Safety Effectiveness of Variable Speed Limit System in Adverse Weather Conditions on Challenging Roadway Geometry

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This paper examined the interaction between roadway geometric characteristics and adverse weather conditions and their impact on crash occurrence on rural variable speed limit freeway corridors through mountainous terrain. As a quantitative measure of the effect of geometrics in adverse weather conditions, a crash frequency safety performance function that used generalized linear regression was developed with explanatory variables including snow, ice, frost, wind, horizontal curvature, and steep grades. This research concluded that the interaction between grades and horizontal curves with weather variables had a significant impact on crash occurrence. The research suggested that distinct variable speed limit strategies should be implemented on segments with challenging roadway geometry.

A variable speed limit (VSL) is a regulatory or recommended speed limit that changes according to real time variables such as traffic conditions or weather. VSL systems are typically installed for congestion management in urban areas (*1–5*). Weather-related VSL systems are used when weather events (fog, ice, rain) might adversely affect driver capabilities and vehicle performance or increase delay. The VSL corridors that are the subject of this research post regulatory speed limits based on real-time weather conditions (*6*). Sign speeds are set by Wyoming's statewide Traffic Management Center and speed updates are relayed to the Wyoming Highway Patrol for enforcement purposes. VSL signs are posted in pairs (on inside and outside lanes) with an average spacing of 6 mi. Figure 1 shows the two types of sign technology used on the study corridors.

Much of Interstate 80 is affected by winter weather events, especially the mountainous segments through Wyoming. During the winter season, heavy snow fall, low visibility, slick pavement surface conditions, high winds, and blowing snow conditions contribute to a high frequency of crashes. On the Wyoming I-80 corridor, winter crashes are almost three times higher than summer crashes and the variations of crashes are much higher in winter than in summer (*6*). To improve the safety and operations along this corridor, VSL systems have been implemented on four segments in Wyoming, totaling 143 mi in length (Figure 2). The first VSL corridor was installed in February 2009 on the Elk Mountain corridor. The Green River corridor was deployed in February 2011. The last two corridors, Evanston and Laramie–Cheyenne, became operational in October 2011.

It is important to evaluate the effectiveness of the VSL systems and to estimate factors that have historically contributed to the likelihood of crash occurrence. The corridors feature mountainous road geometry that includes frequent steep grades and sharp horizontal curves (Figure 2). Because their terrains are mountainous, these corridors feature steep grades of up to 5.24% and radii of horizontal curves as low as 1,008 ft. There are 199 vertical curves and 201 horizontal curves on the 143 mi of VSL deployment.

The current operational procedures for the VSL system do not consider geometric variations when setting appropriate regulatory speed limits. The locations for VSL sign installation were selected based on historic safety issues; most of the segments with significant geometric features could therefore be isolated when setting speeds, which allowed for geometric conditions to be used as a VSL speed-setting variable if the relationship between geometric features, weather, and speed could be developed.

PREVIOUS RESEARCH

For safety to be improved, the reasons why crashes occur must be understood. Several research efforts have modeled crash occurrence. Abdel-Aty and Radwan studied the modeling of traffic accident occurrence and involvement (*7*). Their results showed that annual average daily traffic (AADT), speed, lane width, number of lanes, land use, shoulder width, and median width have a statistically significant impact on crash occurrence. Ahmed et al. investigated the safety effects of roadway geometrics on crash occurrence along a mountainous freeway corridor in which adverse weather played an important role; results showed that segments with steep downgrades increased the crash risk drastically (*8*). Tegge et al. studied safety performance functions (SPFs) in Illinois and found that AADT, access control, land use, shoulder type, shoulder width, international roughness index, number of lanes, lane width, rut depth, median type, surface type, and number of intersections have a significant impact on safety (*9*). In their study about the effect of snow events on interstate highway crashes, Khattak and Knapp observed that long duration, high snow amounts, wind speed, and high traffic volumes during snow events significantly increase crash frequency (*10*). Overall accident risk during rainfall increased by 70 percent when compared with normal conditions according to Andrey and Yagar (*11*). Kalokoata and Seneviratne observed in their study on crash prediction models

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(a) (b) (c)

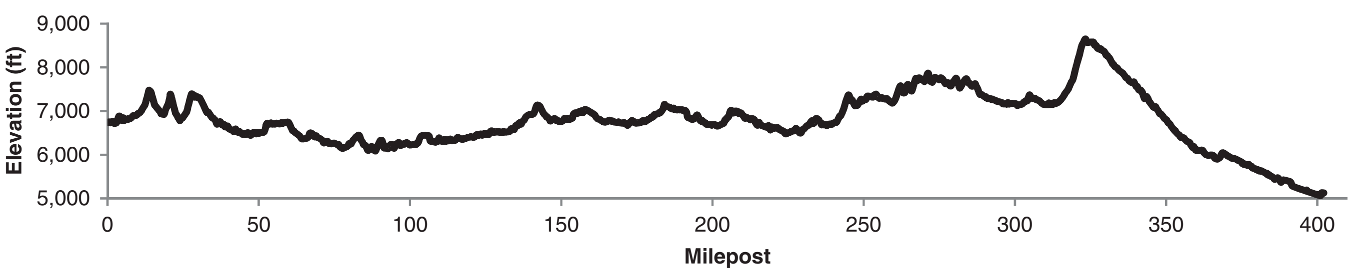
FIGURE 1 Typical VSL signs with flashing beacon: (*a*) LED and (*b* and *c*) scrolling film.

that section length, degree of curvature, right shoulder width, and number of lanes were significant at the 10% level of significance, but percent grade and left shoulder width could not meet the 10% significance level (*12*). Cafiso et al. developed comprehensive accident models for two lane rural highways and found that section length, traffic volume, driveway density, roadside hazard rating, curvature ratio, and number of speed differentials higher than 10 km/h increased crash occurrences significantly (*13*).

Previous research has also investigated the safety effects of different confounding factors on crash occurrence. This research specifically focused on the interaction between roadway geometry and adverse weather conditions and its implications for setting appropriate speed limits.

Researchers have used different approaches to understand the relationship of crash occurrences to geometric characteristics, weather variables, and traffic-related explanatory variables. These approaches

(a)



(b)

FIGURE 2 Wyoming variable speed limit corridors: (*a*) plan and (*b*) profile.

employed statistical models such as multiple linear regression, Poisson regression, zero-inflated Poisson regression, negative binomial (NB) regression, zero-inflated negative binomial regression. In 1986, Jovanis and Chang studied why multiple linear regression was not appropriate for modeling crash occurrence since accident frequency data did not fit well with the basic assumptions associated with the model (*14*). A major assumption with linear regression models is that the frequency distribution of observations must be normally distributed. Most crash frequency data violate this assumption. Crash frequency data also possess special characteristics such as count data and overdispersion. In 1993, Miaou and Lord (*15*) and Saha and Young (*16*) studied the performance evaluation of Poisson and negative binomial regression models in modeling the relationship between truck accidents and geometric design of road sections. This research recommended that Poisson regression or zero-inflated Poisson could be the initial model for establishing the relationship because of the count data aspect of crash frequencies. However, in most crash data, the mean value of accident frequencies is lower than the variance (i.e., overdispersion). If overdispersion is present in crash frequency data, NB or zero-inflated NB would be the appropriate model since it accounts for overdispersion. In most accident data, crash frequencies show significant overdispersion and exhibit excess zeroes. In this case, the zero-inflated NB regression model appears to be the best model.

It is worth mentioning that when a regression model deals with several explanatory variables, correlations between variables (i.e., multicollinearity) could be an issue. The problem with multicollinearity is that when explanatory variables become highly correlated, a larger standard error is produced and determining which explanatory variable is producing the effect on the dependent variable becomes much more difficult. (Large standard errors could be caused by some property other than multicollinearity, such as high amounts of variation in the sample and small sample sizes.) Multicollinearity causes estimators to be biased, inefficient, or inconsistent. It does not, however, have any impact on the forecasting performance of the model, although it can cause coefficients to be insignificant (*7*). Since multicollinearity may mislead the significance of explanatory variables, it is very important to know the causes of multicollinearity and how the problem can be removed from the model. There are several common occurrences that could result in multicollinearity: the use of an explanatory variable, the effect of which is already accounted for from another variable; failure to exclude a category from a categorical variable, which often happens because of improper use of dummy variables; and the use of the same variable or almost same variable more than once. Since multicollinearity may result in an erroneous model, predictor variables that are highly correlated with the dependent variable and correlated minimally with each other should be maintained in the final model. Some of the common methods used to determine multicollinearity include large correlation value among pairs of explanatory variables, low values of t-statistics, use of the variance inflation factor, and variation of coefficient estimates between different model runs.

Lord and Mannering studied the fundamental data and methodological issues related to modeling crash frequencies (*17*). These issues have been shown as potential sources of error in selecting the appropriate model technique, thereby causing erroneous estimates of the parameters used in the model. Of the issues mentioned in that research, overdispersion, time-varying explanatory variables, spatial and temporal correlation, low sample mean and small sample size, omitted variable bias, underreporting, and endogenous variables could result in erroneous estimates in this research. Human factors could also contribute to erroneous estimates of model parameters.

METHODOLOGY

In safety modeling, the most commonly employed approach is the NB regression technique. As discussed in the previous research section, NB and its extensions have been found to be the most accurate modeling techniques for modeling crash occurrence. In most cases, the crash data set possesses overdispersion in the response variable and fits well with NB distribution. In the following sections, NB models with both fixed effects (FENB) and random effects (RENB) are discussed briefly.

The Poisson regression model is the basis of the NB model. When the variance of the response variables exceeds the mean, overdispersion is present, and an NB regression model should be used to handle it. The formulation of NB model is as follows:

$$\ln Y_i = \beta_0 + \beta_i X_i \tag{1}$$

where

Y_i = expected number of accidents in time period i,
β = parameter coefficient vector to be estimated, and
X_i = vector of explanatory variables in time period i.

The NB can also be written as follows:

$$P_r(Y = y|x) = \frac{\Gamma\left(y+\alpha^{-1}\right)}{\left(y!\,\Gamma\left(\alpha^{-1}\right)\right)}\left(\frac{\alpha\mu(x)}{1+\alpha\mu(x)}\right)^{y}\left(\frac{1}{1+\alpha\mu(x)}\right)^{\alpha^{-1}} \tag{2}$$

where P_r is probability distribution.

The mean can be given as

$$E(Y|x) = \mu(x) \tag{3}$$

The variance can be given as

$$\operatorname{var}(Y|x) = \mu(x) + \alpha\mu(x)^2 \tag{4}$$

where α is the overdispersion parameter of the NB model. When α tends toward zero, the distribution of Y becomes a Poisson distribution with equal mean and variance.

Recently, modeling crash occurrence with the use of panel data become widely applied (*15, 18–21*). Because crashes are nonnegative count data and often overdispersed, nonlinear FENB and RENB models might be better choices for panel crash data. To determine this, a Hausman test can be performed to identify the best model between FENB and RENB. Generalized versions of FENB (Equation 1) and RENB (Equation 2) can be set up as follows:

$$\log Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \tag{5}$$

$$\log Y_{it} = \alpha_i + \beta X_{it} + \gamma_1 T_{it} + \varepsilon_{it} \tag{6}$$

for $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T_i$

where

Y_{it} = crash count at corridor i (i = 1, 2, 3, 4) during week t (t = 1 for Week 1, 2 for Week 2, and so forth);
α_i = state specific effects;
X_{it} and T_{it} = confounding factors and time trend, respectively;
β and γ = regression parameters; and
ε_{it} = the error term.

The ordinary least square (OLS) and maximum likelihood are the common statistical procedures used to fit the data. OLS chooses the parameter estimates that minimize the average squared difference between observed and predicted values. Maximum likelihood, on the other hand, chooses the parameter estimates for which the observed data are found most likely. OLS is only applicable for linear regression but maximum likelihood can be applied to any data set for which distribution is known. In that case, if the actual observations follow normal distribution around the mean, the maximum likelihood estimate is the same as the OLS estimate. Increasingly, researchers are using maximum likelihood to choose parameter estimates. In crash analysis, logistic, Poisson, and NB modeling techniques are commonly used to establish the relationship between crash frequency and explanatory variables such as AADT, geometric conditions, and weather variables. In these models, least square cannot be used as the estimation method because of the nonlinear frequency distribution of the response variable. Instead, maximum likelihood is commonly used as the estimation method for crash analysis. As NB regression is used in modeling crash occurrence, the formulation of maximum likelihood for NB models can be shown as follows:

$$L(\beta_j; y, \alpha) = \sum_{i=1}^{n} y_i \ln\left(\frac{\alpha e^{X_i'\beta}}{1+\alpha e^{X_i'\beta}}\right) - \left(\frac{1}{\alpha}\right)\ln\left(1+\alpha e^{X_i'\beta}\right) + \ln\Gamma\left(y_i + \frac{1}{\alpha}\right) - \ln\Gamma(y_i+1) - \ln\Gamma\left(\frac{1}{\alpha}\right) \quad (7)$$

with a matrix of repressors X, a vector of coefficients β, and the NB heterogeneity parameter α.

Many criteria have been developed for comparing the regression models such as Akaike information criterion (AIC), Bayesian information criterion, deviance information criterion, and R^2. Basically these criteria are used to estimate the percentage of variation explained by the regression model. For model selection, these criteria identify which subset of independent variables should be included in regression models. For linear regression models, R_p^2 is commonly used for identifying best subsets. In crash analysis, when SPF need to be developed, the models are nonlinear for most of the cases. For nonlinear models, sometimes R_p^2 does not provide accurate results (*22*). Previous research about developing SPFs used AIC, Bayesian information criterion, and deviance information criterion to identify best set of independent variables (*6, 13, 23*). AIC was used to measure the model complexity and fit as follows:

$$\text{AIC} = -2 * \ln(\text{maximum likelihood}) + 2 * k$$

where k is the number of estimated parameters. The smaller the value of AIC, the better the model is.

DATA DESCRIPTION

Data from multiple sources were used in modeling safety on the four I-80 VSL corridors. These data included crash data, weather data, roadway geometrics, and traffic data. Data from October 2007 to April 2012 were used to ensure there were no major changes to the study area related to roadway geometrics.

The crash data for the study area were obtained from the Wyoming Department of Transportation (DOT) and contained information on accident time, accident location, accident type, impact type, severity level, weather conditions, lighting conditions, road conditions, and roadway geometry for each accident.

Weather data used in this research were collected from a weather forecasting service the Wyoming DOT has used for many years for winter maintenance activities. This service consists of forecasts two or three times daily. It assigns numerical values for each weather variable (snow, frost, ice, and wind) in a ranking system of 0–10, for which 10 represents the worst condition and zero represents ideal conditions (*24*). The weather forecasts were specific to the roadway segment so different forecast data were used for each of the VSL corridors.

Weather data can also be collected from Road Weather Information System (RWIS) stations, which provide the observed weather conditions at a roadway. The use of RWIS weather data instead of forecast data would have been preferred since RWIS represents the weather conditions that actually occurred as opposed to weather that was forecasted. For this research, it was not possible to use RWIS weather data because the stations were installed at the time of VSL system implementation, so weather observations from RWIS were not available. Forecast data were used by the Wyoming DOT for many years and viewed by maintenance personnel as being highly reliable.

The Wyoming DOT maintains a database of roadway geometric features and records different horizontal and vertical alignment parameters. For vertical alignments, the route number, direction of travel, reference marker, and curve length and elevation are stored; for horizontal alignments, the route number, direction of travel, reference marker, delta, length in, curve length, and length out are provided (Tables 1 and 2).

Bidirectional traffic counts were obtained from the Wyoming DOT's permanent traffic stations (*25*). Average daily traffic in winter on the four corridors were as follows: 8,595 for Elk Mountain, 14,320 for Green River, 10,129 for Evanston, and 10,572 for Laramie–Cheyenne. In 2008 there was an average of 1,000 fewer vehicles per day, most likely because of the economic decline in fall of that year.

To determine the effectiveness of the VSL systems on reducing crash frequencies, VSL use was incorporated as a binary explanatory variable with a value of one for time periods after the VSL was implemented and zero for periods before implementation. This research used an aggregated data set over 7-day time period (e.g., 7-day crash frequency, 7-day average daily traffic, and 7-day average weather data) normalized over a standard 100-mi corridor length so that the corridors could be combined into a single model.

A 7-day crash frequency model was used to eliminate the zero inflated issue associated with the low frequency of crashes. Worth mentioning is that various time durations were attempted and a 7-day aggregation level was found to be the best to account for the high variability in weather conditions in this region. Also of note is that it was initially thought of to include a VSL-use variable that reflected the amount of time a speed limit reduction was used during

TABLE 1 Vertical Alignment Information

ID Number	Direction	Reference Marker	Curve Length (ft)	Elevation (ft)
80	Westbound	0.156	600	6,743
80	Westbound	0.543	1,000	6,753
80	Westbound	0.897	600	6,738

TABLE 2 Horizontal Alignment Information

ID Number	Direction	Reference Marker	Δ(°)	Length In (ft)	Curve Length (ft)	Length Out (ft)
80	Westbound	0.222	26.34	0	1,756	0
80	Westbound	1.599	3.13	0	4,690	0
80	Westbound	3.733	69.93	360	1,971	360

NOTE: Δ = angle between the tangents of a horizontal curve.

each 7-day period. Since the VSL systems are weather based, the use of the system within is captured by weather variables for that period. An aggregated VSL-use variable would be highly correlated to the weather variables. Aggregation also prohibits use of actual set speed limits in the analysis.

The normalization of the corridors to 100 mi allowed for crash frequencies on different corridors to be combined into a single model, even with all four corridors having different lengths (Figure 2). The scaling of crash frequency to a common corridor length let the corridors be treated as individual observations in the model. A single observation in the model was for one VSL corridor for one 7-day period. Average daily traffic values were modeled for the 7-day observations by use of weekly modification factors based on observed seasonal variations (Table 3). Only the 6 months of winter (October 15–April 15) were modeled to correspond to the periods of high VSL use.

PRELIMINARY ANALYSIS

A preliminary analysis was conducted on the horizontal and vertical curves to examine important factors potentially contributing to crash occurrence. Grade and curve length of vertical curves may increase the crash risk. Similarly, radius, curve length, and the delta of horizontal curves can also increase the crash risk. Table 4 provides the descriptive statistics of the horizontal and vertical alignments for the four study corridors.

For roadway segments in which weather has a large influence on roadway safety, it is necessary to address variations in the winter seasons from year to year. In Figure 3, a comparison of crash frequencies between summer and winter for the Elk Mountain VSL corridor is shown. On average, there were 203 reported crashes in winter and 72 reported crashes in summer; these reports indicate that winter crashes are 2.82 times higher than summer crashes. Figure 3 also shows the variation between years in winter is much higher than that of summer crashes.

TABLE 3 Average Winter Daily Traffic on Elk Mountain Corridor

Winter	Elk Mountain	Cheyenne–Laramie	Rock Springs–Green River	Evanston–Three Sisters
2006–2007	9,035	10,672	14,179	10,550
2007–2008	9,264	10,939	14,238	10,936
2008–2009	8,462	10,523	14,294	10,010
2009–2010	8,479	10,551	14,409	9,966
2010–2011	8,504	10,569	14,362	10,007
2011–2012	8,267	10,280	14,297	9,728

NOTE: Winter defined as October 15–April 15 each year.

A comparison of the crashes from the periods before and after VSL implementation can be seen in Table 5 for the winter seasons from October 2007 to April 2012. The last column of the table shows the summary results of winter crashes for the four VSL corridors separately. Of note is that crashes have decreased by 41%. Weather and traffic variations are not considered in this value, which is why a full model was estimated (to be discussed in later sections).

MODEL ESTIMATION

Since this research investigated the effect of adverse weather on crash occurrence, geometric characteristics were incorporated with weather variables to develop an SPF. The risk of crashes in the winter season was found to be 82% higher than in summer; the crash risk might have been exacerbated by the challenging roadway geometry (i.e., the confounding effects of the snow or icy roadway conditions and the steep grades and sharp horizontal curve radii) on mountainous freeway corridors (*6*). Other geometric characteristics such as lane width, land use, shoulder width, and median width may have also had an impact on crash occurrence but were excluded from modeling because there was no variation in those variables among the four VSL corridors.

Because sharp horizontal and steep grades may increase the risk of crash occurrence, these geometric variables were used as explanatory variables in this analysis. For developing a weather-based SPF, aggregate forms of roadway geometric conditions that indicated the number of sharp horizontal curve and steep grade sections were incorporated in modeling to correspond with the aggregate crash data. Vertical curve length was included in initial modeling but was found not to have enough variation between corridors to be included. Aggregation of geometric variables were necessary since each corridor's crash frequency for a 7-day period was treated as a single

TABLE 4 Descriptive Statistics of Horizontal and Vertical Alignments

	Vertical Curve[a]		Horizontal Curve[b]		
Statistic	Grade (%)	Curve Length (ft)	Radius (ft)	Curve Length (ft)	Δ(°)
Mean	1.17	1,139	5,761	1,583	21.1
Standard deviation	1.16	621	4,656	1,363	17.4
Minimum	0.01	100	50	34	0.38
Maximum	5.24	3,600	32,892	9,857	102.5

[a]Count = 201.
[b]Count = 309.

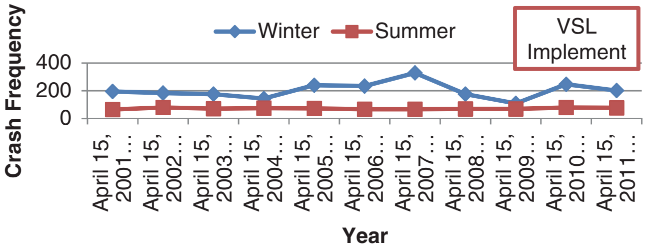


FIGURE 3 Elk Mountain seasonal variation of crash frequency, 2001 to 2012.

observation. Segmentation of the corridor by geometric feature would result in an unreasonably higher number of zero observations for crash modeling.

To include the geometric variables at an aggregated level, it was necessary to set the threshold value of curve radii and grades used to identify sharp horizontal curves and steep grades. The initial threshold values were selected based on the input of Wyoming DOT roadway designers and knowledge of the study corridors. Future research could be performed to identify appropriate threshold values. In this research, grades greater than 4% and radii less than 3,500 ft were considered as the initial threshold values. The geometric data provided by the Wyoming DOT were used to identify steep grades and sharp horizontal curves on the study corridors and are summarized in Table 6. Since crash frequency was for both directions of the roadway, upgrades and downgrades were not treated independently.

The number of horizontal curves having radii less than 3,500 ft had to be normalized by corridor length to compare the VSL corridors and to correspond with the normalized crash frequency. Table 6 shows that the Cheyenne–Laramie corridor has a significantly higher number of normalized sharp horizontal curves when compared with other corridors. Table 6 also shows the total number of steep grades and the normalized steep grades on all four corridors.

In the final data set, four weather parameters (snow, ice, frost and wind), number of horizontal curves, number of steep grades, VSL implementation, and AADT were the explanatory variables considered in the initial model. Statistically insignificant variables (p-values > .05) were removed one at a time until only significant variables remained in the final model. NB, RENB, and FENB models were all estimated (Table 7) to determine which model performed best. As seen by the smaller the value of AIC, the FENB regression was determined to be the best statistical technique for developing SPFs in this research. Interaction terms between the weather and geometric variables were also included in the model. Table 7 presents the results from initial and final models for all three methods. Since the FENB model was determined to be the best performing model, only the results of that model will be discussed.

Safety impacts from the implementation of VSL systems can be estimated from these results. The model coefficient for the VSL variable was estimated as –0.2446, which is interpreted as a reduction of 0.78 crashes per week per 100 mi of VSL corridor length. This crash reduction estimate can then be converted from a weekly to a winter season value to calculate 20.4 crashes avoided per winter season per 100 mi of VSL corridor. To determine the total crashes avoided per season, this value is then multiplied by the ratio of 143/100, to adjust for the total length of the VSL corridors, for an annual crash reduction estimate of 29.1. Of note is that as the number of sharp horizontal curves increases, the crash frequency increases (positive coefficient), which is as expected. Horizontal curvature was found to be significant only in the interaction terms with weather. It was also found that as the number of steep grades increased, the crash frequency decreased, which could be considered counterintuitive. The steep grades may have limited vehicle speeds or prompted more cautious driving behavior, which led to crash reductions. Interactions between horizontal curves and weather variables and grades and weather variables were analyzed. It was found that as the number of sharp horizontal curves increased, the crash frequency in ice and frost conditions increased while the crash frequency during snow conditions decreased. This may indicate that drivers compensated for the more obvious hazardous condition of snow. The interaction of adverse weather conditions and steep grades was not found to be significant in the model.

Because of large differences in the number of horizontal and vertical curves among the VSL corridors (Table 6), the VSL corridors were divided so a more specific modeling analysis could be conducted. The Cheyenne–Laramie and Evanston corridors showed a higher number of sharp horizontal curves and steep grades. To evaluate the VSL effectiveness on these geometrically challenging corridors, the four corridors were split into two categories and additional models were estimated. Table 8 shows the results from initial and final FENB models for both the geometrically challenging corridors (Cheyenne–Laramie and Evanston corridors) and for

TABLE 5 Summary of Crash Frequency in Winter Seasons for VSL Corridors, 2008–2012

Corridor	VSL Implemented[a]	Winter 2007–2008	2008–2009	2009–2010	2010–2011	2011–2012	Average	Crash Reduction After VSL System (%)[b]
Cheyenne–Laramie	0	220	132	183	194	na	182	24
	1	na	na	na	na	138	138	
Elk Mountain	0	329	176	na	na	na	253	28
	1	na	na	109	247	202	186	
Evanston	0	161	118	76	91	na	119	58
	1	na	na	na	na	50	50	
Rock Springs and Green River	0	255	159	149	106	na	188	55
	1	na	na	na	na	85	85	

[a]0 represents periods before VSL implementation and 1 represents periods after VSL is implemented.
[b]Crash reduction of 41%.

TABLE 6 Summary of Number of Sharp Horizontal Curves and Steep Grades

Corridor	Length of Corridor (mi)	Horizontal Curves[a] Number of Horizontal Curves	Normalized Number of Horizontal Curves by 100 mi	Steep Grades[b] Number of Steep Grades	Normalized Number of Steep Grades by 100 mi
Elk Mountain	53	8	15	8	15
Evanston	23	10	43	54	235
Cheyenne–Laramie	42	61	145	9	21
Green River	25	18	72	2	8
Total	143	97	276	73	279

[a]Radii < 3,500 ft.
[b]Grade > 49°.

the other two corridors (Elk Mountain and Green River). For the challenging corridors, the VSL system was shown to reduce crashes (negative coefficient, shown in bold in Table 8) but was not shown to be statistically significant. In this model, only one year of data was available after implementing the VSL system. It is anticipated that more years of data following implementation of the VSL system might result in more conclusive outcomes; however, for the Elk Mountain and Green River corridors, the VSL system was found to be significant. From these results, it can be inferred that the geometric characteristics need to be included in setting appropriate speed limits for the VSL system, especially for the challenging corridors.

CONCLUSIONS

The goal of this research was to estimate the effectiveness of VSL systems and the effect of grades and sharp horizontal curves on crash frequency in adverse weather conditions. To isolate the effects of the geometrics on crashes from the effects of mild versus severe winters,

TABLE 7 Parameter Estimates for Models Incorporating Geometric Variables

Variable	NB Model Initial	NB Model Final	RENB Model Initial	RENB Model Final	FENB Model Initial	FENB Model Final
Snow	0.0205	0.2307***	0.028	NA	0.0256	NA
Ice	0.1062	NA	0.0925	0.1136**	0.0951*	0.105**
Frost	0.02929	NA	−0.0804	NA	−0.0788	NA
Wind	0.2309***	NA	0.147**	0.0867***	0.1438**	0.084***
Horizontal curve	0.0123***	0.0104***	0.0089**	0.0039**	0.0068*	NA
Grade	−0.0017	−0.0033***	−0.002*	−0.0026***	−0.0025*	−0.003**
VSL	−0.0194*	−0.2296**	−0.2009**	−0.2219**	−0.2122**	−0.2446**
GradeSnow	0.0005*	0.0004*	0.0003	NA	0.0003	NA
GradeIce	−0.0003	NA	−0.0003	NA	−0.0003	NA
GradeFrost	0.0021	0.0025*	0.0021	NA	0.0021	NA
GradeWind	−0.0003	NA	−0.0002	NA	−0.0002	NA
HoriSnow	0.0005	0.0008**	0.0005	0.001***	0.0006	0.001***
HoriIce	−0.0008	NA	−0.0007	−0.0011**	−0.0007	−0.001*
HoriFrost	−0.00028	−0.0027*	−0.0016	NA	−0.0016	−0.00255*
HoriWind	−0.0011*	−0.0012**	−0.0005	NA	−0.0008	NA
Constant	0.4259	0.6992**	−1.0229***	−0.6677***	−0.8142**	−0.341*
Observations	428	428	428	428	428	428
Number of corridors	4	4	4	4	4	4
Walk χ^2	NA	NA	226.87***	212.72***	157.32***	145.21***
Log likelihood	−1,554.06	−1,558.64	−1,582.59	−1,589.08	−1,555.22	−1,562.19
AIC	3,142	3,139	3,201	3,198	3,118	3,138

NOTE: NA = not available; hori = horizontal.
*$p < .05$; **$p < .01$; ***$p < .001$.

TABLE 8 Parameter Estimates for FENB Model of Most- and Least-Challenging Corridors

	Elk Mountain and Green River Model		Laramie–Cheyenne and Evanston Model	
Variable	Initial	Final	Initial	Final
Snow	0.3143*	0.3425***	0.0614	0.0862***
Ice	–0.0016	NA	–0.0093	NA
Frost	–0.5448	NA	–0.2636	NA
Wind	0.2376*	**–0.2784****	0.0654	0.0648*
Horizontal curve	–0.0022	NA	0.0145***	0.01256***
VSL	–0.1726	**–0.1683**[a]	–0.1355	**–0.1322**[b]
GradeSnow	–0.0215*	**–0.0234****	0.0003	NA
GradeIce	0.0063	0.0062*	–0.00002	NA
GradeFrost	0.0393	NA	0.0025	NA
GradeWind	0.0273**	0.0306***	–0.00004	NA
Constant	–0.4607	**–0.5871*****	–1.7759***	**–1.6279*****
Observations	210	210	218	218
Number of corridors	2	2	2	2
Walk χ^2	110.74***	111.29***	87.34***	86.06***
Log likelihood	–751.89	–752.73	–786.13	–788.55
AIC	1,525	1,519	1,594	1,587

NOTE: Bold font indicates negative coefficient.
[a] $p = .062$.
[b] $p = .286$.
*$p < .05$; **$p < .01$; ***$p < .001$.

it was necessary to perform a weather-based safety analyses considering geometric variations. With a 7-day crash frequency as the response variable and weather, traffic, and geometric variables as the explanatory variables, a model that used NB, RENB, and FENB techniques was performed, and the FENB model was found to perform best. From the model results, the VSL system was found to be significant in reducing crashes in winter. The model also found that horizontal curves alone had no statistically significant effect on crashes but were significant as an interaction term with weather. Steep grades were found to be statistically significant but had the effect of reducing crashes.

A specific modeling analysis was also conducted on the most geometrically challenging corridors and the less-challenging corridors to compare VSL effectiveness. The VSL system was found to reduce crashes for both types of corridors, but only the less-challenging corridors were found to be a statistically significant difference. Since the data were limited for the challenging corridors for time periods after the VSL systems were deployed, conducting similar analyses once more crash data become available is advised.

Currently the VSL control algorithm does not include geometric variations in selecting appropriate speed limits in adverse winter conditions. The findings of this research indicate that a more effective VSL system could be developed and implemented, one that utilizes geometric variables in additional to real-time weather variables for corridors in which geometrics play a large role.

The aggregation of the corridors into a single model was necessary because of the limited post-VSL data in some of the corridors. As crash data become available, future research will look at corridor-specific models. Empirical Bayes methodology will also be considered as more data become available. Future research will also investigate the areas within each corridor that have the highest crash occurrences, especially during severe weather conditions. Future work will also conduct a benefit–cost analysis associated with the reduction in crash frequency.

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