i \times y_i \times n) + (1 - \gamma_i)\eta_i$$ Equation 2.15

Where γ_i is a weight factor estimated from the over-dispersion parameter from the negative binomial regression relationship and the expected "before" period crash frequency for the treatment sites as shown in Equation 2.18:

$$\gamma_i = \frac{1}{1 + k + y_i \times n}$$ Equation 2.16

yi= Number of the expected crashes of given type per year estimated from the SPF,
ηi = Observed number of crashes at the treatment site during the 'before' period, n = Number of years in the before period, and
k = Over-dispersion parameter.

The overdispersion in the negative binomial model indicates the level of dispersion of crashes around the mean. It should be noted that the estimates obtained from Equation 2-17 are the estimates for number of crashes in the before period. Since it is required to get the estimated number of crashes at the treatment site in the after period, the estimates obtained from Equation 2-17 are to be adjusted for traffic volume changes and different before and after periods. The adjustment factors are given as Equation 2.19.

Adjustment for AADT (ρ_{AADT}):

$$\rho_{AADT} = \frac{AADT_{after^{\alpha_1}}}{AADT_{before^{\alpha_1}}}$$ Equation 2.17

Where, $AADT_{after}$= AADT in the after period at the treatment site, $AADT_{before}$= AADT in the before period at the treatment site, and α_1 = Regression coefficient of AADT from the SPF.
Adjustment for different before-after periods (ρ_{time}) is given by Equation 2.20.

$$\rho_{time} = \frac{m}{n}$$ Equation 2.18

Where, m = Number of years in the after period, and n = Number of years in the before period.

Final estimated number of crashes at the treatment location in the after period ($\hat{\pi}_i$) after adjusting for traffic volume changes and different time periods is given by Equation 2.21.

$$\hat{\pi}_i = \hat{E}_i \times \rho_{AADT} \times \rho_{time}$$ Equation 2.19

The index of effectiveness (θi) of the treatment is given by Equation 2.22.

$$\widehat{\theta}_i = \frac{\widehat{\lambda}_i / \widehat{\pi}_i}{1 + (\widehat{\sigma_i^2} / \widehat{\pi_i^2})}$$ Equation 2.20

Where, $\hat{\lambda}_i$ = Observed number of crashes at the treatment site during the after period. The percentage reduction (τi) in crashes of particular type at each site i is given by Equation 2.23.

$$\widehat{\tau}_i = (1 - \widehat{\theta_i}) \times 100\%$$ Equation 2.21

The odds ratio is given by Equation 2.24.

$$\widehat{\theta} = \frac{\frac{\sum_{i=1}^{m} \widehat{\lambda}_i}{\sum_{i=1}^{m} \widehat{\pi}_i}}{1 + \frac{var(\sum_{i=1}^{m} \widehat{\pi}_i)}{(\sum_{i=1}^{m} \widehat{\pi}_i)^2}}$$ Equation 2.22

Where, m = total number of treated sites and the variance of $\hat{\pi}_i$ can be calculated from Equation 2.25 by Hauer (1997) [29].

$$var\left(\sum_{i=1}^{k} \widehat{\pi}_\iota\right) = \sum_{i=1}^{k} \rho_{AADT}^2 \times \rho_{time}^2 \times var\,(\widehat{E}_\iota)$$ Equation 2.23

The standard deviation ($\hat{\sigma}$) of the overall effectiveness can be estimated using information on the variance of the estimated and observed crashes, which is given by Equation 2.26.

$$\hat{\sigma} = \sqrt{\frac{\theta^2\left[\left(\mathrm{var}(\sum_{i=1}^{k}\hat{\pi}_i) \Big/ (\sum_{i=1}^{k}\hat{\pi}_i)^2\right) + \left(\mathrm{var}(\sum_{i=1}^{k}\hat{\lambda}_i) \Big/ (\sum_{i=1}^{k}\hat{\lambda}_i)^2\right)\right]}{\left[1 + \left(\mathrm{var}(\sum_{i=1}^{k}\hat{\pi}_i) \Big/ (\sum_{i=1}^{k}\hat{\pi}_i)^2\right)\right]^2}}$$ Equation 2.24

Where,

$$var\left(\sum_{i=1}^{k} \widehat{\lambda}_\iota\right) = \sum_{i=1}^{k} \lambda_i\, s\;\; \rho_{time}^2 \times var\,(\widehat{E}_\iota)$$ Equation 2.25

Equation 2.27 is used to estimate the expected number of crashes in the after period at the treatment sites. This estimated expected number of crashes are compared with the observed number of crashes at the treatment sites in the after period to get the percentage reduction in number of crashes resulting from the treatment.

2.3.4 Cross-Sectional Studies

Cross-sectional studies use regression models to compare crash frequencies or rates between sites with and without a safety countermeasure. One of the most important advantages of cross-sectional study is that it does not require the time for implementation of the treatment [30]. Cross-sectional studies involve developing a predictive model and quantifying the safety impacts of highway improvements [31]. To determine safety effectiveness of a treatment, the odds ratio (OR) is calculated to assess the relative crash risk involving treatment sites and reference sites. For this study, NB models were selected, as given in Equation 2.28.

$$Y_i = \exp(intercept + \alpha 1 X_1 + \ \alpha 2 X_2 + \cdots + \alpha n X_n)$$ Equation 2.26

Where,

Y= Observed crash count during a period for site i;

X_n= a series of variables, such as existence of left-turn lane of site I; (Used binary input for categorical variables)

$\alpha_1, \alpha_2, \ldots \alpha_n$= coefficients to be estimated.

Once the model is fitted and coefficients are estimated using observed crash data, the crash modification factor (CMF) for variable n can be then derived as shown in Equation 2.29.

$$\text{CMF} = \exp\ (\alpha_n)$$ Equation 2.27

The expected crash frequency will be multiplied by CMF if the variable n increases or decreases by one unit [32]. CMFs can be estimated using the countermeasure related parameter estimates from the regression model [33]. The elasticity is measured as the percentage change in the dependent variable resulting from a 1 percent change in an independent variable. It is obtained by taking the derivative of the crash frequency with respect to the independent variable in Equation 2.30 [34]:

$$E_i = \frac{\partial Y}{\partial x_i} \text{ x } \frac{x_i}{Y}$$ Equation 2.28

Where,

E : the Elasticity of the i^{th} independent variable with respect to crash frequency;

x_i : the magnitude of the variable under consideration;

Y : the expected crash frequency from the regression model;

α_i : the estimated parameter for the i^{th} independent variable.

A CMF of 1.0 implies no change has occurred, greater than 1.0 indicates crashes have increased and less than 1.0 implies crash reduction after implementation of the countermeasure. CMFs for a comprehensive list of safety treatments are contained in the HSM (2010) Part D or online at the Crash Modification Factor Clearinghouse.

An alternative approach estimates CMFs associated with a change in a given roadway attribute in Equation 2.31 [34]:

$$CMF_{xj} = (1 - e^{(\alpha_j \Delta x_j)})$$ Equation 2.29

Where CMF_{xj} is the crash reduction factor associated with the j^{th} independent variable;
Δx_j is the change in magnitude of the variable under consideration;
α_j is the estimated parameter for the j^{th} independent variable.

3. ROADWAY SEGMENTS

According to the HSM, roadway facilities fall into four major categories: 1) roadway segments, 2) intersections, 3) special facilities and 4) road networks. A roadway segment is a portion of the roadway having a consistent geometrical, operational, and traffic characteristics. Roadways with significant variations in characteristics should be considered and analyzed as different segments [35]. Each following subsection will provide information about the investigated countermeasure related to roadway segments.

3.1 Shoulder Rumble Strips and Passing Lanes

3.1.1 Data Preparation and Description for Initial Analysis

The main dataset used in this study was the historical crash data in Wyoming, which WYDOT records and digitizes. Critical Analysis Reporting Environment (CARE) software was used to access the raw crash data. Traffic data including annual average daily traffic (AADT), truck percentages, implementation dates of countermeasures, and roadway characteristics such as vertical and horizontal road geometry, were obtained from WYDOT. However, several gaps and limitations were encountered in the datasets used in this study, which were overcome using external data sources such as Pathway Video logs, Google Earth Pro®, and Google Map Street Views. Weather data used in this study were obtained from the weather stations information provided by the National Oceanic and Atmospheric Administration (NOAA).

Wyoming was ranked 4th in gas production, and 8th in oil production in 2014 [36]. Figure 3.1 shows the crude oil production for the different counties in Wyoming from 2006 to 2015. A threshold of two percent from the total oil production of the state was investigated in this study. Ten counties in Wyoming produce less than two percent of the total oil production of the state. These counties were considered as non-oil and gas counties.

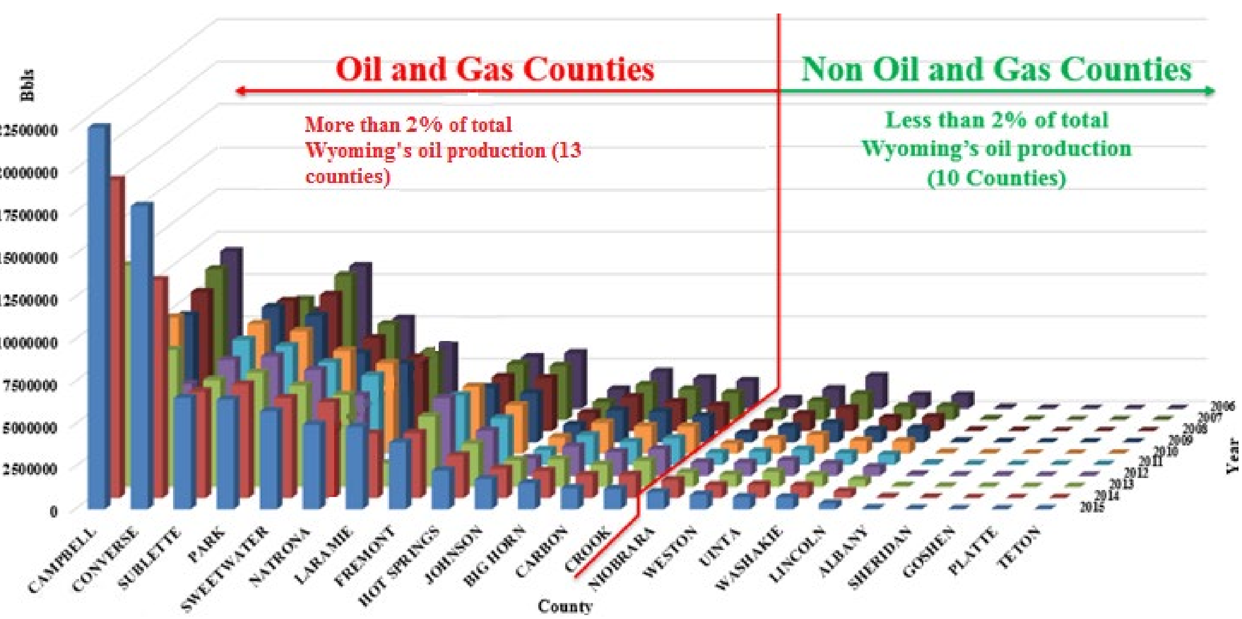


Figure 3.7 Crude oil production from 2006 to 2015 for all counties in Wyoming

Roadways from the top six oil counties (Campbell, Converse, Sublette, Park, Sweetwater, and Natrona) were included in this study and were about 160 miles of two-way two-lane highways. The included highways were US-26/20, US-191, and WY-120. The non-oil counties included in this study were Goshen, Lincoln, Platte, Teton, and Weston, which consisted of US 14, US 16, US 26, US 85 and US 89, about 136 miles of two-way two-lane highways. The roadways were divided into 709 segments (308 segments in oil counties and 401 segments in non-oil counties) using homogeneous segmentation. The data were collected for 12 years from 2003 to 2014.

The average AADT for non-oil and gas counties was about 1,650 vehicle per day (vpd) and 2,200 vpd for oil and gas counties indicating 32 percent higher traffic volumes in oil counties. Similarly, truck percentage in oil and gas counties, 18 percent, compared to 12 percent in non-oil and gas counties. The crash data were separated into two categories: 1) total crashes and 2) Fatal and Injury (F+I) crashes.

Wyoming-specific simple and full SPFs were developed for rural two-way two-lane highways using various prediction models since the SPFs provided in the HSM may not be applicable to Wyoming-specific conditions. Among the five different models applied, Negative Binomial (NB) model provided the lowest AIC for the initial dataset. A lower AIC value indicates a better model fit. The description of variables used in this analysis are provided in Table 3.2. Variables used to develop the SPFs were categorized into four groups. Geometric characteristics, Traffic Data, Crash Data, and Weather Data were the four categories used in this analysis. Each category has two or three variables describing it. Type and level for each variable is shown in Table 3.1.

Table 3.1 Description of variables used in developing SPFs for roadway segments

Dataset	Variable Name	Notation	Variable Type	Description
Geometric Characteristic	Degree of Curvature	DOC	Continuous	Calculated from radius of curvature
	Vertical Grade	VG	Categorical	4 Categories; $VG>2$ is 4, $0<VG<2$ is 3, $-2<VG<0$ is 2, $VG<-2$ is 1. The reference category is 4
	Shoulder Width	SW	Discrete	The measurement unit was in feet
Traffic Data	AADT	AADT	Discrete	Average Annual Daily Traffic in vehicles per day (vpd)
	Vehicles Miles Traveled	VMT	Continuous	Product of AADT and length of segment
	Truck Percentage	Truck	Continuous	Dividing number of trucks by AADT
Crash Data	Total Crashes	Total	Continuous	Total crashes per year per mile for global model; total crashes for other models
	F+I Crashes	F+I	Continuous	Fatal+Injury crashes per year per mile for global model; Fatal+Injury crashes for other models
Weather Data	Rainy Days	Rainy	Discrete	Average number of rainy days in a year
	Snowy Days	Snowy	Discrete	Average number of snowy days in a year

3.1.2 Initial Results

Table 3.2 shows the coefficient estimates of the SPFs developed for oil and non-oil counties. Twelve years of data, from 2003 to 2014, were used to develop the SPFs for oil and non-oil counties in Wyoming.

Table 3.2 Variables' estimates of the developed SPFs using NB Model

(A) Calibrated SPFs for Oil Counties of Wyoming					(B) Calibrated SPFs for Non-oil Counties of Wyoming				
Variable	Total Crashes		F+I Crashes		Variable	Total Crashes		F+I Crashes	
	Estimate	p-value	Estimate	p-value		Estimate	p-value	Estimate	p-value
Intercept	-4.051	0.0001	-4.167	0.0110	Intercept	-4.543	<.0001	-3.506	0.0151
DOC	0.047	0.1878	0.063	0.3051	DOC	0.006	0.1933	-0.008	0.4002
SRS	-0.342	0.0041*	-0.665	0.0002*	SRS	0.033	0.8041	-0.147	0.4772
VG1	0.155	0.4194	-0.167	0.5716	VG1	0.143	0.3845	-0.147	0.5757
VG2	0.147	0.3898	-0.260	0.3068	VG2	0.089	0.5661	-0.114	0.6476
VG3	0.012	0.9471	-0.284	0.2697	VG3	-0.015	0.9136	-0.259	0.2594
SW	-0.006	0.8023	-0.055	0.1180	SW	-0.022	0.4279	-0.029	0.5030
Ln(VMT)	0.972	<.001*	0.673	<.001*	Ln(VMT)	0.791	<.001*	0.691	<.001*
Truck	-0.004	0.8851	0.067	0.0998#	Truck	-0.017	0.5299	-0.060	0.1534
Speed	-0.023	0.0452*	-0.006	0.7010	Speed	-0.002	0.8556	0.001	0.9794
Rainy	-0.001	0.8125	-0.013	0.0020*	Rainy	0.018	0.0012*	0.005	0.5846
Snowy	0.005	0.0082*	0.010	0.0031*	Snowy	-0.006	0.0245*	-0.004	0.3850
Dispersion	0.273		0.299		Dispersion	0.403		0.712	

* Significant at 95 percent confidence level, # Significant at 90 percent confidence level.

Shoulder rumble strips (SRS), natural log of vehicle miles traveled (VMT), speed limit, and number of snowy days per year were significant at 95 percent confidence level for oil counties for total crashes. It was also found that the same variables were significant at 95 percent confidence level, in addition to the number of rainy days for F+I crashes in oil counties. In non-oil counties, log of VMT, number of rainy and snowy days were significant to predict total crashes, but out of these three variables, only log VMT was significant to predict F+I crashes at 95 percent confidence level.

SRS implementation on the selected roadways started in 2002. There are two versions of crash data (before and after 2003) in Wyoming. An observational before-after analysis could not be conducted because there were some discrepancies in crash record. Hence a cross-sectional analysis was conducted and the comparison of safety effectiveness between oil and non-oil counties is provided in Table 3.3.

Table 3.3 Calibrated preliminary CMFs of shoulder rumble strips using cross-sectional analysis for oil and non-oil counties in Wyoming

	Oil Counties	**Non-oil Counties**
Crash Type	CMF (Safety Effectiveness %)	CMF (Safety Effectiveness %)
Total Crashes	0.71* (29%)	1.00 (0%)
F+I Crashes	0.51* (49%)	0.86 (14%)

* Significant at 95 percent confidence level.

Results indicate there is 29 percent reduction in total crashes and 49 percent in F+I crashes due to the implementation of SRS in oil counties. These results comply with previous studies [37]. On the other hand, the SRS were found to have no effect on total crashes but reduce 14 percent of F+I crashes in non-oil counties, although the result was not found to be statistically significant.

CMFs for passing lanes were calibrated using the initial NB model and the before-after EB method. The results obtained are shown in Table 3.4.

Table 3.4 Calibrated preliminary CMFs of passing lanes using before-after analysis with EB for oil and non-oil counties in Wyoming

	Oil Counties	**Non-oil Counties**
Crash Type	CMF (Safety Effectiveness %)	CMF (Safety Effectiveness %)
Total Crashes	0.69* (31%)	0.62* (38%)
F+I Crashes	0.42* (58%)	0.41* (59%)

* Significant at 95 percent confidence level.

Results show that passing lanes were significant in oil and non-oil counties at 95 percent confidence level. In non-oil counties, the safety effectiveness of passing lanes was 38 and 59 percent for total and F+I crashes, respectively. For oil counties, the safety effectiveness was 31 and 58 percent for total and F+I crashes, respectively. A previous study on WY59 found that implementation of passing lane segments reduced total and F+I crashes by 42 and 66 percent, respectively [38]. The passing lanes on that segment of WY59 was implemented in an oil-county. Results obtained from this analysis comply with the previous study conducted in Wyoming. However, the previous study used simple SPFs, which do not consider the contribution and potential effect of other geometric and weather characteristics.

3.1.3 Challenges

This section discusses issues associated with development of Wyoming-specific SPFs and CMFs for roadways segments, mainly related to the implementation dates and existence of countermeasures.

Although shoulder rumble strips (SRS) were not selected for evaluation as a countermeasure for roadway segments in the first phase of this project, it was important to assess their safety effectiveness in presence of other countermeasures such as passing lanes and overlays. Shoulder rumble strips were widely implemented in Wyoming starting in 2002. It was found through scrutinizing Pathway Video Logs that the SRS may have been removed because of an overlay project. The video logs indicated that SRS were reinstated after several years for these locations. This intermittent presence of SRS is due to cost effective project management strategies in Wyoming. Several roadway segments with new overlay application should be combined to allow for a wide jurisdiction reimplementation of SRS. Observational before-after studies assume a consistent presence of countermeasures. Once a location receives a certain treatment, it is assumed that it always exists in the after period. Figure 3.2 shows an example of the roadway ML 34 at MP 42.173 where SRS existed in 2012 and were removed in 2014 when a new overlay was performed. This could cause issues when assuming the presence of SRS after the initial implementation date.

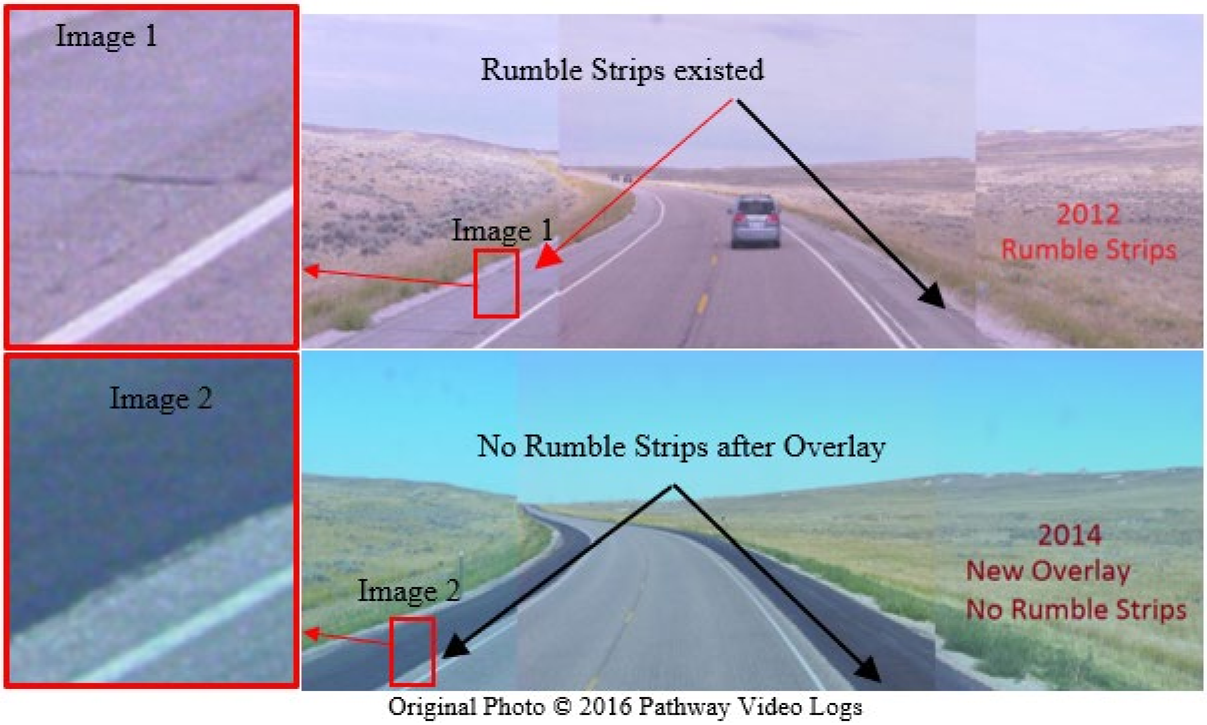


Figure 3.8 Inconsistent safety performance of shoulder rumble strips due to overlay

Additional effort was given, and analyses were carried out, to address this particular issue. The research team has invested considerable time reviewing video logs to make sure that countermeasures being evaluated are present consistently throughout the evaluation period. In addition, the analyses were re-performed using the updated information obtained from the video logs to provide a reliable and accurate results. Results from updated analyses are discussed in the final results section in this chapter.

3.1.4 Potential Solutions to Overcome the Challenges

The limitations discussed in the previous section could be overcome by adopting different methodologies and data imputation techniques. Cross-sectional analysis can be utilized when calibrating CMFs for certain countermeasures if the implementation dates are not known and there is missing data in the before period. However, it has its disadvantages as well. Cross-sectional analysis does not account for the regression to mean bias (RTM). Therefore, cross-sectional analysis may overestimate or underestimate the safety effectiveness of the treatment.

Implementation dates for treatments could also be estimated using non-traditional data sources. Scrutinizing Google Earth Pro® time-lapse satellite imagery provided a general approximation for the implementation dates of the countermeasures. Moreover, Pathway video logs were also used to provide an estimation for the implementation dates.

According to WYDOT, shoulder rumble strips will be removed for two years after implementing an overlay treatment. However, it is a rough assumption, which may not be applicable for all cases. Pathway video logs could also be used as a guide whether the shoulder rumble strips existed in a certain year or not. There are two possible ways to overcome the effect of the shoulder rumble strips intermittent situation. Only a few of the investigated roadway segments have the intermittent application. To overcome that limitation, those particular sections were excluded from the analysis. This particular solution was adopted and applied in this study. The obtained results are shown in the final results section.

Another approach could be considering every off situation as a before period and every on situation as an after period. Data related to overlay implementation should be included in the analysis as well. This alternative approach could provide more reliable results. However, it needs additional effort and analysis, which may be included in future studies and phases.

3.1.5 Final Results

Eliminating the segments where the SRS were removed resulted in a smaller sample size than the original collected data, especially in the before period. The analysis period was reduced to seven years (2008 to 2014) from 12 years. Data for the SPFs for roadway segments were collected from 10 counties in Wyoming: five oil counties (Big Horn, Johnson, Converse, Sublette, and Sweetwater) and five non-oil counties (Goshen, Niobrara, Platte, Sheridan, and Weston). The roadways included US 191, US 14, US 16, US 18/20, US 26, US 85, and WY 59. A total of 174 roadway miles were considered as reference sites (sites that did not receive treatment), which consisted of about 107 miles in non-oil counties and 67 miles in oil counties. Using homogeneous segmentation method 514 segments, 283 segments in non-oil counties and 231 segments in oil counties were obtained.

In the final dataset, there were 40 percent higher traffic volumes and 4.5 percent higher truck percentage in oil counties compared to non-oil counties. Crash rate in oil counties was observed to be 0.85 total crashes/year/mile while in non-oil counties it was observed to be 0.65 total crashes/year/mile. Again, oil-counties experienced 0.25 F+I crashes/year/mile compared to 0.18 F+I crashes/year/mile in non-oil counties.

For treatment sites of shoulder rumbles strips, 46.82 miles were selected, which consisted of 31 miles in oil counties and 15.82 miles in non-oil counties. Treatment sites for passing lanes were selected from US 85 and WY 59 combining a total of 71 miles of roadway segments; 26 miles in oil counties and 45 miles in non-oil counties.

Among the five count models, Log-Normal model provided the lowest AIC, which indicates the best fit model. Global models combining oil and non-oil counties were calibrated and specific models separating oil and non-oil counties. SPFs for combined data from oil and non-oil counties are shown in Table 3.5 and specific SPFs for oil and non-oil counties are provided in Table 3.6.

Table 3.5 Variable estimates and significance level for SPFs using Log-Normal Model for rural two-way two-lane highways in Wyoming (Data 2008-2014)

Variable	Total Crashes		F+I Crashes	
	Estimate	p-value	Estimate	p-value
Intercept	-6.165	<.0001*	-7.559	<.0001*
DOC	0.006	0.2421	0.010	0.2078
VG1	0.446	0.0043*	0.462	0.1148
VG2	-0.147	0.3188	-0.621	0.0238*
VG3	0.170	0.2653	0.065	0.8141
SW	-0.033	0.0082*	-0.085	0.0002*
Ln(VMT)	0.951	<.0001*	1.105	<.0001*
Truck	-0.055	<.0001*	-0.057	0.0005*
Rainy	-0.012	0.0093*	-0.023	0.0048*
Snowy	0.016	0.0027*	0.027	0.0092*
Scale	0.243		0.135	

* Significant at 95 percent confidence level.

Table 3.6 Variable estimates and significance level for SPFs using Log-Normal Model for oil and non-oil counties in Wyoming (Data 2008-2014)

	(A) SPFs for Total and F+I Crashes for Oil Counties				(B) SPFs for Total and F+I Crashes for Non-oil Counties			
Variable	Total Crashes		F+I Crashes		Total Crashes		F+I Crashes	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	-6.3445	<.0001	1.1958	0.2838	-6.8694	<.0001	-9.9791	<.0001
DOC	-0.0195	0.4512	-0.0313	0.6582	0.0080	0.0568**	0.0105	0.0745**
VG1	0.4951	0.0745**	0.6677	0.5183	0.6720	0.0136*	1.5499	0.0033*
VG2	-0.0055	0.9820	0.3147	0.7239	0.1144	0.6579	0.4625	0.3603
VG3	0.4606	0.0523**	0.7418	0.3862	0.2385	0.3403	0.5452	0.2971
SW	-0.0238	0.1003	-0.0916	<.0001*	-0.0497	0.0278*	-0.0905	0.0993**
Ln(VMT)	0.8700	<.0001*	1.1477	<.0001*	0.9923	<.0001*	1.1057	<.0001*
Truck	-0.0542	0.0569**	-0.3676	0.0001*	-0.0478	<.0001*	-0.0206	0.3042
Rainy	0.0142	0.3802	-0.1362	<.0001*	-0.0144	0.0044*	-0.0199	0.0419*
Snowy	-0.0221	0.3265	0.1280	0.2838	0.0278	0.0004*	0.0491	0.0001*
Scale	0.2560		0.1454		0.2228		0.1139	

* Significant at 95 percent confidence level, ** Significant at 90 percent confidence level.

For the combined SPFs, logarithm of Vehicles Miles Traveled (VMT),vertical grades, shoulder width, truck percentage, and average number of rainy and snowy days per year were statistically significant at 95 percent confidence level for total and F+I crashes. The results indicated that steep downgrade increases total crashes. For an increase of a one-foot shoulder width, 3 percent total crashes and 8 percent F+I crashes are decreased. Park et al. (2015) also found a reduction in total and F+I crashes with the increase of shoulder width [39]. Vehicle miles traveled is mainly responsible for increasing the number of crashes, as it increases the exposure factor, which is in line with the literature [15]. Every 1 percent increase in the truck percentage reduces 5 and 6 percent total and F+I crashes, respectively. A previous study showed that increasing percentage of trucks, lowers the crash rate [40]. This could be because drivers are more cautious around large trucks. The average number of snowy days increases total and F+I crashes while average number of rainy days reduces the crashes. Drivers usually are more cautious in rainy and snowy conditions than they are in normal weather conditions. Hawkins (1988) found that reducing the vehicle speed, increasing the gap between vehicles, and using warning signs decrease the crash frequency in rainy conditions [41]. However, in snowy conditions, drivers have less control over the vehicles on slippery roads resulting from black ice and blowing snows. Reducing the speed or using warning signs may not be useful to control crashes in this situation [41]. An increase of one snowy day per year results in an increase of 2 percent of total crashes and 3 percent of F+I crashes. Saha et al. (2015) found crashes increase with the increase of snowy days in Wyoming [42].

The specific SPFs for oil counties have a smaller number of significant variables while the SPFs for non-oil counties have almost similar significant variables as the combined one. The estimates differ by a small margin.

An observational before-after analysis with Empirical Bayes (EB) using developed, Wyoming-specific full SPFs (Table 3-5) was conducted to quantify the safety effectiveness of shoulder rumble strips (SRS). Three years of before period and four years of after period were considered for this analysis for 71 miles of roadway segments from Natrona, Weston, and Crook Counties. The calibrated Crash Modification Factors (CMFs) are provided in Table 3.7.

Table 3.7 Calibrated final combined CMFs of shoulder rumble strips (SRS) using before-after with EB for rural two-way two-lane highways in Wyoming

Crash Type	CMF (Safety Effectiveness %)
Total Crashes	1.05 (-5%)
F+I Crashes	0.45* (55%)

* Significant at 95 percent confidence level.

Shoulder rumble strips (SRS) reduced 55 percent of F+I crashes, at 95 percent significance level, but were not effective in reducing total crashes. The obtained results comply with a study using data from Georgia, Kentucky, Minnesota, Missouri, and Pennsylvania [43]. Shoulder rumble strips are more significant in oil counties than non-oil counties for total crashes. The safety effectiveness of SRS was higher than a previous study conducted recently in Wyoming [37]. Moreover, the safety effectiveness of SRS was higher than the initial analysis provided in this study. This might be due to the less treatment sites used in the analysis and more accurate implementation dates. Fewer segments were selected to eliminate the intermittent SRS application encountered in the initial analysis. The obtained CMFs are shown in Table 3.8.

Table 3.8 Calibrated final CMFs of shoulder rumble strips (SRS) using before-after analysis with EB for oil and non-oil counties in Wyoming

	Oil Counties	**Non-oil Counties**
Crash Type	CMF (Safety Effectiveness %)	CMF (Safety Effectiveness %)
Total Crashes	0.40* (60%)	0.69 (31%)
F+I Crashes	0.18* (82%)	0.16* (84%)

* Significant at 95 percent confidence level.

CMFs for passing lanes were calibrated using the same developed Wyoming-specific full SPFs (Table 3.4). Four years in the before period and four years in the after period were considered in the before-after analysis with EB method. Table 3.9 shows the estimated CMFs for passing lanes.

Table 3.9 Calibrated final combined CMFs of passing lanes using before-after with EB for rural two-way two-lane highways in Wyoming

Crash Type	CMF (Safety Effectiveness %)
Total Crashes	0.58* (42%)
F+I Crashes	0.66* (34%)

* Significant at 95 percent confidence level.

Passing lanes were found to be statistically significant to reduce crashes at 95 percent confidence level. They were more effective in reducing total crashes estimating a reduction of 42 and 34 percent of total and F+I crashes, respectively. Passing lanes were more significant in oil counties compared to non-oil counties for total crashes. Also, the final results of this study indicate higher percentage of crash reduction because of implementation of passing lanes comparing to the initial results of this study and the previous study conducted on WY59 [38]. The results are provided in Table 3.10.

Table 3.10 Calibrated final CMFs of passing lanes using before-after analysis with EB for oil and non-oil counties in Wyoming

	Oil Counties	Non-oil Counties
Crash Type	CMF (Safety Effectiveness %)	CMF (Safety Effectiveness %)
Total Crashes	0.39* (61%)	1.29 (-29%)
F+I Crashes	0.41** (59%)	0.36** (64%)

* Significant at 95 percent confidence level, ** Significant at 90 percent confidence level

3.2 Headlight Signs

Seven roadway sections in Wyoming used the MUTCD "Turn on Your Headlights for Safety Next XX Miles" headlight sign as shown in Figure 3.3. All roadways having the headlight signs are classified as principal or minor arterial two-way two-lane roads. The first implementation of the signs was back in 1994 on US287/WY789. The latest signs were implemented in 2012 on WY220 and WY59.

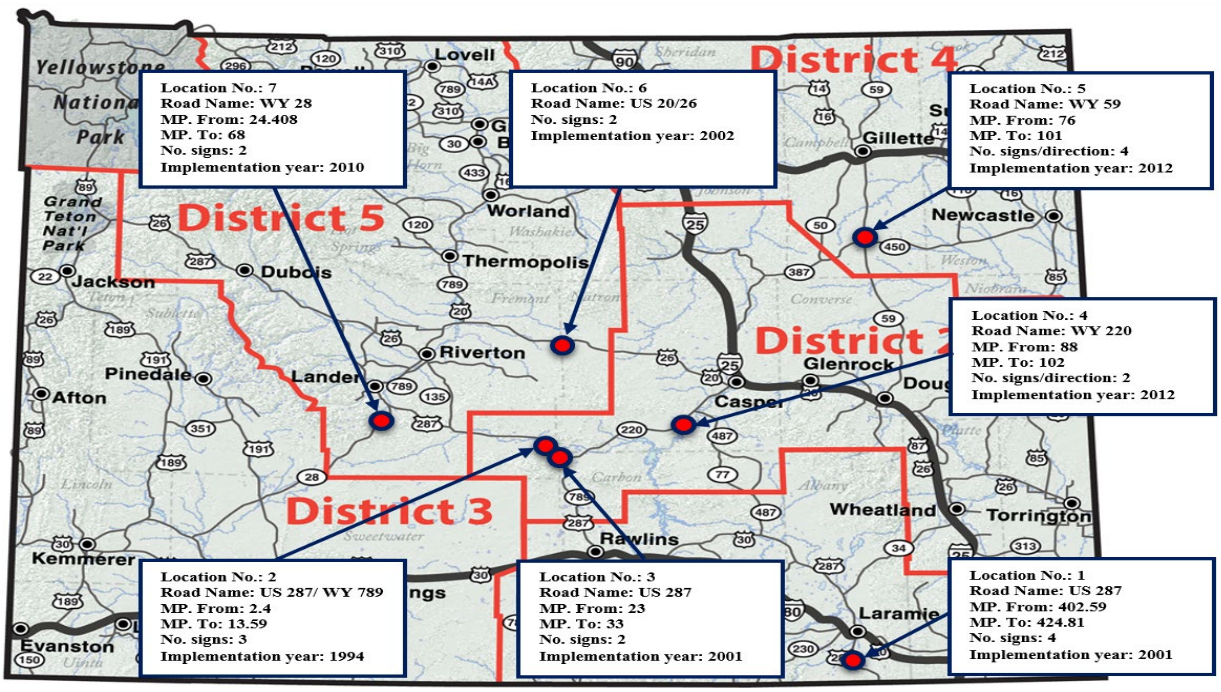


Figure 3.3 Headlight Sign Locations in Wyoming (Adopted from WYDOT)

3.2.1 Data Preparation and Description

To develop CMFs for the headlight signs, crash data were extracted from the CARE package. It should be noted that crash data in the CARE package does not include Vehicle Identification Numbers (VINs). VINs are needed to identify vehicles equipped with automatic Daytime Running Lights (DRLs) in the crash reports. A full list of VINs for vehicles involved in crashes was obtained from WYDOT and matched to crashes in the CARE package. Ten years of traffic data (2004-2013) were also acquired from WYDOT. A Total of 106,622 crashes for the years 2004-2013 were collected with complete VINs.

Only target crashes, i.e., head-on and opposite side-swipe crashes, with the following criteria were considered in the study: crashes occurred on two-lane rural highways, posted speed is greater than 55 mph, daytime crashes, no alcohol or drug involved, and no animal crashes. The dataset was further split into crashes for locations with headlight signs, and crashes for locations without headlight signs. To identify what headlight technology a vehicle might have, the website: https://www.decodethis.com was used. This website classifies DRL into three groups: “Standard DRL,” “No DRL,” and “Optional DRL.” A total of 6,713 VINs — 6230 randomly sampled target crashes for locations without headlight signs, and all 483 target crashes occurred on locations with headlight signs — were checked to determine the type of headlight technology equipped in vehicles involved in crashes. Only crash data belonging to the “No DRL” and “Standard DRL” were used in the analysis. Figure 3.4 shows the crash rates, frequencies, and percentages according to DRL equipment for locations with and without headlight signs. Data showed that 70 and 77 percent of vehicles involved in crashes in locations with and without headlight signs are non-DRL equipped vehicles, respectively.

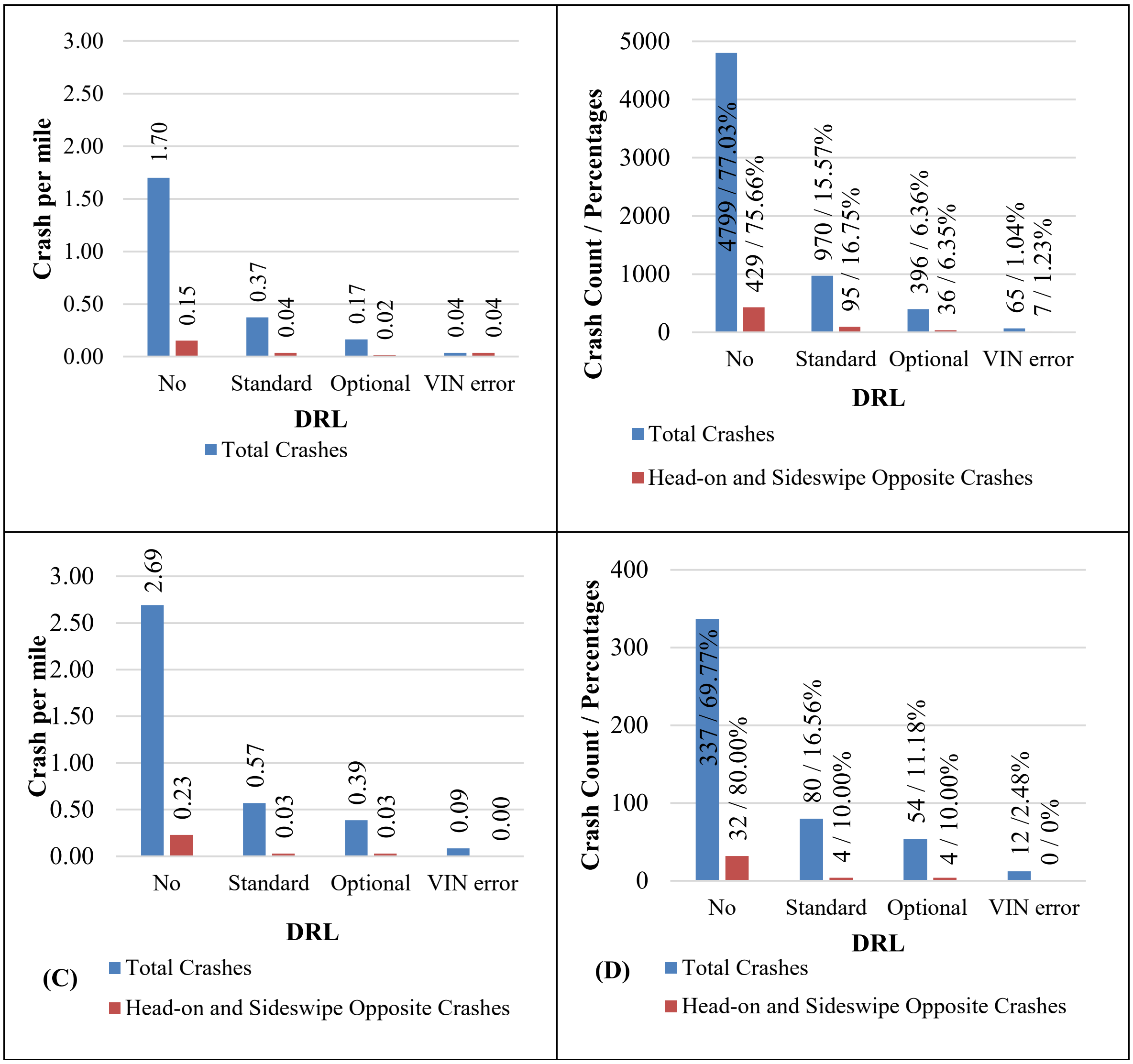


Figure 3.4 Rates, frequencies and percentages of total and target crashes

A) Crashes per mile for location without headlight signs
B) Crash frequencies and percentage for locations without headlight signs
C) Crashes per mile for location with headlight signs
D) Crash frequencies and percentage for locations with headlight signs

Table 3.11 provides descriptive statistics of rates for total and target crashes for the headlight and non-headlight sign sections from 2004 to 2013. While WY28 experienced the highest number of total crashes per million vehicle miles traveled (MVMT) among all the headlight sections, US 287 had the highest rate of head-on and opposite sideswipe crashes (target crashes). Moreover, the table shows that while the non-treated sections had slightly higher crash rates per MVMT for total crashes, the treated sections had higher crash rates for target crashes on average.

Table 3.11 Descriptive statistics of crash rates for headlight and non-headlight sign sections

Segment	Crash rate for total crashes per MVMT (from 2004 to 2013)				Total # of crashes	Crash rate for target Crash per MVMT (from 2004 to 2013)				Total # of Target Crashes
	Min	Mean	Max	St.dev		Min	Mean	Max	St.dev	
US 287 *	0.66	1.04	1.38	0.26	308	0	0.05	0.11	0.03	15
US287 / WY 789 *	0	0.97	2.18	0.64	33	0	0.03	0.28	0.08	1
US 287 *	0	0.72	1.82	0.51	23	0	0.05	0.28	0.11	2
WY 220 *	0.75	1.03	1.36	0.23	157	0	0.02	0.12	0.04	3
WY 59 *	0.4	0.71	1.02	0.18	252	0	0.03	0.08	0.03	11
US20/26 *	0.42	0.68	0.9	0.16	283	0	0.03	0.07	0.02	11
WY 28 *	1.22	2.04	3.36	0.57	426	0	0.04	0.12	0.04	8
WY22	0.92	1.38	1.82	0.34	741	0.016	0.07	0.20	0.06	36
US 191	0.7	0.97	1.27	0.20	2243	0	0.01	0.03	0.01	28
US 278	0.31	0.45	0.55	0.06	1072	0	0.01	0.01	0.003	17
WY 59	3.27	4.79	6.4	1.03	3153	0.016	0.05	0.11	0.03	35
WY 220	0.59	0.78	0.96	0.11	2725	0	0.01	0.02	0.01	31
US85	0.45	0.58	0.79	0.09	1456	0.003	0.01	0.02	0.004	25
US 30	0.7	0.89	1.29	0.16	636	0	0.03	0.08	0.02	21
US 189	0.65	0.8	0.92	0.08	664	0	0.01	0.03	0.01	7
US 26 II	0.48	0.96	1.58	0.34	126	0	0.03	0.07	0.03	3
WY 789	0.69	0.99	1.42	0.26	296	0	0.04	0.08	0.03	13
WY 414	0.59	0.81	1.31	0.22	258	0	0.01	0.03	0.01	3
WY 387	0.56	0.87	1.26	0.22	283	0	0.03	0.06	0.02	10
US 14	0.55	0.71	0.85	0.09	1203	0	0.002	0.01	0.004	3
US 16	0.48	0.89	1.27	0.23	477	0	0.01	0.02	0.01	4
US 191	0.46	0.93	1.66	0.35	257	0	0.01	0.07	0.02	4
WY 120	0.69	1.05	1.47	0.22	453	0	0.01	0.02	0.01	3
US 26	0.68	1.02	1.34	0.22	288	0	0.02	0.06	0.02	7
Average treated	0.49	1.03	1.72	0.36	211.71	0	0.04	0.15	0.05	7.29
Average non-treated	0.75	1.11	1.54	0.25	960.65	0	0.02	0.05	0.02	14.71

3.2.2 Data Limitations and Availability

Headlight signs were implemented on different years as shown in Figure 3.3. Early implementation of the headlight sign countermeasure was in 1994 on an 11-mile section on US287/WY789. The recent implementation of the countermeasure took place in 2012 at two locations. It is worth mentioning that the AADT data for Wyoming's highway road network are available from 2003 to present only. This would introduce limitations to conduct observational before-after studies for this specific countermeasure as there is no AADT data existing for the before period. This led to the use of the odds ratio and ratio of the odds ratio analyses as the major methodologies adopted for this countermeasure.

With the increase in number of vehicles equipped with DRLs and automatic low-beam headlights, many drivers do not comply with regulatory headlight signs. To investigate the effect of the DRL technology penetration on the safety effectiveness of regulatory headlight signs, information about compliance to the headlight light sign and the existence of DRL technology for the crashed vehicles in the before and after periods are essential. However, it is impossible to obtain such information for the historical crash data.

3.2.3 Results

The odds for locations with the headlight sign were 24 percent versus 20 percent for locations without headlight signs resulting in an odds ratio of 1.17 (Table 3.12). This implies that locations with headlight signs receive 17 percent more total crashes than locations without headlight signs, controlling for the DRL factor. The confidence intervals were calculated to range from 0.91 to 1.51 indicating no significant effect of having DRL in crash reduction for two way highways with the presence of headlight signs.

The odds for the locations with the headlight sign were 13 percent versus 22 percent for locations without headlight signs for target crashes, which included head-on and side-swipe opposite crashes. An odds ratio of 0.56 was obtained. This implies that locations with headlight signs experienced 44 percent less target crashes than locations without headlight signs having DRL equipment controlled. Confidence intervals were calculated to range from 0.19 to 1.63. Confidence intervals indicate that there is no significant effect of having DRL on head-on and sideswipe opposite crashes for two-way highways with the presence of headlight signs.

Table 3.12 Two-Way contingency table with odds and odds ratio for total and target crashes

Crash Type	Section description	DRL equipped Vehicles	Non-DRL equipped Vehicles	Odds	Odds Ratio
Total Crashes	with Headlight signs	80	337	23.74%	1.17
	without Headlight signs	970	4799	20.21%	
Target Crashes	with Headlight signs	4	32	12.50%	0.56
	without Headlight signs	95	429	22.14%	

The NHTSA (2011), used the ratio of odds ratio (ROR) to show the effectiveness of using DRL technology in reducing crashes [6]. A case-control analysis using ROR was adopted for this treatment. Ratio of odds ratio (ROR) for the headlight sign as a safety countermeasure had a value of 0.45, which indicates a 54.64 percent reduction in target crashes, controlling for DRL technology. However, the result from the ROR was not significant at a 95 percent significance level, as shown in Table 3.13.

Table 3.13 Ratio of odds ratio analysis for headlight sign controlling for the DRL technology

Simple odds and odds ratio analysis	Headlight Locations				
		Target crashes	Control crashes	Odds	OR
	DRL	4	76	0.05	0.50
	No DRL	32	305	0.10	
	Non-Headlight Locations				
		Target crashes	Control crashes	Odds	OR
	DRL	95	875	0.11	1.11
	No DRL	429	4370	0.10	

ROR @ 95% confidence level	Lower bound	ROR	Upper bound
	0.11	0.45	1.97
	Lower bound %	Effectiveness %	Upper bound %
	-35.54%	54.64%	84.82%

4. INTERSECTIONS

A total of 174 intersections from 23 cities in 20 counties in Wyoming were chosen as study sites considering the availability of traffic volume data. Intersections with collector roads in major approaches were selected to ensure that traffic data is available from WYDOT. In the case of unavailability of minor approach traffic volume data, minor approach AADTs were estimated by vehicle ratio using the Google Earth Pro® imageries. It can be assumed that throughout the observed period (2005 to 2014), the geometric characteristics of the sites remained the same.

4.1 Data Collection

4.1.1 Data Source

Crash data for the intersections were collected from the CARE package. These data were imported into the Geographic Information System (GIS) mapping tool to assign intersection-related crashes to intersections. To classify intersection-related crashes, the intersection influence area should be defined. This depends on the intersection geometry, traffic control, and operating features [30]. In a study carried out in Indiana, a circular influence area of a 250-foot radius from the center of the intersection was used [31]. Channelized intersections influence area was defined within 20 feet beyond the gore of islands or the point at which the turn lane attains [33]. Safety effects could be overestimated if a larger safety influence area is applied to smaller intersections misclassifies roadway segment crashes as intersection crashes [30]. In this data analysis, the 250-foot criterion defined the intersection influence area. Crashes by severity (i.e., total, F+I, and PDO), and crashes by types of collision (i.e., angle, rear-end, head-on, sideswipe) were categorized from the extracted data.

Intersection characteristics data such as number of shared and through lanes in each approach, presence of exclusive left and right-turn lanes, angle of intersection skewness, presence of medians (raised or flush), signal heads configurations (3, 4 or 5 lights) were collected from Google Earth Pro® imageries. This was done manually for every intersection considered in this study. Yearly signal system and timing data were not collected due to unavailability of such archived data.

Traffic volume data were collected from WYDOT. The base conditions set for developing SPFs for four-leg signalized (4SG) intersections in the HSM include AADT ranges up to 67,000 for major and up to 33,000 for minor approaches. AADT data for all intersections were within this range.

Weather data was collected from the NOAA weather stations. The NOAA's National Centers for Environmental Information (NCEI) provides public access to records for weather data and information. Number of rainy days and snowy days for each intersection were collected from the stations using a proximity of five nautical miles radius from the stations [44].

4.1.2 Data Preparation and Description

The number of four-leg signalized intersections considered from each county of Wyoming are shown in Figure 4.1. The number of four-leg signalized intersections in Casper, Natrona County and Laramie, Cheyenne County are 26 and 22, respectively. It is anticipated that crash frequencies and patterns at intersections will differ by cities or counties depending on various characteristics of cities. Figure 4.1 provides the number of four-legged signalized intersections, population, land area, density and crash counts in by cities of Wyoming under study.

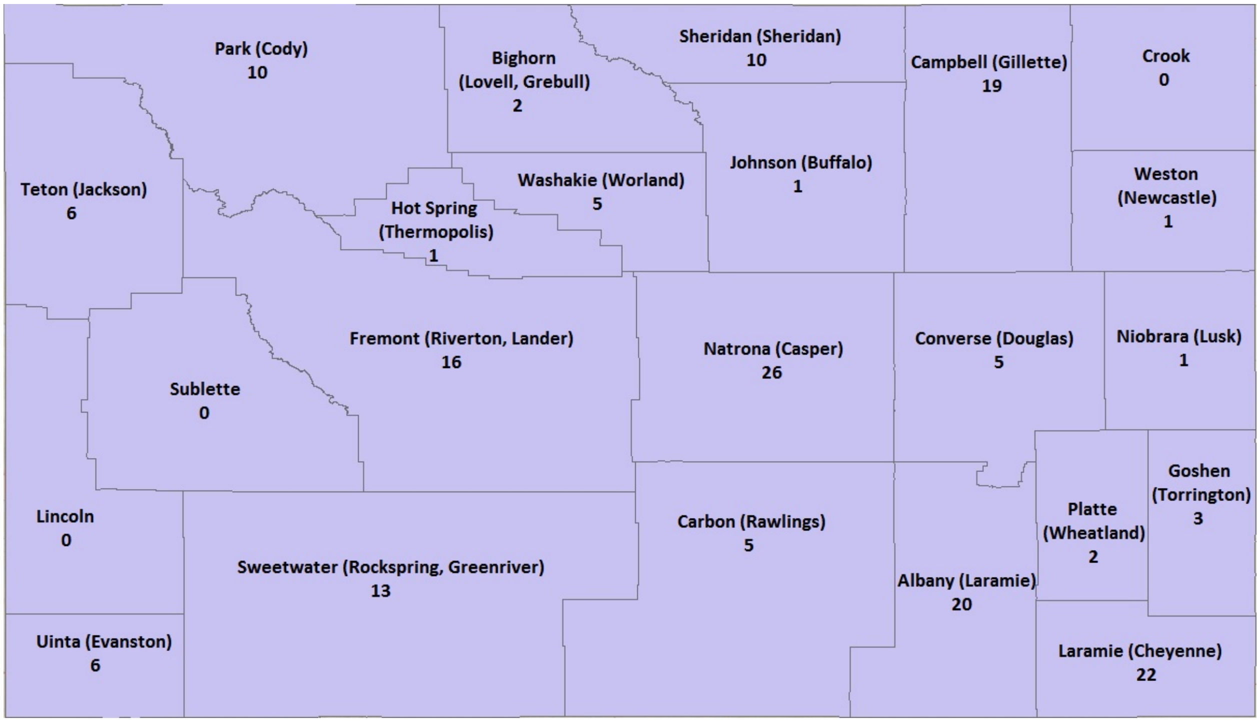


Figure 4.1 Number of four-leg signalized intersections considered from each county of Wyoming

Table 4.1 Different characteristics of cities that contribute to affecting crash frequencies in intersections

County	City	Population 2010	Land Area (sq.mi.)	Density (pop./ sq.mi.)	Crash/sq. mi/pop	4-leg Signalized Intersections
Laramie	Cheyenne	59466	24.52	2425.2	0.727	22
Natrona	Casper	55316	26.9	2056.4	1.334	26
Albany	Laramie	30816	17.74	1737.1	0.781	20
Campbell	Gillette	29087	18.97	1533.3	1.285	19
Sweetwater	Rock Springs	23036	19.34	1191.1	1.050	11
Sheridan	Sheridan	17444	10.93	1596	0.362	10
Sweetwater	Green River	12515	13.72	912.2	0.072	2
Uinta	Evanston	12359	10.27	1203.4	0.189	6
Fremont	Riverton	10615	9.86	1076.6	0.599	9
Teton	Jackson	9577	2.91	3291.1	0.166	6
Park	Cody	9520	10.2	933.3	0.422	10
Carbon	Rawlins	9259	8.24	1123.7	0.125	5
Fremont	Lander	7487	4.66	1606.7	0.222	7
Goshen	Torrington	6501	4.62	1407.1	0.059	3
Converse	Douglas	6120	4.58	1336.2	0.099	5
Washakie	Worland	5487	4.56	1203.3	0.076	5
Johnson	Buffalo	4585	4.46	1028	0.011	1
Platte	Wheatland	3627	4.1	884.6	0.020	2
Weston	Newcastle	3532	2.55	1385.1	0.009	1
Hot Springs	Thermopolis	3009	2.38	1264.3	0.017	1
Big Horn	Lovell	2360	1.1	2145.5	0.010	1
Big Horn	Greybull	1847	1.81	1020.4	0.028	1
Niobrara	Lusk	1567	2.07	757	0.009	1

The first step in allocating appropriate resources is to improve safety, identification of intersection crash "hotspots," "blackspots," "high risk", or "high collision concentration locations. Some researchers [45] [46] incorporated powerful analytical tools in GIS software such as buffer, nearest neighbor method, simple density, and Kernel Density Estimation (KDE) methods of crash cluster identification. These methodologies help in visualizing spatial distribution of crashes. KDE is a geostatistical-based approach for identifying crash hotspots in a road network. In GIS the result of a KDE has a density value that is weighted according to distance from the features for example crash frequency. The distribution of effects is represented by the diameter of that circle by heat map.

In almost all cases, crashes form clusters in geographic spaces. Actual crash locations are random, which can occur anywhere spatially and temporally, but we can attempt to quantify how likely it is that intersection related crashes would take place at a particular intersection. A crash density map of Wyoming is generated using GIS at city levels.

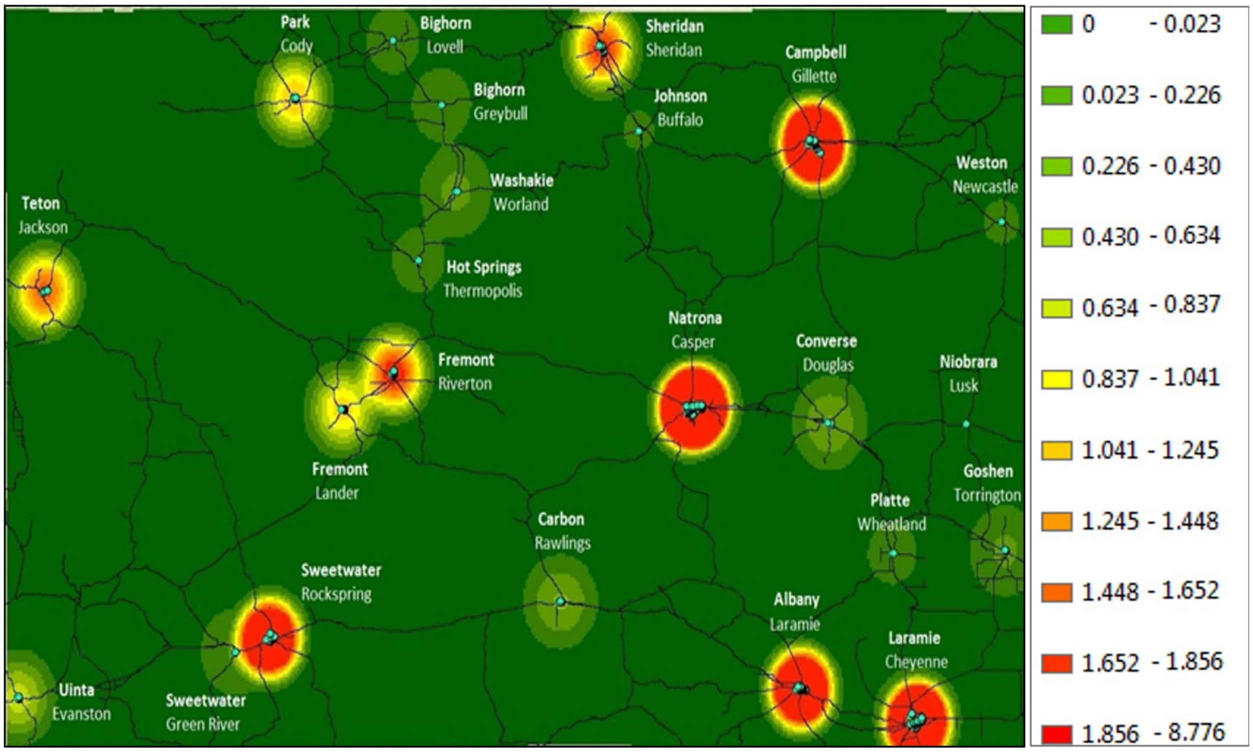


Figure 4.2 Kernel density map using intersection crashes (crash/sq. mile)

Spatial distribution of intersection crashes are shown in Figure 4.2. The likelihood of crash occurrence depends on many factors such as road geometry, driver characteristics, and location characteristics. Cities with high population and large metropolitan areas tend to have more crash density. Figure 4.2 shows the heat map of crashes per square miles for four-leg signalized intersections for the year 2005 to 2014. This map can be interpreted as a predictive risk surface for the intersection crashes.

Crash density (crashes/sq. mile) values are normalized using population of the cities, and the following observations are deduced from the crash density map:

- Casper has the largest red region (diameter of 22.8 miles) and therefore the highest crash density (1.33 crashes/capita/sq. miles) in Wyoming.
- Casper, Gillette, Rock Spring, Cheyenne and Laramie can be considered as the most hazardous locations having the highest crash densities.
- Sheridan, Riverton, and Cody indicate medium hazard levels while Jackson, Lander, and Evanston indicate low hazard levels.

A total of 174 observations were used in the analysis, which accounted for about 12,000 crashes in which around 23 percent were Fatal +Injury (F+I) crashes and the remainder were the property damage only (PDO) crashes, as shown in Figure 4.3.

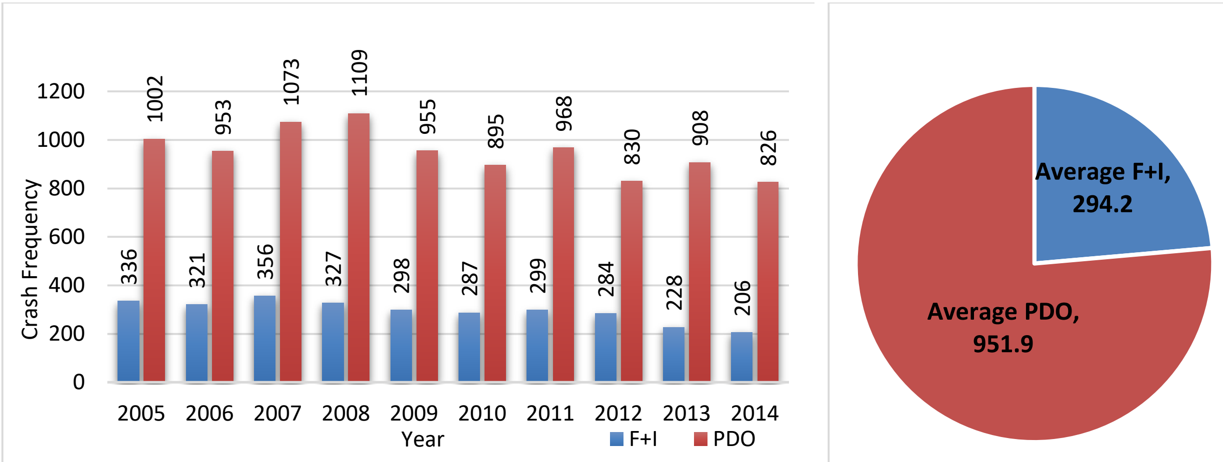


Figure 4.3 Crash frequencies and average yearly crash rates by severity

The average yearly F+I crashes were 294.2 which is 23 percent of total crashes. F+I crashes were 336 (25 percent) in 2005 and were reduced to 206 (20 percent) in 2014. Therefore, intersection PDO crashes increased throughout the period.

Crash frequencies and crash proportions by crash types (maneuvers) are shown in Figure 4.4 and Figure 4.5, respectively. Percentages of rear-end and angle crashes are the highest among all crash types. Therefore, turning maneuvers should be emphasized more to understand crash trends.

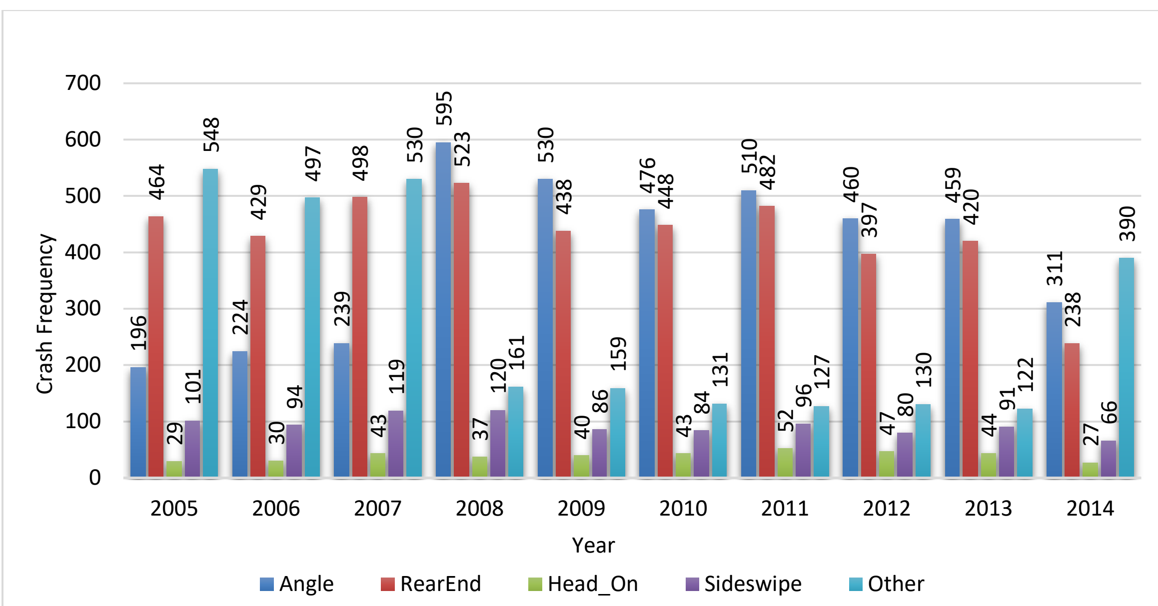


Figure 4.4 Crash frequencies by crash type

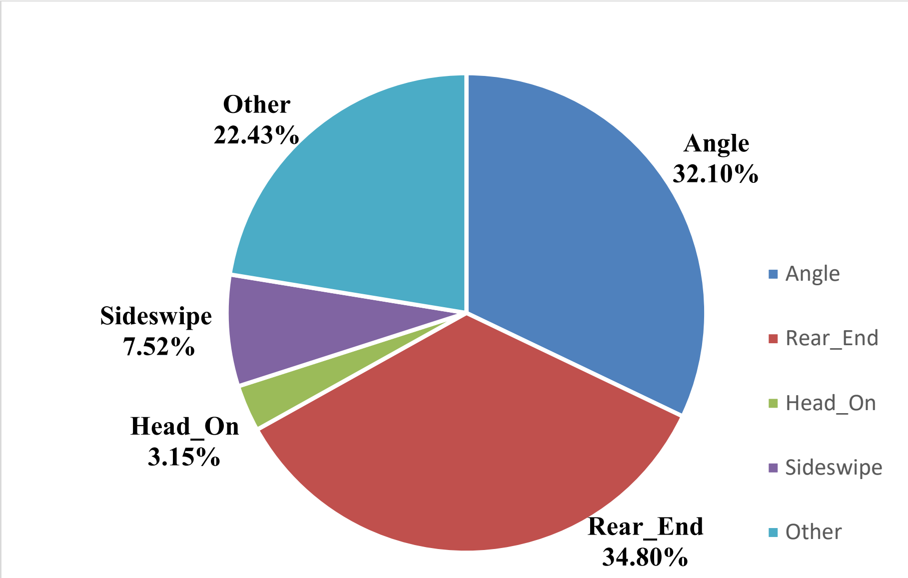


Figure 4.5 Crash proportions by crash type

Intersection crash proportions by type of collision for Wyoming were compared to crash proportions provided in the HSM in Table 4.2 and Table 4.3 for multi-vehicle and single vehicle, respectively. Crash proportions by the HSM were calculated based on data from the Highway Safety Information System (HSIS) data for California (2002-2006) [15].

Table 4.2 Comparison of crash distribution by types between Wyoming and HSM for multi-vehicle

Crash Types		Rear-End	Head-On	Angle	Side-Swipe	Other
F+I	WY	0.400	0.050	0.390	0.020	0.117
	HSM	0.450	0.049	0.347	0.099	0.055
PDO	WY	0.387	0.031	0.348	0.102	0.111
	HSM	0.483	0.030	0.244	0.032	0.211

Two crash severity levels and five crash types were considered for the comparison in which all crash types seem to have similar distribution except rear-end, angle, and sideswipe crashes. Intersection crash proportions for Wyoming are higher than the HSM proportions for angle crashes by 5 percent for F+I crashes and 10 percent for PDO crashes. Therefore, angle crashes should be analyzed extensively to determine contributing factors. PDO sideswipe crash proportions for Wyoming were 7 percent more than the HSM. Simple SPFs were calibrated for Wyoming conditions with similar crash types, as provided in the HSM. Moreover, full SPFs were calibrated to examine impacts of various factors on angle and sideswipe crashes at four-leg signalized intersections in Wyoming.

Table 4.3 Comparison of crash distribution by types between Wyoming and HSM for single-vehicle

Crash Severity		Parked Vehicle	Animal	Fixed Object	Object	Other	Non-collision
F+I	WY	0.000	0.029	0.234	0.541	0.065	0.135
	HSM	0.001	0.002	0.744	0.072	0.040	0.141
PDO	WY	0.000	0.167	0.544	0.022	0.249	0.018
	HSM	0.001	0.002	0.870	0.070	0.023	0.034

According to the Wyoming Highway Patrol (WHP), animal crashes were found to be the highest throughout central and northwest Wyoming. The cities of Lander, Riverton, Greybull, Thermopolis, and Cody are some areas included in this analysis. Most wildlife-vehicle collisions occur in the fall and winter [47]. Wildlife-vehicle crashes at intersection should be further analyzed in future studies to get an increased level of understanding about when, where and why wildlife is most likely to be present near the road.

4.1.3 Challenges and Potential Solutions

Some challenges were faced during data collection task for signalized intersections. These challenges were mitigated by using data imputation techniques.

Google Earth Pro® was used as a source of geometric characteristics data for the intersections. Historical satellite imageries collected manually from Google Earth Pro® from previous years were blurry. Therefore, it was not possible to ensure geometric characteristics remained constat throughout the study period (2005-2014), as shown in Figure 4.6.

Signal head configurations (3, 4, or 5 lights) cannot be classified from the Google Earth Pro® imageries. This information should be collected for further analysis in future. Signal timing and phasing are controlled by local transportation authorities. Due to unavailability of historical data of signal timing and phasing, it was not feasible to perform this step, and it should be studied in the future.

Original Photo: © 2017 Google Earth Pro®

Figure 4.6 Inspection of intersection characteristics variation by year from Google Earth Pro®

Crash data are compiled into two CARE packages of different time durations. Both CARE packages are needed for an extensive analysis and to identify intersections crash trends in Wyoming since 1994. Moreover, most of the treatments (e.g., signalization of intersections, adding turn lanes, etc.) were implemented before 2000. The first version of the CARE package was from 1994 to 2010 and the updated version was from 2005 to 2015. These two versions showed different crash frequencies for overlapping years. Total number of crashes from a previous package of CARE does not match the later one. Therefore, data were extracted from the latest package only (2005-2015) to maintain consistency.

Another issue with crash data was identifying intersection-related crashes. Intersection data taken from CARE with the "non-mile posted" location option show crashes with the name of the intersection of occurrence. Two intersections in Cheyenne with their crash locations were plotted in GIS, as shown in Figure 4.7. Three types of crashes from CARE: 1) mile-posted crashes, 2) non mile-posted crashes, and 3) without considering mile-posted and non-mile-posted crashes, were visualized in GIS to identify intersection-related crashes. Figure 4.7 shows that non-mile posted crashes, identified as intersection-related crashes, are also located outside the 200-foot intersection influence area. Therefore, more investigations may be required using original crash reports, which may also require labor intensive manual work. Collision diagrams can be constructed from original crash reports to understand crash patterns occurred at intersections to differentiate intersection-related versus roadway segment-crashes in the vicinity of intersections.

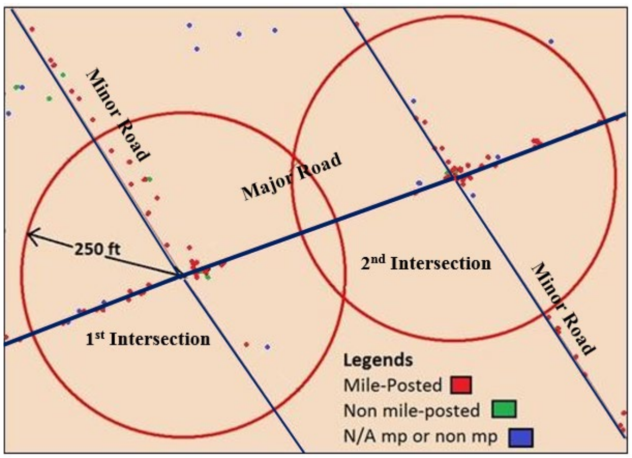


Figure 4.7 Identification of intersection-related crashes in GIS

For selected intersections, traffic volumes were available for the study years in annual average daily traffic (AADT) for at least the major approach roadways. The minor roadway AADTs were assumed as a percentage of major roadway AADT considering the existing traffic ratio at each intersection from Google Earth Pro® imageries. However, this procedure could be inaccurate as it assumes traffic volume for a specific instant time. For more accurate results, minor AADTs should be estimated based on field data collection, which is always associated with cost and time. Therefore, developing a traffic demand model could be a feasible solution for that issue.

4.2 Results

4.2.1 SPFs for Intersections

Several statistical techniques were used to calibrate Wyoming-specific SPFs for four-leg signalized intersections; e.g., Negative Binomial (NB), Zero Inflated Poisson (ZIP), and Zero Inflated Negative Binomial Models (ZINB). The HSM provides SPFs for single and multi-vehicle crashes by severity for four-leg signalized intersection. SPF calibration is needed to account for variations among different jurisdictions, such as driver population, age, crash reporting threshold, and adverse weather. Table 4.4 describes the data and variables used in this study.

Table 4.4 Description of variables

Data Set	Name of variables	Type of Variables	Description of Variables
Geometric Characteristics	$Lane_{maj}$	Categorical	Number of lanes in major approach roadway of the intersection
	$Lane_{min}$	Categorical	Number of lanes in minor approach roadway of the intersection
	RL_{maj} RL_{min} RL	Categorical	Presence of right-turn lane in major & minor approach or any approach of the intersection
	LL_{maj} LL_{maj}	Categorical	Presence of left-turn lane in the intersection in major & minor approach or of the intersection
Traffic Data	$AADT_{maj}$	Discrete	Annual Average Daily Traffic in major approach roadway
	$AADT_{min}$	Discrete	Annual Average Daily Traffic in minor approach roadway
Crash Data	Total	Discrete	Total crashes per year per intersection
	F+I	Discrete	Fatal+Injury crashes per year per intersection
	PDO	Discrete	Property Damage Only crashes per year per intersection
	Angle	Discrete	Angle crashes per year per intersection
	Rear-end	Discrete	Rear-end crashes per year per intersection
	Head-on	Discrete	Rear-end crashes per year per intersection
	Sideswipe	Discrete	Rear-end crashes per year per intersection

Model estimates for crash severity for single and multiple vehicle crashes for simple SPFs are shown in Table 4.5.

Table 4.5 Wyoming-specific simple SPF coefficients of generalized and single and multiple vehicle crashes

Crash Types		Intercept (a)	AADTmaj (b)	AADTmin (c)	Overdispersion Parameter
All Vehicle Crash	Total	-5.92	0.76	0.34	0.29
	F+I	-8.20	0.79	0.40	0.35
	PDO	-6.13	0.77	0.32	0.30
	Total	-6.29	0.79	0.34	0.33
Multiple Vehicle Crash	F+I	-8.93	0.83	0.42	0.41
	PDO	-6.46	0.80	0.32	0.34
	Angle	-6.94	0.77	0.32	0.39
	Rear-End	-8.92	0.94	0.36	0.39
	Sideswipe	-8.69	0.91	0.20	0.50
	Head-On	-5.96	0.43	0.31	0.51
Single Vehicle Crash	Total	-5.77	0.48	0.37	0.25
	F+I	-7.37	0.60	0.29	0.15
	PDO	-6.00	0.42	0.41	0.45

All Estimates are at 95th Significance Level.

The intercept values of Wyoming-specific SPFs are larger than the HSM calibrated SPFs intercept values. This could be due to smaller AADT for minor and major approaches of Wyoming intersections than the ones considered in the HSM. This may indicate that predicted crashes in Wyoming are higher than their national average counterparts. Moreover, the characteristics of Wyoming intersections in terms of geometric features, driver's characteristics, and weather are different from the features used in the HSM calibration. Adverse weather conditions and a higher population of elderly drivers characterize Wyoming intersections, which might have an impact on the crash frequencies.

Wyoming-specific full SPFs are shown in Table 4.6 using other geometric characteristics of four-leg signalized intersections. Models were developed by crash severity and types of maneuvers. This table shows impacts of adding left-turn and right-turn lanes on intersection-related crashes. The literature showed that rear-end and angle crashes benefit most from these treatments [48]. Number of through lanes also affect the number of intersection-related crashes.

Three SPFs were developed for four-leg signalized intersections for different crash severities (Total, F+I, and PDO). Average $AADT_{maj}$ and $AADT_{min}$ values were used to represent the AADT for the study years (2005-2014) for each intersection. The predictors of developed SPFs shown in Table 4.6 are significant at a 95 percent confidence level.

Table 4.6 Wyoming-specific full SPF coefficients for four-leg signalized intersections

Crash Types	Total Crash	F+I	PDO
Intercept	-8.0088	-9.5092	-7.81
ADT_{maj}	0.9119	0.7975	0.8617
$AADT_{min}$	0.1381	0.2219	0.1346
$Lane_{maj}$	-0.0546	0	0
$Lane_{min}$	0.5226	0.5532	0.4915
LL_{maj}	-0.2496	0	-0.4
LL_{min}	0	0	0.1709
RL_{maj}	0.2647	0	0.286
RL_{min}	0.3819	0	0.3535
RL	0	0.3804	0
Dispersion	0.0668	0	0.0384

All Estimates are at 95th Significance Level.

The variable estimates of all severity types of crashes showed trends of crashes for that specific type of severity. For total crash models, increasing number of major approach lanes had positive effect on crash reduction. The result is in line with a study conducted by Bauer and Harwood (1996) [49]. The number of total lanes at an intersection that represents the size of that intersection could be a surrogate to traffic volume [50]. Therefore, number of lanes could be correlated with AADT. These variables were kept in the model to evaluate their safety effectiveness regardless possible correlation with AADT. Adding right-turn lanes showed increased crash frequencies for total and PDO crashes by 25 and 29 percent, respectively, for major approaches, as well as 38 and 35 percent, respectively, for minor approaches. From an operation standpoint, addition of right-turn lane may increase the potential for rear-end and sideswipe crashes on the departure lanes as the vehicles turning onto the crossroad may conflict with other traffic streams [48].

4.2.2 CMFs for Left-Turn and Right Turn-Lanes

Full SPFs developed for Wyoming were used to calculate crash modification factors by cross sectional methodology. Adding left-turn lanes in major approaches of four-leg signalized intersections was found to reduce total crashes and PDO crashes by 22 and 33 percent, respectively. Meanwhile, adding left-turn lanes at minor approaches and adding right-turn lanes at major and minor approaches increases total and PDO crashes. Table 4.4 describes the data and variables used in this study.

5. ITS AND SPECIAL FACILITIES

To properly understand the effect that snow fence installations have on the roadway and its users, crash data was acquired from the CARE crash database software. This allowed for the milepost limitations to be applied and, from there, data were trimmed to only display and analyze that which occurred during the winter season (October 15–April 15). This study investigated the safety effectiveness of snow fence implementations by comparing crash data before and after the installation of fences between MP 325 and MP 344 along Interstate 80 (Route ML80) in Southeastern Wyoming using odds ratios, naïve before-after, and before-after with Empirical Bayes that uses a Negative Binomial Wyoming-specific SPFs.

5.1 Data Collection

5.1.1 Data Source

Data included in this study is a combination of weather data and crash data. The primary sources of data were the CARE software collected from October 2003 to April 2011 and aggregated on a winter weather season basis, and reconstructed hourly winter weather data for the investigation location that was collected from three adjacent 7.5-mile sections.

5.1.2 Data Description

To understand and quantify the safety effectiveness of snow fence implementations in Wyoming, an area from MP 325 to 344 along Interstate 80 (ML80B) was selected for investigation. This section of roadway was selected primarily due to the heavy presence of snow fences. Furthermore, this section of I-80 is characterized by mountainous terrain, intense adverse weather conditions, and high traffic volumes (relative to other Wyoming highways and freeways).

The snow fences included along Interstate 80 between MP 325 and 344 have been either constructed or reconstructed in 2007. For this reason, the investigation period for this particular study spans from 2003 to 2011. More specifically, the study investigates various data from October 15, 2003, to April 15, 2011. This was done to more accurately understand crashes and weather conditions that occurred only during the winter weather season, which is typically defined as October 15 to April 15 for analysis purposes. In total, the investigation period includes eight full winter weather seasons, with four coming before the implementation of snow fences, and four coming after.

5.1.3 Challenges and Limitations

Many complications in evaluating the effectiveness of snow fence implementations came in the consistency of design throughout the study area. WYDOT currently displays standard design specifications for only one fence type (at two separate heights). However, a visual inspection of many fences along the study area shows that there are many more than two separate fence sizes and designs. This raises the question of difference in safety performance based on fence type and design.

Additionally, the weather data involved in this study does not originate from a state agency, as such data has not been made available on an archived basis. The acquisition of data from systems coincident with the roadway network, such as RWIS, is ideal for such a study, but is not available at this time.

Finally, the overall lack of information and previous studies on snow fences and their effect on traffic safety has been found somewhat lacking. Snow fence design seems to be an extremely under-investigated engineering implementation. Snow fences act as an extremely economic method of snow management, which is increasingly significant when dealing with transportation agencies whose funding may not allow for additional spending on auxiliary areas (such as snow removal) in the realm of transportation. It has been historically proven that snow fence implementation can be, on average, up to 100 times cheaper than traditional snow plowing techniques [51]. This is primarily, but not solely, derived from a Wyoming study that is used as a basis for many snow fence studies conducted today, but its relevancy, as a 10+ year old study, may be questioned.

5.1.4 Potential Recommendations to Overcome Challenges

The issue of contrasting snow fence designs and their suspected differences in safety and storage performance is something that will ultimately come down to additional studies. Decomposing the crash analysis performed in this study, to only compare crashes at locations of same-type snow fences — which will likely occur only after all different designs and sizes of fences along the investigation location have been synthesized and distinguished — is essential to the understanding of their performance.

The lack of readily available archived winter weather data for Wyoming roadways is something that is in the process of being resolved. The data used in this study certainly has relevance and proximity to the crash investigation location, but currently, weather data from the Meteorological Assimilation Data Ingest System (MADIS) of the National Centers for Environmental Prediction (NCEP) are being processed. This is an extremely promising and rich data source that will hopefully provide more accurate and aligned weather data to the crash investigation location.

5.2 Results

5.2.1 Weather Conditions

See Table 5.2 for a brief overview of weather data gathered during the winter season for the investigation location. Note that the mobile and blowing snow rates found in Table 5.1 are not given as velocities, but as a total depth, in millimeters, per hour of time.

Table 5.2 Weather data from study location

	Average 2.5 m Wind Speed (m/sec)	Average Mobile Snow Rate (mm/hr)	Average Blowing Snow Rate (mm/hr)	Total Snowfall (mm)	Average Air Temp (°C)
2004-2007	6.013	0.196	0.104	300.6	-0.478
2007-2010	6.272	0.231	0.144	332.6	-1.423
	↑ 4.37%	↑ 17.9%	↑ 38.5%	↑ 10.6%	↓0.945 °C

5.2.2 SPFs for Freeways

The SPFs utsed for the safety analysis of snow fence implementations followed the model of a simple SPF where the included parameters were AADT and segment length. Additionally, these SPFs were calibrated for Wyoming-specific conditions, which included mountainous terrain and the winter weather season. Table 5.2 shows coefficients involved in the NB model for this analysis.

Table 5.2 Wyoming-specific SPFs for interstate freeways during winter months

Crash Type	Intercept Estimate	Log(AADT) Estimate	Dispersion (k)
F+I	-8.2786	2.1192	0.1501
PDO	-11.3416	3.1278	0.2512
Total	-12.7676	3.5971	0.3857

Calibration for the Crash Modification Factors (CMFs) for several countermeasures were conducted. Below are the countermeasures and the preliminary results obtained for the CMF calibration.

5.2.3 CMFs for Snow Fence

The odds ratio and subsequent ratio of odds ratios were determined to understand the relationship between total crashes that occur in the winter weather period and target crashes (adverse weather crashes) that occur in the same period. The comparison between target and total crashes was done before and after the implementation, and the results can be found in Table 5.3.

Table 5.3 Contingency table with odds ratio for total and F+I crashes

	Total				F+I			
	Total Crashes	Target Total Crashes	Odds	Odds Ratio	F+I Crashes	Target F+I Crashes	Odds	Odds Ratio
Before Implementation	496	268	54%	0.72	156	87	56%	0.77
After Implementation	457	342	75%		107	78	73%	

As seen in the above table, the odds ratio for total crashes was 0.75, indicating a lesser portion of crashes during adverse weather was experienced prior to the implementation of snow fences. The odds ratio for the F+I crashes was found to be 0.77. This value indicates, similar to the total crash OR, that a higher portion of the fatal and injury crashes, during adverse weather conditions, came after the installation of the snow fences. However, confidence intervals for the total crashes and the F+I crashes were 0.57 to 0.88 and 0.52 to 1.14, respectively, which indicates no statistically significant effect as a result of snow fence implementation with regard to either crash type during the winter weather season. The ratio of odds ratios shows that the ratio of ORs for total crashes (0.72) and for F+I crashes (0.77) is equal to 1.07. This is promising as it indicates that there has been less of an increase in fatal and injury crashes since the implementation of snow fences, when compared to the total crashes.

The naïve before-after analysis yielded straightforward results. The comparison of F+I and PDO crashes before and after the implementation year showed numerous results. Of the total crashes that occurred during all-weather types, 31 percent were F+I before the implementation of snow fences and 23 percent were F+I after, showing a 31.41 percent decrease in fatal and injury crashes. Additionally, there was a 2.94 percent increase in PDO crashes after the implementation of snow fences. Crashes that occurred under adverse weather conditions during winter months were expected to be more representative of the true effect of the snow fences. There was a 10.34 percent decrease seen in fatal and injury crashes that occurred in adverse weather, but a 45.86 percent increase in PDO crashes and a 27.61 percent increase in total crashes. These results do not seem reliable as they suggest a significant increase in total and PDO crashes after the time of snow fence implementation. The before-after analysis using EB showed predictably more refined results as the SPFs used for this analysis took AADT and segment length into account. By involving these parameters in the model, their expected contributions to crashes were taken into account and a hopefully truer representation of the safety effectiveness of the snow fences was found.

This allowed for the safety effectiveness of the snow fence implementations, or CMFs to be calculated (as well as their standard error to test statistical significance). These cumulative analysis results can be found in Table 5.4.

Table 5.3 Naïve Vs EB analysis results for the snow fences

	Analysis Method							
	Naïve (All Weather)		Naïve (Adverse Weather)		EB (All Weather)		EB (Adverse Weather)	
Crash Type	CMF (Safety Effectiveness)	S.E.	CMF (Safety Effectiveness)	S.E.	CMF (Safety Effectiveness)	S.E.	CMF (Safety Effectiveness)	S.E.
F+I	0.69	0.64	0.9	0.61	0.41	0.047	0.38	0.051
	(31.41%)	64.11%	**(10.34%)**	61.17%	**(59.09%)**	4.75%	**(61.98%)**	5.15%
PDO	1.03	0.71	1.46	0.78	0.77	0.056	0.94*	0.08
	(-2.94%)	70.55%	(-45.86%)	78.32%	**(23.21%)**	5.57%	(5.98%)*	7.99%
Total	0.92	0.85	1.28	0.86	0.75	0.047	0.84	0.063
	(7.86%)	85.34%	(-27.61%)	85.98%	**(25.3%)**	4.72%	**(15.67%)**	6.33%

Bold indicates significant crash reduction, S.E. = Standard Error
*Indicate statistical insignificance

The before-after analysis using EB offers extremely promising results as CMFs of 0.75 and 0.84 for total crashes in all weather conditions and adverse weather conditions, respectively, indicate significant increases in safety. Additionally, the CMFs for F+I crashes in all weather and adverse weather conditions were 0.41 and 0.38, respectively. These results indicate significant safety increases as a result of the presence of snow fences for multiple crash types during the winter weather season in all weather conditions and adverse weather conditions.

6. CONCLUSIONS AND RECOMMENDATIONS

Many transportation agencies assume that safety will be achieved solely by compliance to roadway design standards, known as nominal safety. Yet traffic crashes continue to increase or fluctuate from year to year, even on newly constructed roadways. Contrasting fatalities in Wyoming to the national average revealed that Wyoming experiences higher fatality rates compared to the national level in the United States, adhering only to standards will not address this issue. Shifting and moving to substantive safety should be considered. This could be achieved by quantifying the safety performance of roadway facilities in Wyoming following a scientific-based approach. Moreover, to allocate limited resources more appropriately, evaluation of the safety effectiveness of various countermeasures is a crucial step. The focus of this study was to validate applicability and transferability of the HSM to Wyoming-specific conditions. In addition, this study elucidated data limitations and challenges to conduct traffic safety analyses in Wyoming. It proposes alternative solutions to overcome data limitations and challenges to implement a scientific-approach following the HSM.

The main tasks accomplished in this study included developing safety performance functions (SPF) for Wyoming-specific conditions followed by calibrating crash modification factors (CMFs) for different countermeasures implemented in Wyoming's road network. The unique nature of the mountain plains region due to the difference in traffic characteristics and composition, roadway characteristics, and weather conditions than the states represented in the HSM posed as a limitation to the study. The individual tasks carried out to achieve the study goals included identifying existing data, data imputation and validation, preliminary data analysis, advanced analysis, conducting comparisons with the HSM, and providing recommendations.

Crash data, roadway characteristics, weather data, traffic volumes, energy activities in different counties, and implementation dates and locations for treatments were all required. A number of data sources were used to prepare and develop these various datasets. Many gaps and limitations were identified and discussed throughout the different chapters. Non-traditional data sources were used to overcome limitations and fill in the gaps.

The study focused on developing and calibrating CMFs for three groups of roadway facilities: 1) roadway segments, 2) intersections, and 3) ITS and special facilities. Calibrating reliable CMFs required having SPFs for the site-specific conditions. A number of statistical techniques were used to develop SPFs in this study. Negative Binomial models (NB), Zero Inflated Poisson (ZIP) models, and Zero Inflated Negative Binomial models (ZINB) were adopted. Comparisons between the obtained models were performed to select the most accurate and reliable SPFs.

Several SPFs were developed for roadway segments. Initially, general SPFs for roadway segments were developed including simple and full SPFs. Simple SPFs only account for the Average Annual Daily Traffic (AADT). To account for other confounding factors affecting crash prediction, full SPFs were developed. Roadway segments were categorized into two groups; roadways in oil and gas counties and roadways in non-oil and gas counties. Separate SPFs were established for the two roadway groups. In addition, simple and full SPFs for four-leg signalized intersections were calibrated.

The HSM provides multiple statistical techniques to calibrate CMFs. Odd, odds ratio, ratio of odds ratio, cross-sectional studies, observational before-after studies using Empirical Bayes (EB) method, and before-after studies using naïve method were the methods used to calibrate the crash modification factors. Each method has its own strengths and weaknesses. Obtained results for SPFs and CMFs for the various roadway facilities are provided in their corresponding sections.

6.1 Conclusions

Shoulder Rumble Strips and Passing Lanes

- Shoulder rumble strips reduced 55 percent of F+I crashes in rural two-way two-lane highways in Wyoming. Shoulder rumble strips were more effective in oil counties.
- Passing lanes reduce total and F+I crashes by 42 and 34 percent, respectively.
- Passing lanes were more effective in reducing crashes in oil counties.

Headlight Signs

- The results of observational before-after and cross-sectional analyses showed no significant effect of the headlight use signs.
- The odds ratio analysis showed that 77 percent of vehicles involved in crashes were not equipped with DRL. There was no significant difference between DRLs and non-DRL equipped vehicles on sections with or without headlight signs on total, head-on and sideswipe opposite crashes.
- The field study showed a very low compliance rate of only 12 percent to the headlight signs. Headlight signs are behavior-based countermeasure. Hence compliance rates should be considered when evaluating the safety effectiveness of behavior-based countermeasures such as headlight signs.

Intersections

- The Negative Binomial (NB) model was the best model to predict the safety performance of four-leg signalized intersections.
- Most significant variables for crash predictions for four-leg signalized intersections included traffic volume (AADT) for major and minor approaches, number of lanes and presence of turning lanes at intersections.
- Angle, rear-end, and sideswipe crashes showed different results than the HSM. Intersection crash proportions for Wyoming were higher than the HSM proportions for angle crashes by 5 percent for F+I crashes and 10 percent for PDO crashes.
- Adding right-turn lanes on major approaches showed an increase in crash frequencies for total and PDO crashes by 25 and 29 percent, respectively. Adding right-turn lanes at minor approaches increased total and PDO crashes by 38 and 35 percent, respectively. Adding left-turn lanes at major approach reduced total crashes and PDO crashes by 22 and 33 percent, respectively. Meanwhile, adding left-turn lanes at minor approaches and adding right-turn lanes at major and minor approaches increased total and PDO crashes.

Snow Fences

- Calculated ratio of ORs for total crashes (0.72) and for F+I crashes (0.77) is equal to 1.07. This is promising as it indicates that there has been less of an increase in fatal and injury crashes since the implementation of snow fences, when compared to the total crashes.
- The naïve before-after analysis indicated during all-weather types, 31 percent were F+I before the implementation of snow fences and 23 percent were F+I after, showing a 31 percent decrease in fatal and injury crashes after the implementation of snow fences.
- There was a 10 percent decrease seen in F+I crashes that occurred in adverse weather, but about 46 percent increase in PDO crashes and about 28 percent increase in total crashes.
- The before-after analysis using EB found CMFs of 0.75 and 0.84 for total crashes in all weather conditions and in adverse weather conditions, respectively, indicating significant safety effectiveness.

- The CMFs for F+I crashes in all weather conditions and in adverse weather conditions were 0.41 and 0.38, respectively, again, indicating significant safety increases as a result of snow fences.

6.2 Recommendations

Even though many issues encountered throughout the study were resolved, there are multiple areas that can be addressed for future work. These include:

- Crash data are currently compiled into two separate CARE packages, the first version available for CARE ranges from 1994 to 2010 and the second version covers 2005 to 2016. The overlapping years between the two versions were found to have discrepancies in crash frequencies.
- Lack of archived implementation dates posed a serious limitation to this study. Implementation dates for treatments had to, at times, be estimated using non-traditional data sources.
- There are two possible ways to overcome the effect of shoulder rumble strips intermittency. The first is to exclude these particular sections from the analysis. This solution was adopted and applied in this study. The alternative approach could be considering every off situation as before period and every on situation as after period. Data about overlay implementation also should be included in the analysis. This alternative approach could provide more reliable results, however, it needs additional effort and analysis, which might be done in future studies and phases.
- Information about compliance to the headlight light sign and the existence of DRL technology for the crashed vehicles in the before and after periods are essential to investigating the effect of the DRL technology penetration on the safety effectiveness of regulatory headlight signs. However, it is impossible to obtain such information for the historical crash data. This is another issue that can be addressed in future studies.
- The issue of contrasting snow fence designs and their suspected differences in safety and storage performance is something that will ultimately come down to additional studies.
- The weather data that was used in this study certainly has relevance and proximity to the respective crash investigation locations, but currently, weather data from the Meteorological Assimilation Data Ingest System (MADIS) of the National Centers for Environmental Prediction (NCEP) are being processed as hopefully superior alternatives.

Currently, several additional countermeasures are being considered for future work. These countermeasures include, but are not limited to, roadway widening and overlay, climbing lanes, centerline rumble strips, combining shoulder and centerline rumble strips, roadway information systems (DMS), and VSL. The analyses of these various countermeasures in the future will not only aid the understanding of the safety effectiveness of various Wyoming roadway treatments, but some have a particularly strong correlation to the upcoming connected vehicles and the future work in this field, which will take place on Wyoming roads.

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