Special Collection: Low-Volume Roads

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Safety Performance Functions of Low-Volume Roadways

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Abstract

The Fixing America's Surface Transportation Act (FAST Act) mandates a Highway Safety Improvement Program (HSIP) for all states that "emphasizes a data-driven, strategic approach to improving highway safety on all public roads that focuses on performance." To determine the predicted crashes on a specific roadway facility, the most convenient and widely used tool is the first edition of Highway Safety Manual (HSM), which provides predictive models [known as safety performance functions (SPFs)] of crash frequencies for different roadways. Low-volume roads (LVRs) are defined as roads located in rural or suburban areas with daily traffic volumes of less than or equal to 400 vehicles per day (vpd). LVRs cover a significant portion of the roadways in the U.S. While much work has been done to develop SPFs for high-volume roads, less effort has been devoted to LVR safety issues. This study used 2013–2017 traffic count, and roadway network and crash data from North Carolina to develop six SPFs for three LVRs, which can be used to predict total crashes, as well as fatal and injury crashes. This study also performed a sensitivity analysis to show the influence of traffic volumes on expected crash frequencies. The SPFs developed in this study can provide guidance to state and local agencies with the means to quantify safety impacts on LVR networks.

The Fixing America's Surface Transportation Act (FAST Act) mandates a Highway Safety Improvement Program (HSIP) for all states that "emphasizes a data-driven, strategic approach to improving highway safety on all public roads that focuses on performance" (*1*). Because of the emphasis on data-driven strategies, many studies have focused on understanding the crash occurrence and its association with a wide variety of variables. The methods included in the first edition of the Highway Safety Manual (HSM) are widely used to predict crashes on specific roadway facilities (*2*). Part C of this manual provides a list of predictive models that can be used to estimate crash counts on a roadway using other variables such as segment length, traffic volume, and geometric characteristics. These models, known as safety performance functions (SPFs), are useful for estimating crashes with the aim of prioritizing safety improvement projects and different design alternatives. The HSM provides a series of SPFs (for both segments and intersections) for three major facility types: 1) rural two-lane two-way roadways; 2) rural multilane highways; and 3) urban and suburban highways. For each location type, these SPFs can be used to estimate the total number of crashes expected during a given time under certain base conditions. There is a strong recommendation that these SPFs are needed to be either calibrated or re-estimated using local condition data to attain high precision.

A significant aspect of the HSIP rulemaking is the requirement that states must collect and use a subset of Model Inventory of Roadway Elements (MIRE) for all public roadways, including low-volume roads (LVRs). LVRs are defined as roads that have an annual average daily traffic (AADT) of less than 400 vehicles per day (vpd), which is typically significantly lower than the AADT of higher functional roadways. The majority of the LVRs are part of the three non-federal aid-system (NFAS) roadway functional classes: 1) rural local (7R); 2) urban local (7U); and 3) rural collector (6R). Together, the three NFAS roadway functional classes account for around 75% of the total roadway mileage in the U.S. The Departments of Transportation and local transportation agencies use traffic volume count programs to collect traffic volume data. However, the focus of these programs is higher functional class roadways (interstates and principal arterials). Traffic counting on LVRs is more selective and sparser throughout the network. North Carolina has a handful of count locations on its local network. Most of these count stations

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provide short-term traffic counts that many agencies convert into AADT estimates by applying one or multiple adjustment factors. While much work has been done to develop SPFs for high-volume roads, less effort has been spent toward low-volume road safety issues. This study acquired count, roadway, and crash data for NFAS roads to examine the feasibility of developing SPFs separately for each of the three functional classes (6R, 7R, and 7U). The SPFs can be used to predict total crashes as well as fatal and injury crashes on these roadways.

Objectives

This study aims to mitigate the current research gap by developing SPFs for the lower functional classes in North Carolina. The study results can be used by practitioners in data-driven safety analysis and to support decision making.

Literature Review

Improving roadway safety remains a top priority of transportation and safety planners. The traffic safety research field includes a wide array of research areas and the most prominent of them is crash data analysis by which assessment of the safety of a transportation facility (e.g., interstates, arterials, intersections) can be conducted. The conventional approach has been to establish relationships between crash frequency and traffic characteristics, roadway inventory, and environmental factors. The development of a crash prediction model is a means of capturing complex interactions in safety data, as well as using engineering judgment and analytical assumptions about the crash occurrence. Lord and Mannering conducted a systematic review of crash frequency studies and their limitations (*3*). Savolainen et al. conducted a similar study on injury severity related studies in 2011 (*4*). In 2014, Mannering and Bhat summarized analytic methods used in these two areas with the inclusion of future directions (*5*). The key approach in most of the studies is to identify the relationship between a large variety of variables and crash occurrence or crash severity.

The majority of model development techniques and approaches focus on higher functional classes because of the availability of adequate data. By contrast, only a few studies have focused on the safety performance of LVRs because of the difficulty of obtaining adequate and reliable data for model development. This section summarizes safety studies on LVRs. Zegeer et al. also investigated the association between roadway width and crash occurrence on low-volume (AADT $\leqslant$ 2,000 vpd) rural roads (*6*). Roadways with relatively wider shoulders showed lower crash rates, while shoulder type (paved or unpaved) was not statistically significant. Caldwell and Wilson compared injury crash rates on unpaved county road segments to injury crash rates on all roads in Wyoming (*7*). The likelihood of being involved in a crash on county roads was found to be more than five times higher than on all roads. In their study, Stamatiadis et al. (*8*) identified several contributing factors on LVRs (AADT $\leqslant$ 1,000 vpd). Achwan and Rudjito examined road crash characteristics on LVRs by using data from rural areas (*9*). The study showed that the key vulnerable groups were motorcyclists and pedestrians. In his study, Madsen concluded that 75% of the injured persons and 60% of those killed in LVR crashes were occupants of nonfarm vehicles (*10*). The lack of retroreflective signs and taillights on slow-moving vehicles were identified as major contributing factors for these crashes. In a study on speed limits on gravel roads in Kansas, Liu and Dissanayake performed a survey of county agencies and conducted analysis by incorporating speed (*11*). In a subsequent study, Liu and Dissanayake developed logistic regression models to identify the factors most associated with crash injury on gravel roads in the same state (*12*). The results revealed that failure to use safety equipment, intoxication, failure to yield, distraction, speeding, aging drivers, and ruts/potholes increased the probability of more severe crash occurrence. NCHRP Synthesis 321, Roadway Safety Tools for Local Agencies: A Synthesis of Highway Practice, introduced many effective safety tools to reduce crashes on LVRs (*13*). Two proactive safety tools that are included in this report are: Roadway Safety Audits (RSA) and Roadway Safety Audit Reviews (RSAR). The report "Low-Cost Local Roads Safety Solutions" reported the effectiveness of several key countermeasures that are suitable for low-volume transportation networks (*14*). Dell'Acqua and Russo analyzed safety conditions using the network approach for a few Italian roadways within the Province of Salerno (*15*). Two SPFs were developed for low-volume two-lane rural roads located on flat/rolling area with a vertical grade of less than 6% and mountainous terrain with a vertical grade of more than 6%.

The literature review indicates a gap in SPF development on LVRs because of the absence of key variables like AADT. The current study aims to mitigate this research gap by developing SPFs for NFAS roads.

Predictive Methods: An Overview

The predictive method uses the empirical Bayes (EB) method to calculate the expected number of crashes for a defined period before and after a safety treatment has been implemented at a particular site. The EB method can handle two major issues: sparse datasets and regression to the mean (RTM). For short durations, many sites have no or few crashes. It is unlikely that a short period can entirely capture the true frequency of crashes, which results in prediction inaccuracy. RTM bias can occur when a site experiences an abnormally high or low number of crashes in one year followed by a return to a more typical crash frequency the following year. The EB method uses both the observed number of crashes at a site and the predicted number of crashes at similar sites based on the SPFs.

An SPF is an equation used to predict the average number of crashes per year at a location as a function of exposure (i.e., AADT and length) and, in some cases, roadway or intersection characteristics. SPFs can be used either: 1) by developing a localized SPF for the facility and certain crash types; or 2) by calibrating existing SPFs (e.g., HSM SPFs). The predicted number of crashes (N) at a particular site can be estimated by multiplying three components: base SPF ($C_{\text{Predicted}}$), Crash Modification Factors (CMFs), and a calibration factor, C, as shown in Equation 1.

$$N = C_{\text{Predicted}} \times C \times \prod^{\text{CMF}} \tag{1}$$

For example, exposure is represented by the segment length and AADT associated with the roadway segment as shown by the following baseline SPF:

$$C_{\text{Predicted}} = \exp[\beta_0 + \beta_1 \times \ln(L) + \beta_2 \times \ln(\text{AADT})] \tag{2}$$

where

$C_{\text{Predicted}}$ = the predicted crash frequency under base conditions,

β_0, β_1 = parameter coefficients,

L = segment length, and

AADT = Annual Average Daily Traffic.

CMFs account for deviations from base conditions in relation to the roadway and geometric characteristics, and traffic control devices. In some cases, (e.g., crash data variation between different jurisdictions or different time periods within the same jurisdiction), applying a calibration factor, C, may be a more efficient approach than developing a new SPF that requires more time and data. Calibration factors can be estimated by:

$$C = \frac{\sum_{i=1}^{n} N_{\text{obs},i}}{\sum_{i=1}^{n} N_{\text{pre},i}} \tag{3}$$

where

$N_{\text{obs},i}$ = the observed annual average crash frequency,

$N_{\text{pre},i}$ = predicted annual average crash frequency, and

n = sample size, equal to the number of sites in the calibration process.

The EB method is based on a weighted average principle. It has been widely used in many safety studies and is recommended by the Highway Safety Manual (HSM) (*2*, *16–25*). It uses a weight factor, w to combine observed (C_{Observed}) and predicted crash frequencies ($C_{\text{Predicted}}$) to estimate the expected crash frequency, C_{Expected}:

$$C_{\text{Expected}} = w \times C_{\text{Predicted}} + (1 - w) \times C_{\text{Observed}} \tag{4}$$

where

C_{Expected} = the expected crash frequency,

$C_{\text{Predicted}}$ = the predicted crash frequency obtained from the SPF,

C_{Observed} = the observed crash frequency,

w = a weight factor that depends on the over-dispersion parameter (k) of each SPF:

$$w = \frac{1}{1 + C_{\text{Predicted}} \times k}.$$

Methodology

In his book "The Art of Regression," Ezra Hauer states: "A parametric SPF is a mathematical function of traits (variables) and parameters. The activity of fitting a parametric SPF to data alternates between choosing the variables from which the model equation is to be made, determining the form of the function (i.e., how the variables and parameters should combine into an equation), estimating the value of the parameters, and examining the goodness of the fit" (*26*). The schematic of this concept is presented in Figure 1.

The SPF development for NFAS roads in North Carolina includes several steps:

- Step 1: Develop the database. Acquiring crash, roadway inventory, and traffic volume data assigning crashes to the corresponding segments of the roadway network.
- Step 2: Exploratory data analysis. After compiling data for candidate independent variables, perform correlation analysis to identify the best predictors. Perform exploratory data analysis to identify patterns and clusters.
- Step 3: Develop SPFs. Develop negative binomial models for the desired roadway networks separately for all five injury types—fatal injury (K); incapacitating injury (A); non-incapacitating injury (B); possible injury (C); and no injury or property damage only (O)—as well as for KABC crashes only. Validate models using residual plots. If the residual plots are not in the range of the best fit model, develop decision trees or other data partitioning algorithms to identify potential clusters

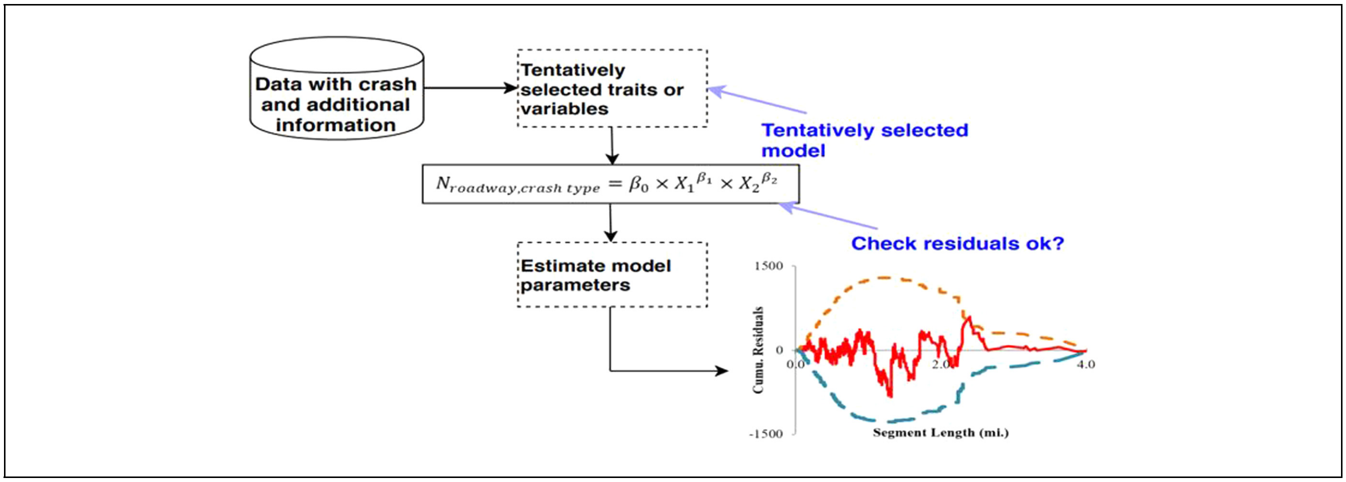

Figure 1. Schematics of parametric SPF development (adapted from 16).

inside the data. Instead of using the whole data, develop SPFs for the clustered data and cross-examine the residuals again. Repeat the previous steps until a good-fit model has been developed.

Data Preparation and Exploratory Data Analysis

To better understand the relationship between various roadway characteristics and safety performance on NFAS roads in North Carolina, it was first necessary to assemble a comprehensive database of traffic crash, roadway inventory, and traffic volume data for the study network. The data were obtained from different sources for the five-year period from 2013 to 2017 (see Figure 2). The precision of SPFs largely depends on the quality of the data. SPF development requires a comprehensive crash database that contains various information and data such as route id, route name, milepost, control section, geographic coordinates, collision type, and severity type among others.

Table 1 shows annual crash frequencies on NFAS roads in North Carolina. The data show that 444,863 crashes happened during the study period (30% of these crashes involve some type of injury). From 2013 to 2017, NFAS roads experienced a 12% increase in crashes. Table 2 lists the crash frequencies by roadway category and injury type. Around 80% of the low-volume road crashes occurred on two-way undivided roadways (around 80% of the two-way undivided roadways are two-lane roadways).

Because only 1% of the study crash data had geographic coordinates, the researchers used the route number and the milepost to geolocate crashes on the network. Figure 2 illustrates the flowchart diagram of data preparation activities. The crash database does not differentiate between segment and intersection-related crashes, though past studies have shown the significance of making this distinction (*27*). This study considered all crashes without separating segment and intersection-related crashes. The SPFs developed in this study can be improved by excluding intersection-related crashes if more data become available (e.g., distance of crash location from the closest intersection).

For each functional class (6R, 7R, 7U) two SPFs were developed: one for total crashes (KABCO) and another one for KABC crashes. The original dataset contained several candidate predictors. Shoulder type, shoulder width, median type, and median width were considered for the analysis. After performing a correlation analysis, only two variables were found to be the best predictors: segment length (mi) and AADT (vpd).

Table 3 lists descriptive statistics of the key measures. The total length of the rural local roadways—considered in the analysis—is 8,161 mi (around 75% of the analyzed LVR network). Urban local (7U) comprise a smaller proportion of the LVR than the other two roadways. The minimum threshold of the segment length is considered as 0.10 mi (approximately 500 ft.). The average segment length ranges from 0.27 to 0.66 mi. The traffic volume is lower on rural local roadways (mean: 590 vpd) when compared with urban local (mean: 2,233 vpd) and rural collector (mean: 1,060 vpd) roadways. As LVR databases lack detailed information about various geometric variables (for example, shoulder width, median width, median type), the current study is limited to the model development process based on two key variables (length and AADT).

Before developing the SPFs, it was important to examine how the number of yearly crashes changed with respect to segment length and traffic volume. Figure 3 shows the distributions of KABCO crash frequencies and Figure 4 KABC crash frequencies (in scatter plot format)

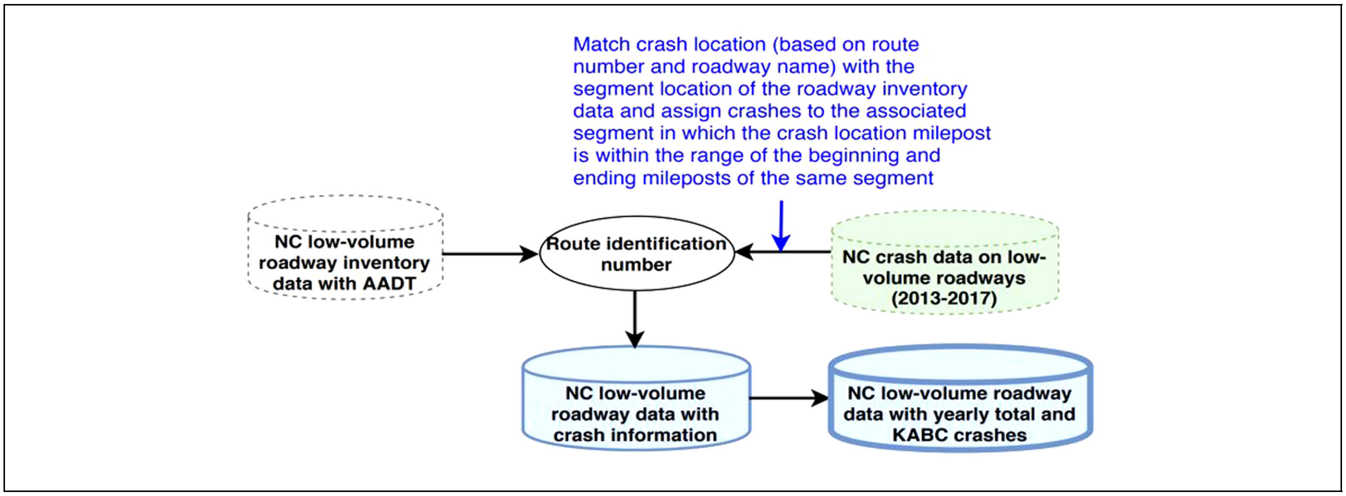

Figure 2. Flowchart of the data preparation.

Table 1. Yearly Crash Distributions by Injury Types

Year	K	A	B	C	O	Unknown	Total
2013	483	706	6,716	16,685	56,577	2,446	83,613
2014	468	719	6,840	16,998	56,410	2,492	83,927
2015	506	796	7,040	18,955	60,282	2,783	90,362
2016	519	1,009	7,216	19,138	62,585	2,792	93,259
2017	496	1,515	7,545	17,494	63,722	2,930	93,702
Grand total	2,472	4,745	35,357	89,270	299,576	13,443	444,863

Note: K = fatal injury; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = no injury or property damage only.

Table 2. Crash Distributions by Roadway Category and Injury Types

Roadway category	K	A	B	C	O	Unknown	Total
One-way, not divided	16	44	499	1,663	6,596	329	9,147
Two-way, divided, positive median barrier	39	69	932	4,116	12,128	229	17,513
Two-way, divided, unprotected median	121	271	3,485	12,913	38,558	910	56,258
Two-way, not divided	2,294	4,350	30,322	70,154	232,695	11,873	351,688
Unknown	2	11	119	424	9,599	102	10,257
Grand total	2,472	4,745	35,357	89,270	299,576	13,443	444,863

Note: K = fatal injury; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = no injury or property damage only.

by segment length and traffic volume for the three functional classes of interest. The plots show that most of the crashes occurred when the segment lengths were smaller than 2 mi. For both crash severity groups (KABCO and KABC) and all roadways, segment length shows a positive correlation with the number of KABCO or KABC crashes. The trends are very affirmative for rural local and rural collector roadways. For traffic volume, these patterns are somewhat positive. Rural local roadways show a clear trend between traffic volume and yearly KABCO or KABC crash frequencies. This exploratory data analysis (EDA) provides hints about whether and how crashes on North Carolina NFAS roads depend on segment length and traffic volume.

Safety Performance Functions (SPFs)

SPFs were developed using AADT data from permanent sites and short-term counts. The model structure, the over-dispersion parameter, and the log-likelihood of each SPF are listed in Table 4. Regression models examine the average effects of the associated variables and ignore

Table 3. Descriptive Statistics

Roadway functional class	Number of segments	Total segment length (mi)	Crash severity	Statistic	Count of yearly crashes	Length (mi)	AADT (vpd)
Rural local (7R)	12,386	8,160.70	KABCO	Min.	0	0.1	5
				Max.	110	7.0	19,950
				Mean	2	0.7	590
				SD	6.01	0.5	710.2
			KABC	Min.	0	0.1	5
				Max.	38	7.0	19,950
				Mean	3	0.7	590
				SD	1.54	0.5	710.2
Urban local (7U)	3,097	848.8	KABCO	Min.	0	0.1	10
				Max.	48	1.8	110,000
				Mean	1	0.3	2,233
				SD	3.02	0.2	4,005.1
			KABC	Min.	0	0.1	10
				Max.	15	1.8	110,000
				Mean	0.21	0.3	2,233
				SD	0.72	0.2	4,005.1
Rural minor collector (6R)	3,110	1,849.10	KABCO	Min.	0	0.1	5
				Max.	148	4.1	9,200
				Mean	3	0.6	1,349
				SD	8.15	0.5	1,059.3
			KABC	Min.	0	0.1	5
				Max.	47	4.1	9,200
				Mean	0.67	0.6	1,349
				SD	2.21	0.5	1,059.3

Note: AADT = annual average daily traffic; vpd = vehicles per day; K = fatal injury; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = no injury or property damage only; min. = minimum; max. = maximum; SD = standard deviation.

subgroup effects in the model development. As a result, model developments are often geared toward the population mean, without consideration of the special site-specific patterns. This study performed decision tree algorithms to determine the clustering effect. The results support the model development for each functional class separately.

The model fitting is judged by its residuals, which are the differences between the number of recorded crashes and the predicted crash counts. A model is thought to fit well if the residuals are close to zero. The Cumulative Residual (CURE) plot is a good visualization to show how well or poorly an SPF can predict crashes for various values of an independent variable, which is plotted on the x-axis of the plot. A horizontal stretch of the CURE plot implies unbiased estimates in a region of the variable. By contrast, in regions where the CURE plot consistently drifts up or down the estimates are biased. The CURE plot for an unbiased SPF needs to be in the boundary of two standard deviations. The CURE plots for both segment length and AADT are shown in Figures 5 and 6. Figure 7 illustrates the observed versus expected KABCO crashes for three functional classes.

By sorting the data by each variable (AADT, segment length, or any other predictor variable of interest), CURE plots can be created to assess the precision of the functional form of these variables in the model. The CURE plots developed for 6R, 7R, and 7U are mostly within the boundary of two standard deviations. The few places where the CURE plots are outside the two standard deviation boundaries are shown in black parabolic shapes. For example, the CURE plot corresponding to 7R KABC crashes (top right of Figure 5) shows an area where the residuals are slightly outside the boundary. This indicates that the estimates developed for segment lengths between 4 and 5.5 mi will be somewhat biased.

Sensitivity Analysis

The goal of the sensitivity analysis was to determine the impact of AADT estimation errors on the expected crash frequencies and, therefore, the final ranking of the sites. North Carolina DOT can adopt the developed SPFs and use them in the EB method to determine the most promising locations based on the expected crash frequencies. The sensitivity analysis was separately performed for

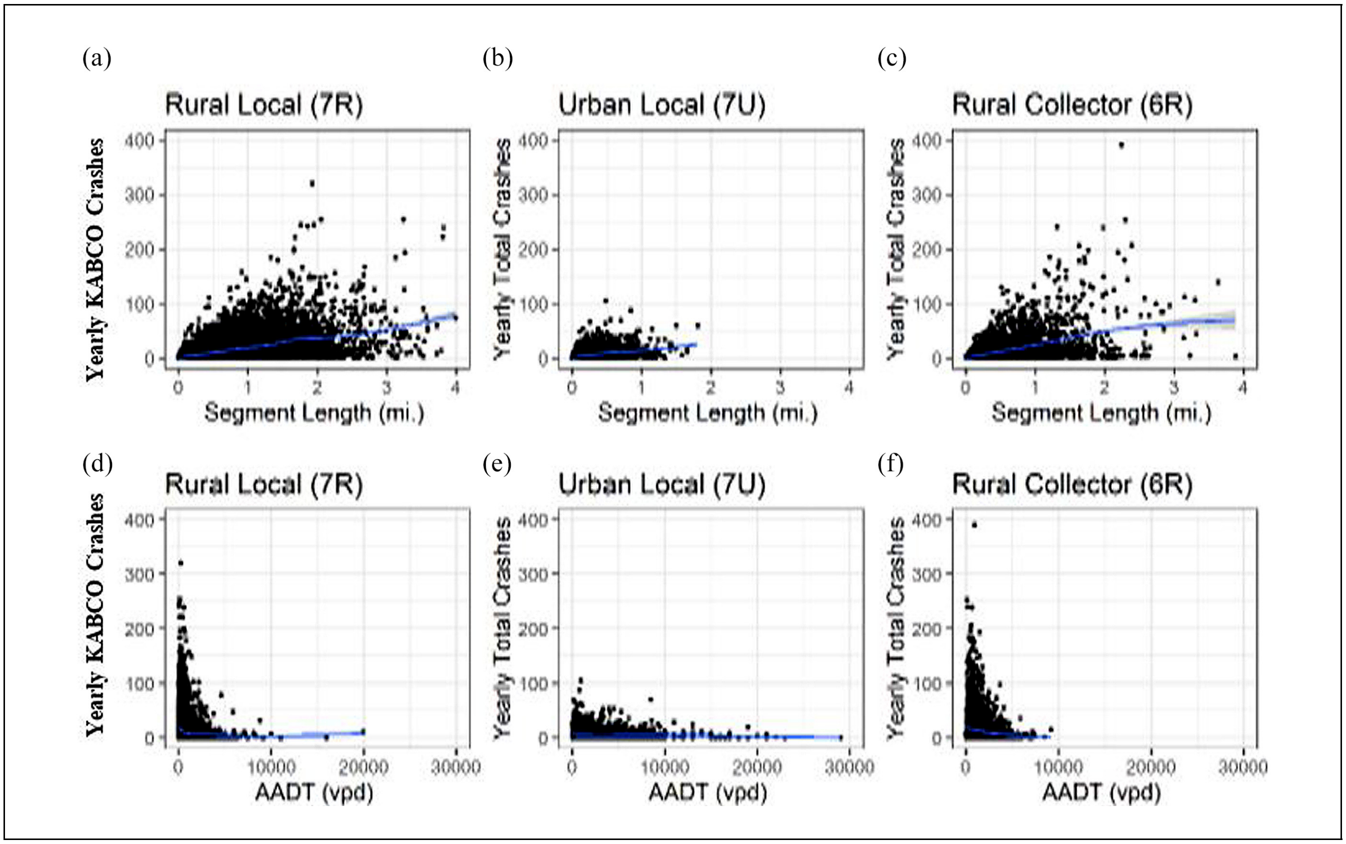

Figure 3. Segment length and AADT vs. yearly KABCO crashes.

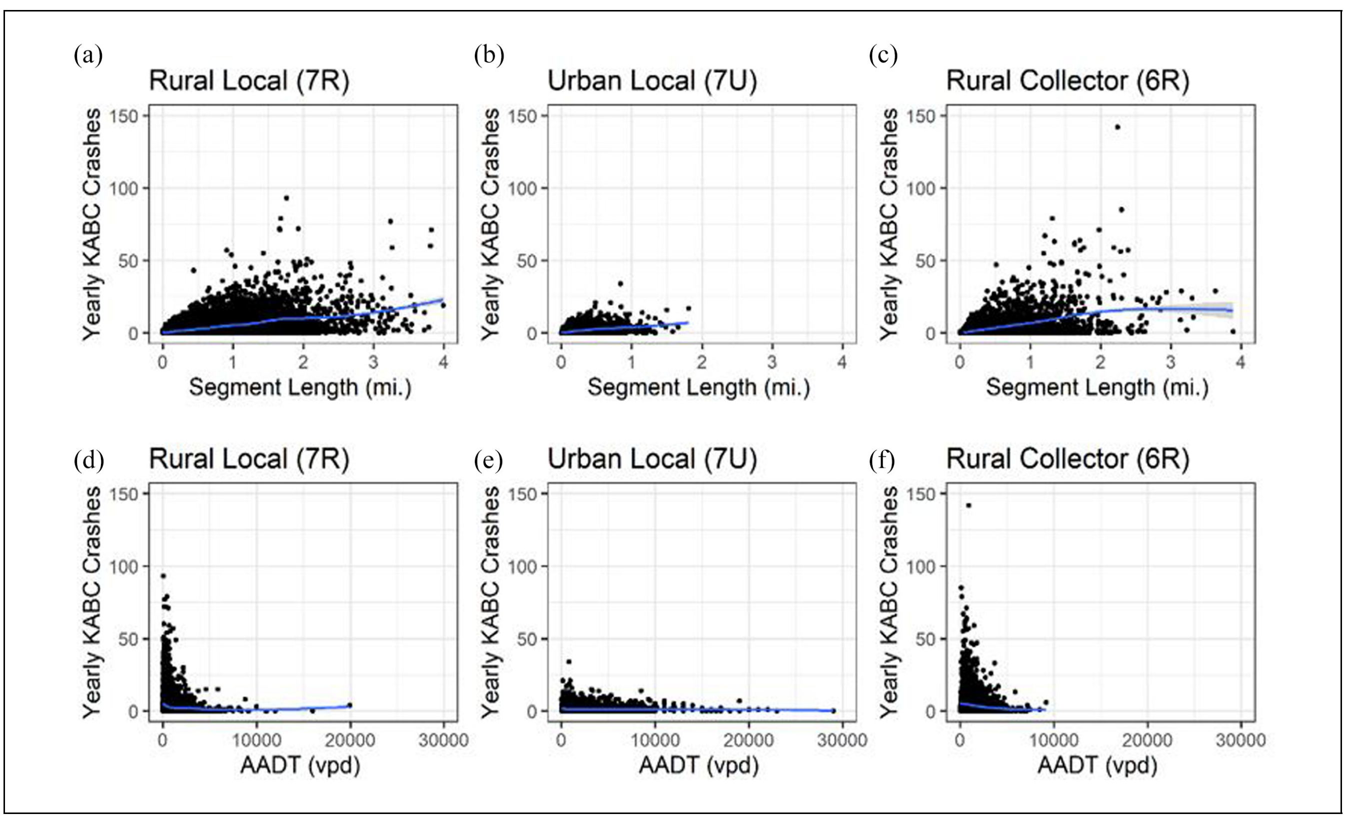

Figure 4. Segment length and AADT vs. yearly KABC crashes.

Table 4. Developed SPFs

Roadway functional class	Crash severity	Safety performance function	Over-dispersion parameter	Log-likelihood
Rural local (7R)	KABCO	$N_{7R,\,tot} = 2.479 \times Length^{0.962} \times AADT^{0.035}$	0.353	20090.20
	KABC	$N_{7R,\,kabc} = 0.632 \times Length^{1.005} \times AADT^{0.034}$	0.348	–5624.30
Urban local (7U)	KABCO	$N_{7U,\,tot} = 1.691 \times Length^{0.842} \times AADT^{0.071}$	0.952	–808.10
	KABC	$N_{7U,\,kabc} = 0.488 \times Length^{1.062} \times AADT^{0.071}$	0.772	−1,286.60
Rural collector (6R)	KABCO	$N_{6R,\,tot} = 2.432 \times Length^{0.988} \times AADT^{0.090}$	0.406	10,188.20
	KABC	$N_{6R,\,kabc} = 0.641 \times Length^{1.023} \times AADT^{0.084}$	0.326	–826.70

Note: SPF = safety performance functions; AADT = annual average daily traffic; K = fatal injury; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = no injury or property damage only.

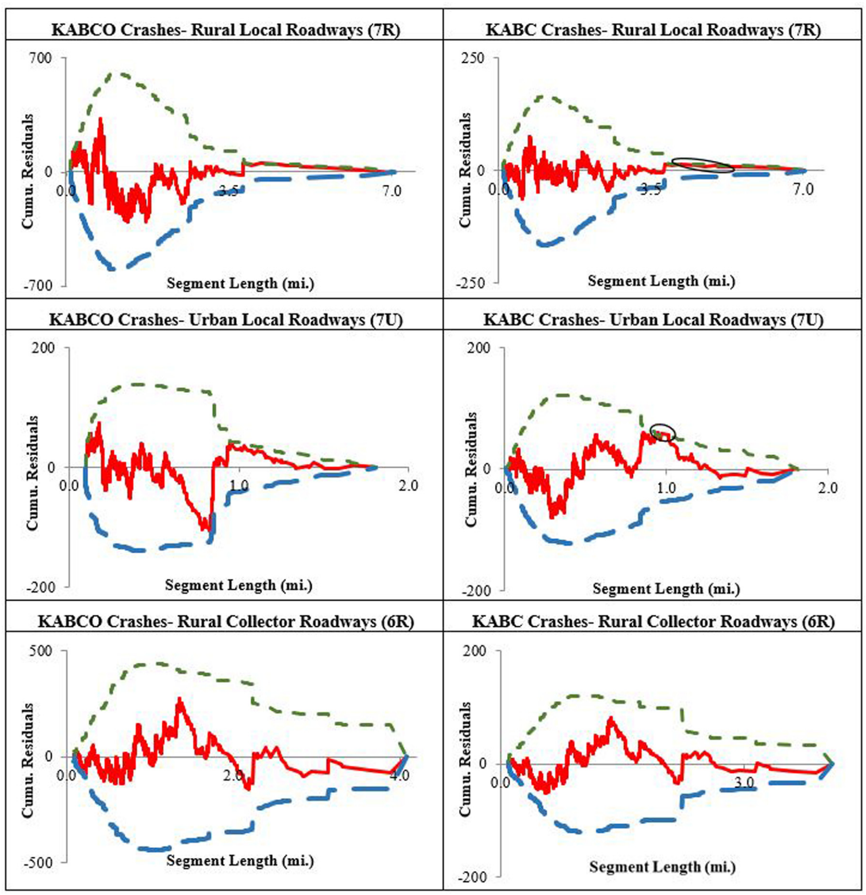

Figure 5. CURE plots by segment lengths.

each functional class and crash severity group (KABCO and KABC). The analysis involved the following steps:

- Step 1: Apply the EB method.
- Step 2: Determine the rank of each segment based on the results obtained from Step 1.
- Step 3: Determine the percentile of the rank of each segment.
- Step 4: Increase the AADT of each segment by 10%, 50%, 100%, 250%, and 500% by keeping the rest of the segments and variables unchanged.
- Step 5: Repeat Steps 1 to 4 separately for each segment and AADT percentage increase. The end result is repeating Steps 1 to 4 185,930 times = [(3,110 segments in 6R) + (12,386 segments in

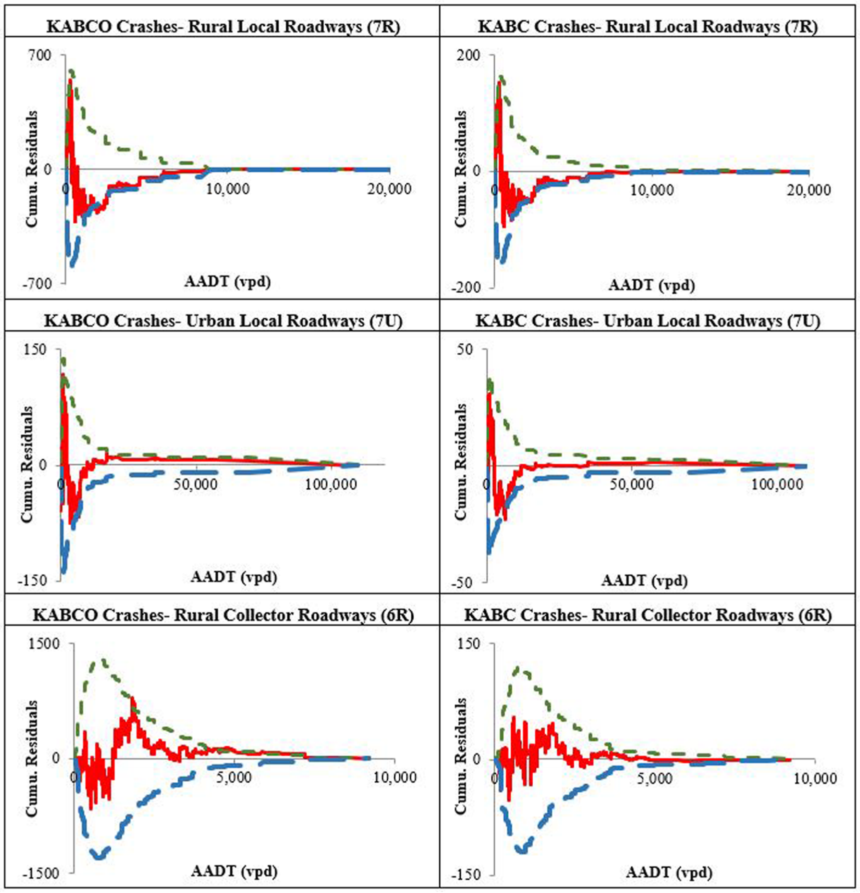

Figure 6. CURE plots by AADT.

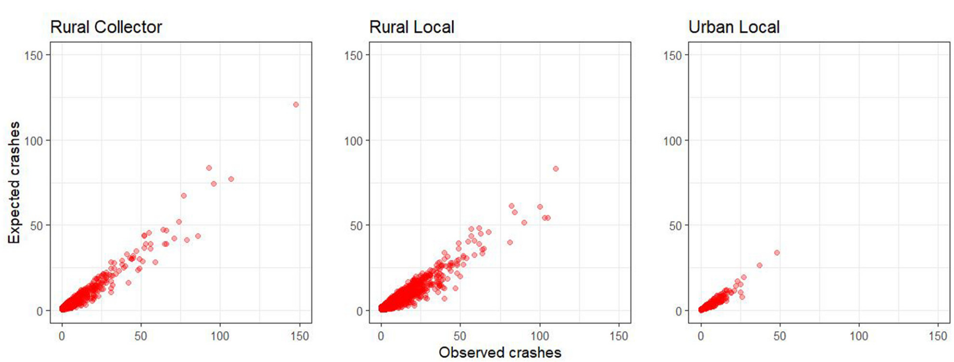

Figure 7. Observed vs. expected crashes.

7R) + (3,097 segments in 7U)] × (5 AADT percentage increases) × (2 crash severity groups).

- Step 6: Calculate the percentile rank change of each segment by comparing the initial rank of each segment (no AADT change) against the rank obtained when AADT was increased by a certain percentage.

Figures 8 to 10 show the distribution of the rank percentile changes for different AADT groups and functional

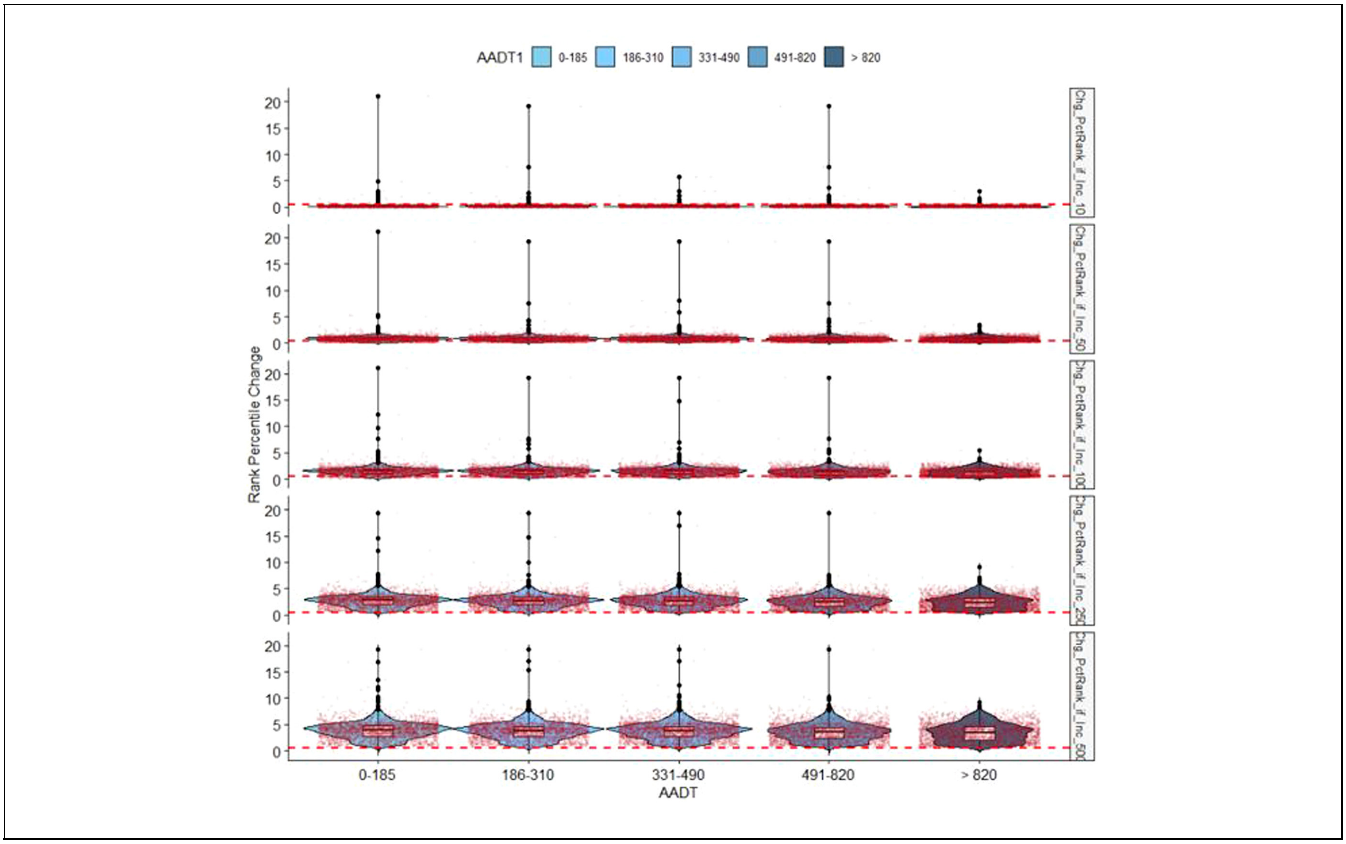

Figure 8. Rank percentile change for different AADT groups (rural local).

classes in box-violin plot format. It shows that a 10% increase in AADT will not have a significant effect on the expected crash frequencies and therefore the final segment ranking. Higher percentage changes of AADT values are associated with higher percentile rank changes. This trend is visible for all functional classes. These figures also show that the average percentile rank changes are overall higher for 6R and 7U compared with those of 7R. Further, because the traffic volume of the majority of rural local roads is lower than 2,000 vpd, the box-violin plots for higher volumes (greater than 2,000 vpd) are skewed toward lower percentile rank changes. This trend can be partially attributed to the fact that the AADT coefficients (0.035 and 0.034) of the two SPFs developed for 6U (for KABCO and KABC crashes respectively) are significantly smaller than those of the other two functional classes. Another potential reason that relates to the small AADT coefficients is that the sample size of 7R (12,386) is significantly larger than those of 6R (3,110) and 7U (3,097). Further, the CURE plots of 7R (Figure 6) show that the residuals for the AADT range 0–10,000 vpd are not close to zero, indicating that the SPFs may need to be improved. One possible improvement is to divide 7R into subgroups based on geography or roadway/geometric characteristics and develop separate SPFs for each subgroup. Other potential improvements may include changing the form of the SPFs, adding more variables and interaction terms, and changing the objective functions that are used to arrive at the parameter estimates. In general, the results show that AADT estimation errors can affect the expected crash frequencies and associated percentile rank changes.

Conclusion

Predictive models help identify roadway locations with the greatest potential for safety improvement and quantify the expected safety performance of different facilities. This approach combines roadway inventory, traffic volume, and traffic crash data. The results can be used to support decision making and allocation of safety funds and also help to better understand how data-driven safety analysis is affected by AADT. The models and associated risk mapping not only help agencies make smart decisions but also inform the public as to what safety benefits they can expect from their investment (*28*). Many safety studies focused on major highway facilities (e.g., freeways, arterials, interchanges, or intersections) or on the effectiveness of specific treatments (e.g., traffic control devices, barriers, edge line, rumble

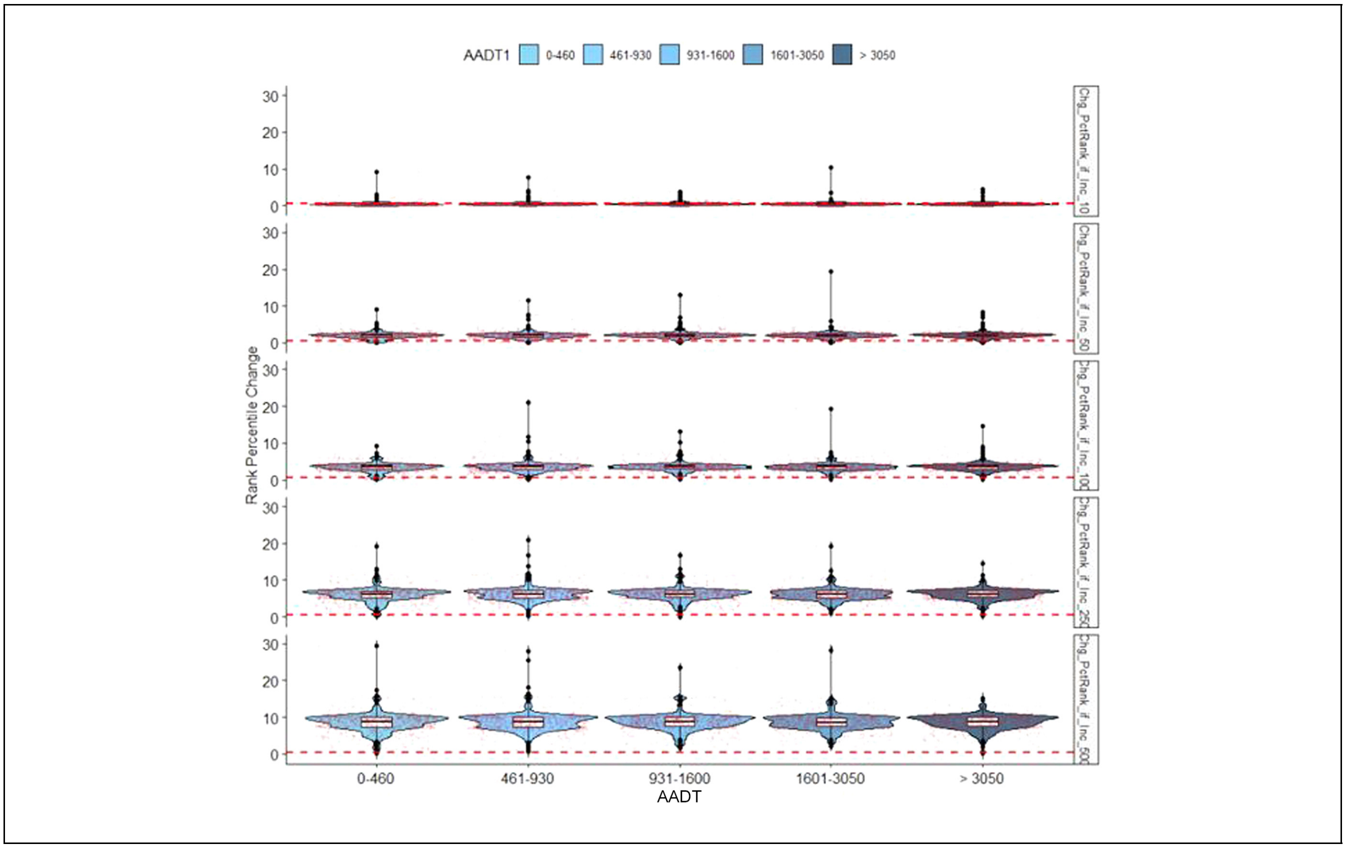

Figure 9. Rank percentile change for different AADT groups (urban local).

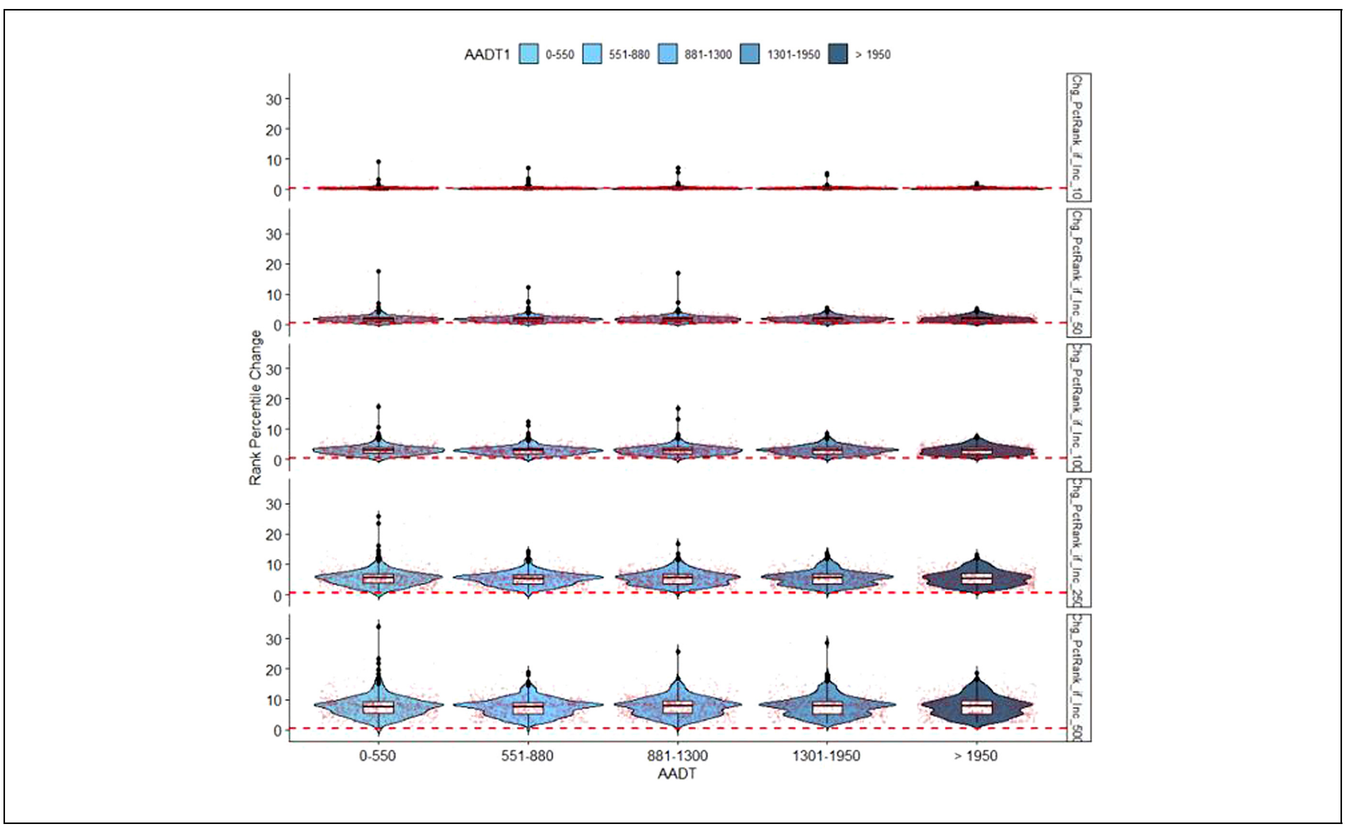

Figure 10. Rank percentile change for different AADT groups (rural collector).

strips). Little effort has been dedicated to the safety improvements on LVRs. This lack of effort is because of the unavailability of adequate data on the LVR network. In many cases, the most recent information regarding LVRs is not recorded electronically.

This study acquired roadway inventory, traffic volume, and crash data for five years (2013–2017) in North Carolina. This study has provided three major contributions. First, it developed a procedure of using local roadway network data in estimating the safety performance of these roadways. Researchers can adopt this procedure in reproducing the models using local data. Second, this study developed SPFs for three roadway functional classes in North Carolina separately for total crashes (KABCO) and KABC crashes. The models are validated by visually examining the developed CURE plots, which was not performed in other "low-volume SPF" studies. The third contribution of this study is the impact analysis of AADT estimation errors on safety analysis. The results show that AADT values on NFAS roads affect the expected crash frequencies and associated percentile rank changes.

There are several limitations of this study. This study did not separate segment and intersection-related crashes as the current study did not acquire the distance values to the intersections from the crash locations. This study did not perform an extensive analysis of the outlier values of AADT. The general perception is that the LVRs have lower AADT compared with high functional roadways. However, a definite threshold has not been determined yet. Future studies can cross-examine some of the outlier AADT values used in this current study for the refinement of the data and more precise SPFs.

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Author Contributions

The authors confirm the contribution to the paper as follows: study conception and design: Ioannis Tsapakis, Subasish Das; data collection: Subasish Das, Ioannis Tsapakis; analysis and interpretation of results: Subasish Das; Ioannis Tsapakis; draft manuscript preparation: Subasish Das; Ioannis Tsapakis; Songjukta Datta. All authors reviewed the results and approved the final version of the manuscript.

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