INFLUENCE OF CALIBRATION FACTORS ON CRASH PREDICTION ON RURAL TWO-LANE, TWO-WAY ROADWAY SEGMENTS

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ABSTRACT

Calibration factors are applied in the Highway Safety Manual predictive method for rural two-lane, two-way roadway segments to adjust the estimate for local conditions. This research aims to evaluate and recommend improvements related to the estimation of these calibration factors. An aggregated and disaggregated analysis was performed to study the influence of different calibration factors on the prediction of the number of crashes in North Carolina. As a result, those calibration factors based on both types of road elements (horizontal curves and tangents) led to overestimating and underestimating the number of crashes on tangents and horizontal curves, respectively. Furthermore, the calibration factors based on fatal-and-injury crashes allowed a more accurate estimation of the predicted number of crashes than those calibrated considering all severity levels. Therefore, it is recommended to apply a different calibration factors for each type of road element and each type of crash severity.

INTRODUCTION

In 2010, the American Association of State Highway and Transportation Official (AASHTO) released the Highway Safety Manual (AASHTO, 2010). The Highway Safety Manual (HSM) is the product of more than 10 years of effort and thousands of hours to develop fact-based analytical tools and techniques to quantify the potential safety impacts of planning, design, operations, and maintenance decisions (Xie et al., 2011). Part C of the HSM contains the predictive methods for rural two-lane roads, rural multilane highways, and urban and suburban arterials. The main purpose of the predictive methods in Part C of the HSM is to estimate the average crash frequency for existing conditions, alternatives to existing conditions, or proposed new roadways.

The HSM predictive method is based on three components to estimate the predicted number of crashes at a site:

1. Base model, which is a Safety Performance Function (SPF),
2. Crash modification factors (*CMFs*) to adjust the estimate for site-specific conditions, which may be different from the base conditions, and
3. A calibration factor (*C*) to adjust the estimate for local conditions.

These components are combined in the following general form:

$$N_{predicted} = N_{spf} \cdot \prod_{i=1}^{n} CMF_i \cdot C \qquad (1)$$

where $N_{predicted}$ is the predicted average number of crashes for a specific site; N_{spf} is the predicted number of crashes determined for base conditions; CMF_i are the crash modification factors for a specific site; and C is the calibration factor to adjust the predicted number of crashes for local conditions.

The SPF for rural two-lane, two-way roadway segments is defined as follows:

$$N_{spf} = L \cdot AADT \cdot 365 \cdot 10^{-6} \cdot e^{-0.312} \qquad (2)$$

where N_{spf} is the total number of crashes considering all types of crashes and severities; L is the length of the roadway segment (miles); and $AADT$ is the annual average daily traffic volume (vehicles per day).

The HSM proposed a total of 12 *CMFs* for rural two-lane, two-way roadway segments, which are defined in Table 1. In addition, the calibration factor (C) is calibrated based on the ratio between the total number of observed crashes and the sum of the predicted number of crashes on all homogeneous segments based on a sample of locations for a given roadway type in a jurisdiction. The HSM predictive method was developed on the basis of data from a subset of states. Thus, several studies have been carried out to identify the calibration factor for other states (Xie et al., 2011; Findley et al., 2012a; Brimley et al., 2012; Lubliner, 2011; Williamson and Zhou, 2012; Mehta and Lou, 2013; Shin et al., 2015a; Smith et al., 2017; Srinivasan et al., 2016; Srinivasan et al., 2011), to study the sample-size needed to calibrate the models (Banihashemi, 2012; Trieu et al., 2014; Shin et al., 2015b; Alluri et al., 2016; Shirazi et al., 2016), and to compare this method with the use of jurisdiction-specific SPFs (Srinivasan and Carter, 2011; Brimley et al., 2012; Mehta and Lou, 2013; Smith et al., 2017; Srinivasan et al., 2016; Lord et al., 2010; Lu et al., 2014; Li et al., 2017).

As a result, these studies identified different weaknesses of the HSM predictive method for rural two-lane, two-way roadway segments, which can be grouped into the following issues: (i) Influence of risk exposure, (ii) Homogeneity of road segments, (iii) Crash modification factors, (iv) Calibration factor, (v) Crash reporting thresholds, (vi) Functional form, and (vii) Sample-size. Regarding the calculation of calibration factors, the HSM assumes a proportional relationship between the number of predicted crashes under base conditions (N_{spf}) and the number of predicted crashes in a specific jurisdiction or state ($N_{predicted}$). Table 2 shows the calibration factors for rural two-lane, two-way roadway segments in some states of the United States. The interpretation of these calibration factors must be executed carefully, because each state has varying crash reporting thresholds, weather conditions, animal populations, and terrain that may contribute to its local crash performance in unique ways. These calibration factors should not be compared directly, but can provide useful insight about the potential variation between geographic areas, crash patterns, and driver population characteristics. The variability between these calibration factors could be indicative of the importance of accurate calibration factors for a specific jurisdiction.

Although all previous studies indicate that a calibration factor is needed to adjust the predicted number of crashes for local conditions, some studies concluded that the relationship between N_{spf} and $N_{predicted}$ might not be proportional. Regarding this, Srinivasan et al. (2016) proposed the following function to adjust the estimate for local conditions:

$$N_{predicted} = a \cdot (HSM_{predicted})^b \qquad (3)$$

Likewise, the relationship between N_{spf} and $N_{predicted}$ for rural two-lane, two-way roadway segments might depend on the type of the alignment as well as on the level of crash severity. Findley et al. (2012) found significant differences between the calibration factor for horizontal curves and tangents (Table 2). In addition, Xie et al. (2011) identified a substantial difference between the calibration factor based solely on fatal-and-injury crashes and based on all types of severity. This phenomenon is closely related to the crash reporting threshold and the distribution of crash types in each state.

The HSM predictive method estimates the total number of crashes for rural two-lane, two-way roadway segments, i.e., this prediction includes all types of crashes and severities. However, each state has its own crash reporting thresholds, which has an important effect on the transferability of the crash data (Xie et al., 2011; Shin et al., 2015a).

In North Carolina, if people are involved in a crash but there are no injuries, the drivers are typically responsible for reporting the crash. Nevertheless, private citizens have to report the crash within 72 hours if they are involved in a crash that results in injury, death, or more than $1,000 of damage to their vehicles. This reporting approach differs in other states (Table 3). In this way, a reported crash in Washington and California might not be reported in North Carolina. This phenomenon, called underreporting, might lead to biased results and a difficult interpretation of the phenomenon (Yamamoto et al., 2008). Thus, some researchers recommend considering only fatal-and-injury crashes for the calibration of SPFs (Xie et al., 2011; Shin et al., 2015a).

Thus, this research aims to study how the type of road alignment and crash severity influence the calculation of calibration factors and, consequently, the prediction of road crashes.

OBJECTIVES AND HYPOTHESES

The main objective of this research was to overcome the weaknesses related to the calculation of the calibration factors on rural two-lane, two-way roadway segments through the HSM predictive method. As mentioned above, the relationship between the number of predicted crashes under base conditions (N_{spf}) and the number of predicted crashes in a specific jurisdiction or state ($N_{predicted}$) might depend on the type of alignment as well as on the level of crash severity (Findley et al., 2012a; Xie et al., 2011).

Thus, several calibration factors were obtained and analyzed for different crash severities and types of road elements. The comparison between these calibration factors was carried out through an aggregated and disaggregated analysis. The aggregated analysis was focused on the prediction of the number of crashes on entire road segments, whereas the disaggregated analysis was carried out according to the type of road element, i.e., horizontal curve and tangent.

This study was based on two main hypotheses. The first one is that the calibration factor varies depending on the severity of road crashes, whereas the second one is that a calibration factor based on both types of road elements (horizontal curves and tangents) is not able to properly assess road safety on each type of road element. Therefore, a calibration factor for each type of road crash (by injury severity) and each type of road element will allow engineers to more accurately estimate the number of crashes on rural two-lane, two-way roadway segments.

METHODOLOGY

This research was focused on the analysis of the HSM predictive method through different calibration factors obtained in North Carolina (US). A total of 27 two-lane rural road sections located along NC-96, NC-42, and NC-268 roadways were selected. The horizontal alignment for each road section was recreated by means of the methodology proposed by Camacho-Torregrosa et al. (2015), whereas the cross-section of each road element was determined through aerial images. Crash and traffic data were also obtained. Different calibration factors were developed for the state of North Carolina for fatal-and-injury crashes and for each type of road element. These calibration factors were compared with those proposed by Findley et al. (2012) and Smith (2017), which were calibrated in the same state and based on all injury severity crashes (fatal, injury, and Property Damage Only crashes), to analyze the influence of the type of crash in the calculation of calibration factors. It should be noted that the analyses performed in this effort are potentially limited by the accurate reporting of the location and details of crashes, in addition to whether crashes are reported to the appropriate law enforcement agency. To the extent possible, the analyses conducted followed HSM recommendations except where comparisons to alternative methods are presented. A variety of analytical and statistical techniques were applied to the data, which included the calculation of the Mean Absolute Deviation (*MAD*) and the Root Mean Square Error (*RMSE*) and the analysis of Cumulative Residuals (CURE) plots.

DATA DESCRIPTION

Road segments

A total of 27 two-lane rural road sections located in North Carolina with no geometric changes in the time period selected for crash data were selected for the study. This required the geometric recreation of approximately 150 km (90 miles) of highway covering 350 horizontal curves and 375 tangents.

Length, radius, and the presence or absence of spiral transition were identified from this geometric recreation. Lane width, shoulder width and type, number of driveways, and roadside design were obtained from aerial images for each road element. These road segments are located in the Piedmont of North Carolina and are assumed to have a grade flatter than 3% (level grade) and do not contain centerline rumble strips, passing lanes, lighting, or automated speed enforcement. A superelevation rate that was adequate according to the AASHTO design guide was assumed for each horizontal curve (Table 4).

Traffic and crash data

Traffic volume and crash data were provided by the North Carolina Department of Transportation (NCDOT). *AADT* and the number of reported crashes were identified for each homogeneous road segment and horizontal curve between 2012 and 2016.

Only reported fatal-and-injury crashes were considered over this period of time. As a result, a total of 223 reported crashes were analyzed, 130 of which occurred on horizontal curves and 93 on tangents. It should be noted that the number of locations in this study is much greater than the

HSM recommendation (30-50 locations), even though the total crash threshold recommended by the HSM is not met (100 crashes per year as a minimum). Property Damage Only (PDO) crashes are not always reported and, consequently, to consider all types of crashes might lead to biased results (Xie et al., 2011; Shin et al., 2015a). For this reason, it is more accurate and reliable to expand the results from the estimated number of fatal-and-injury crashes than to extrapolate from the total number of crashes (PDO crashes and fatal-and-injury crashes).

Additionally, the crash distribution for rural two-lane, two-way roadway segments in North Carolina was studied based on the reported crashes on NC-41, NC-42, NC-43, NC-96, and NC-268 highways from 2012 to 2016. These highways have similar characteristics to the road segments considered in this research regarding cross-section, roadside design, and vertical alignment (level grade). The main objective was to compare this crash distribution with the crash distribution contained in the HSM, which is based on crash data from Washington.

According to the crash severity level, both crash distributions were very similar to each other (Figure 1). The percentage of fatal and injury crashes (p_i) was 33.4% and 32.1% for North Carolina and Washington, respectively. In addition, similar percentages were obtained for single and multiple-vehicle crashes in total (Table 5). However, the crash distributions were different from each other according to the disaggregated collision type. To this regard, “collision with animal” and “rear-end collision” showed greater percentages in North Carolina, whereas “ran off road” and “angle collision” presented higher values in Washington.

This means that the proportion of related crashes (p_{ra}) in North Carolina (0.391) is different from that proposed by the HSM (0.574). This proportion was used to calculate CMF_{1r} and CMF_{2r} and was estimated as the sum of the percentages related to single-vehicle run-off-the-road, and multiple-vehicle head-on, opposite-direction sideswipe, and same-direction sideswipes crashes.

Therefore, the values considered in this research for p_{ra} and p_i were 0.391 and 0.334, respectively. Additionally, Table 5 allows engineers and practitioners to more accurately estimate the number of a particular type of crash in North Carolina.

Crash modification factors and calibration factors

The *CMFs* proposed by the HSM to estimate the number of predicted crashes on rural two-lane, two-way roadway segments were calculated according to Chapter 10 of the HSM. Table 6 shows a statistical summary of these factors.

The calibration factor attempts to adjust the predicted number of crashes for local conditions. In North Carolina, Findley et al. (2012) proposed a calibration factor for each type of road element (1.33 for horizontal curves and 1.00 for tangents), whereas Smith et al. (2017) proposed a calibration factor for each region of the state (1.78 for coast, 0.78 for mountain, and 1.21 for piedmont). These calibration factors were obtained considering all types of severities, i.e., PDO crashes, injury crashes, and fatal crashes.

However, this study only considers fatal-and-injury crashes, so new calibration factors were calculated for this type of crashes through the following expression:

$$C = \frac{\sum N_{observed}}{\sum N_{predicted\_HSM}} \qquad (4)$$

where C is the calibration factor; $N_{observed}$ is the number of reported fatal-and-injury crashes; and $N_{predicted\_HSM}$ is the number of predicted crashes according to Equation 5.

$$N_{predicted\_HSM} = N_{spf} \cdot \prod_{i=1}^{12} CMF_i = L \cdot AADT \cdot 365 \cdot 10^{-6} \cdot e^{-0.312} \cdot \prod_{i=1}^{12} CMF_i \qquad (5)$$

where L is the length of the roadway segment (miles); $AADT$ is the annual average daily traffic volume (vehicles per day); and CMF_i are the *CMFs*.

A calibration factor was estimated for each type of road segment (horizontal curve and tangent) and for both road segment types jointly. To avoid the influence of the road segment selection on the calibration of these factors, each calibration factor was calculated as the average of the calibration factors obtained from 25 iterations. These iterations were based on the random selection of the road segments. In addition, to identify how important the sample-size is in the calculation of the calibration factors, different sample-sizes were considered: 90%, 80%, 70%, 60%, and 50% of the road segments. This new methodology allows engineers to obtain more accurate calibration factors and assess how sensitive these factors are regarding crash data.

Table 7 shows how the calibration factors change as a function of the sample-size used in the analysis for rural two-lane, two-way roadway segments in North Carolina. It should be noted that the mean values for each type of road segment were very similar between the different sample-sizes and the standard deviation was low. This reveals the high reliability of the calibration factors. This sensitivity analysis shows that the HSM recommended sample size may not be required to provide reliable results. For each of the road segment types, the mean values for the calibration factor did not change substantially when using a sample size of between 50% and 90% of the full dataset in this study. However, the standard deviation did decrease as the sample size increased. Therefore, to apply a single calibration factor for all types of road segments (C=1.34) might lead to underestimating the predicted number of crashes at horizontal curves (C=1.57) and overestimating it on tangents (C=1.15). This research supports the identification of this phenomenon.

ANALYSIS

This research presents an aggregated analysis, which estimated the number of predicted crashes on entire road segments, and a disaggregated analysis, which is focused on the study of the number of predicted crashes on each type of road element, i.e., horizontal curves and tangents. To this regard, the predicted number of crashes on a certain road segment was calculated as the sum of the predicted number of crashes for all road elements along the segment.

Both analyses were carried out considering the following parameters of goodness of fit:

i. Mean Absolute Deviation (*MAD*):

$$MAD = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \qquad (6)$$

ii. Root Mean Square Error (*RMSE*):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i|^2} \qquad (7)$$

iii. Cumulative Residuals (CURE) Plots: This method consists of plotting the cumulative residuals for each independent variable. The aim is to graphically observe how well the function fits the data set. The CURE method has the advantage of not being dependent on the number of observations, as are many other traditional statistical procedures. In general, a good cumulative residuals plot is one that oscillates around 0. Thus, a good fit is given when the residuals do not stray beyond the $\pm 2\sigma^*$ boundaries.

$$\sigma^* = \sqrt{\sigma_i^2 \cdot \left(1 - \frac{\sigma_i^2}{\sigma_T^2}\right)} \qquad (8)$$

where σ^* is the limit of the cumulative residuals; σ_i^2 is the variance of the cumulative residuals until the element *i*; and σ_T^2 is the total variance of the cumulative residuals. It should be noted that the residuals are calculated as the difference between the observed and predicted number of crashes and must be ordered from lowest to highest value.

Table 8 summarizes the calibration factors studied in this research, which were calibrated in North Carolina (US).

Crash severity influence

Two comparisons were used to analyze the influence of the type of crash severity on the prediction of the number of fatal-and-injury crashes. In the first comparison, $HSM_{\text{Findley et al.}}$ was compared with $HSM_{\text{new, type}}$ because both models are based on different calibration factors for each road element (horizontal curve and tangent), whereas $HSM_{\text{Smith et al.}}$ was compared with $HSM_{\text{new, all}}$, because both models included a single calibration factor for both types of road element.

All models showed similar values for *MAD* and *RMSE* (Table 9). However, the most important results are provided by the evaluation of the CURE plots. Regarding this, $HSM_{\text{new, type}}$ and $HSM_{\text{new, all}}$ produced better adjustments than $HSM_{\text{Findley et al.}}$ and $HSM_{\text{Smith et al.}}$, since the percentage of points out of the limits of these plots, for both length and *AADT*, was substantially lower for $HSM_{\text{new, type}}$ and $HSM_{\text{new, all}}$.

These results can be graphically observed in Figure 2 (traffic volume) and Figure 3 (segment length). Although $HSM_{\text{new, all}}$ slightly improved the results obtained through $HSM_{\text{Smith et al.}}$, $HSM_{\text{new, type}}$ showed an important improvement compared to $HSM_{\text{Findley et al.}}$. $HSM_{\text{Findley et al.}}$ underestimates the predicted number of fatal-and-injury crashes for both types of road segments, i.e., horizontal curves and tangents. Therefore, the use of calibration factors based on fatal and injury crashes allowed a more accurate estimation of the number of fatal-and-injury crashes than the application of a calibration factor based on all types of crash severities multiplied by the percentage associated with fatal and injury crashes (p_i).

Road element influence

The influence of the type of road element was studied by comparing $HSM_{new,\ type}$ with $HSM_{new,\ all}$. Although both models showed similar values for *MAD* and *RMSE*, the CURE plots indicated that $HSM_{new,\ type}$ can more accurately estimate the number of fatal-and-injury crashes than $HSM_{new,\ all}$, because $HSM_{new,\ type}$ showed a lower percentage of points out of the CURE plot limits (Table 9). Regarding the aggregated analysis, both models provided a good fit relative to the observed number of crashes, since the residuals did not stray beyond the CURE plot limits, with the exception of a few points (Figure 2 and Figure 3). This might lead to the claim that both $HSM_{new,\ type}$ and $HSM_{new,\ all}$ can be used to estimate the predicted number of fatal-and-injury crashes on an entire road segment. However, the disaggregated analysis revealed that $HSM_{new,\ type}$ should be used instead of $HSM_{new,\ all}$ because $HSM_{new,\ type}$ is able to more accurately predict the number of fatal-and-injury crashes on both types of road elements (horizontal curves and tangents), whereas $HSM_{new,\ all}$ tends to overestimate and underestimate the number of fatal-and-injury crashes on tangents and horizontal curves, respectively. These results were obtained for both variables of the CURE plots, i.e., considering both the volume traffic and the road element length. Therefore, different calibration factors should be calculated for each type of road element to assess road safety.

The same conclusions were identified by analyzing the results obtained through the calibration factors proposed by Smith et al. (2017). Although $HSM_{Smith\ et\ al.}$ appropriately estimated the predicted number of fatal-and-injury crashes on an entire road segment, the disaggregated analysis showed that the number of fatal-and-injury crashes on tangents and horizontal curves were overestimated and underestimated, respectively.

DISCUSSION

The HSM predictive method estimates the total number of crashes for rural two-lane, two-way roadway segments, i.e., this prediction includes all types of crashes and severities. However, various studies suggest that a calibration factor for each type of crash severity can provide more accurate results (Xie et al., 2011). This research supports this recommendation, since the new calibration factors based on the fatal-and-injury crashes resulted in a more accurate prediction of the number of this type of crash than the calibration factors proposed by Findley et al. (2012) and Smith et al. (2017), which were obtained considering all types of crash severity. Therefore, different calibration factors should be developed for each type of crash severity. These efforts led to a recommendation to develop calibration factors for fatal-and-injury crashes and extrapolate the results to other types of crash severities. This can help avoid the bias produced by the underreporting of Property Damage Only crashes.

Most previous studies only analyzed the number of crashes in general terms, i.e., through an aggregated analysis. This leads to calibration factors that could provide a false confidence in the results of the number of crashes for entire road segments because the individual prediction on horizontal curves and tangents is not reliable (Findley et al., 2012a). The disaggregated analysis showed that to consider a single calibration factor for both types of road elements leads to overestimating and underestimating the number of fatal-and-injury crashes on tangents and horizontal curves, respectively. This means that a single calibration factor cannot properly identify which road elements pose a risk for drivers. Therefore, a specific calibration factor for each type of road element would allow highway engineers to obtain more reliable results. The results of this study show that a substantial difference exists between calibration factors for horizontal curves and tangents, which suggests that significant improvements in predictive estimates of crashes can be achieved through applying separate calibration factors for these road elements. Developing calibration factors for each road element type may improve reliability of calibration factors over time and positively affect credibility of the results through lower annual variability in calibration factor values.

Additionally, a new methodology to estimate the calibration factors was introduced in this research. To avoid the influence of the road element selection on the calculation of these factors, 25 random iterations were carried out considering different sample-sizes. This analysis provided information about the impact of sample size on the appropriate development of the calibration factors proposed for North Carolina. This sensitivity analysis shows that the HSM recommended sample size may not be required to provide reliable results.

Finally, a preliminary study of crash distribution is recommended to apply the HSM predictive method. According to Xie et al. (2011) and Shin et al. (2015a), the percentage associated with the number of fatal-and-injury crashes (p_i) and the proportion of related crashes (p_{ra}) might be significantly different from those proposed by the HSM, since the driver culture, infrastructure characteristics, and crash reporting threshold can be different for each state. In fact, the North Carolina crash distribution is similar to the Washington crash distribution regarding crash severity, but not when considering the type of crashes. Therefore, values of p_i and p_{ra} equal to 0.334 and 0.391, respectively, for North Carolina are recommended instead of the application of the percentages proposed by the HSM.

CONCLUSIONS

New calibration factors for horizontal curves and tangents based on fatal and injury crashes were developed for North Carolina two-lane rural roads. A total of 27 two-lane rural road sections were considered in the research, including 350 horizontal curves and 375 tangents.

These calibration factors were compared with those proposed by Findley et al. (2012) and Smith et al. (2017) to analyze the influence of the type of crash severity and the type of road element on the prediction of the number of fatal-and-injury crashes through the HSM predictive method. Two different analyses were considered: aggregated and disaggregated analysis.

As a result, those calibration factors based on both types of road elements led to overestimating the number of fatal-and-injury crashes on tangents and underestimating fatal-and-injury crashes on horizontal curves. Likewise, the new calibration factors based on fatal-and-injury crashes allowed a more accurate estimation of the predicted number of this type of crash than the calibration factors proposed by Findley et al. (2012) and Smith et al. (2017).

Therefore, it is recommended to use a different calibration factor for each type of road element and each type of crash severity. This study also suggests using the number of fatal-and-injury crashes when developing calibration factors to extrapolate the results to other types of crash severities with the objective of avoiding the bias produced by the underreporting of Property Damage Only crashes and producing more reliable results.

This research effort was focused on the estimation of the calibration factors, while future research is expected to analyze the development of state-specific SPFs from the point of view of the influence of risk exposure, homogeneity of road segments, and the functional form in an effort of broader HSM predictive method improvements and evaluation.

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Table 1. Crash Modification Factors for rural two-lane, two-way roadway segments.

CMF	Description	Base condition
$\boldsymbol{CMF_{1r}}$	Lane width	12 feet (3.66 m)
$\boldsymbol{CMF_{2r}}$	Shoulder width and type	6 feet (1.83) and paved
$\boldsymbol{CMF_{3r}}$	Horizontal curves: length, radius, and presence or absence of spiral transitions	None
$\boldsymbol{CMF_{4r}}$	Horizontal curves: superelevation	Varies according to AAHSTO
$\boldsymbol{CMF_{5r}}$	Grades	Level grade
$\boldsymbol{CMF_{6r}}$	Driveway density	5 driveways per mile
$\boldsymbol{CMF_{7r}}$	Centerline rumble strips	None
$\boldsymbol{CMF_{8r}}$	Passing lanes	None
$\boldsymbol{CMF_{9r}}$	Two-way left-turn lanes	None
$\boldsymbol{CMF_{10r}}$	Roadside design	3
$\boldsymbol{CMF_{11r}}$	Lighting	None
$\boldsymbol{CMF_{12r}}$	Automated speed enforcement	None

Table 2. Calibration factors in the United States.

State	Calibration factor (C)	Research Effort
Alabama	1.392	Mehta and Lou (2013)
Arizona	1.079	Srinivasan et al. (2016)
Florida	1.005	Srinivasan et al. (2011)
Illinois	1.40	Williamson and Zhou (2012)
Kansas	1.48	Lubliner (2011)
Maryland	0.6956	Shin et al. (2015a)
Michigan	1.278	DOT of Michigan (2012)
North Carolina	1.33 (horizontal curves); 1.00 (tangents)	Findley et al. (2012)
	1.78 (coast); 0.78 (mountain); 1.21 (piedmont)	Smith et al. (2017)
Oregon	0.74	Xie et al. (2011)
Utah	1.16	Brimley et al. (2012)

Table 3. Crash reporting thresholds for some states in the United States.

State	Crash Reporting Threshold
Washington	$700
California	$750
North Carolina	$1,000
Oregon	$1,500
Maryland	If any vehicle needs to be towed

Table 4. Geometric characteristics of the road elements.

Road feature	Horizontal curves					Tangents				
	Min.	Max.	Mean	Median	St. Dev.	Min.	Max.	Mean	Median	St. Dev.
Length (miles)	0.004	0.645	0.135	0.104	0.095	0.003	0.931	0.132	0.073	0.160
AADT (vpd)	538	7,700	1,885	1,289	1,669	538	7,700	1,946	1,289	1,713
Radius (feet)	121.9	123,264.8	4,655.6	1,386.5	12,462.6	na	na	na	na	na
Lane width (feet)	8	12	9.937	10	1.058	8	12	9.963	10	1.046
Shoulder width (feet)	8	12	9.937	10	1.058	2	6	3.139	3	1.233
Roadside Hazard Rating	2	6	3.106	3	1.210	3	5	3.795	3	0.975
DD (driveways per mile)	0	63.3	11.2	9.0	11.9	0	185.7	18.2	9.7	24.5

NOTES:
Min=Minimum; Max=Maximum; St. Dev.=Standard deviation; AADT=Annual Average Daily Traffic; DD=Driveway Density; CCR=Curvature Change Rate; na=not applicable; Crashes=Number of fatal-and-injury crashes
1 mi = 1,609.34 m, 1 ft = 0.3048 m.

Table 5. Crash distribution: collision type.

Collision type	**North Carolina**	**HSM**
SINGLE-VEHICLE CRASHES		
Collision with animal	31.3%	12.1%
Collision with bicycle	0.3%	0.2%
Collision with pedestrian	0.3%	0.3%
Overturned	3.3%	2.5%
Ran off road	32.6%	52.1%
Other single-vehicle crash	2.8%	2.1%
Total single-vehicle crashes	70.4%	69.3%
MULTIPLE-VEHICLE CRASHES		
Angle collision	1.2%	8.5%
Head-on collision	1.3%	1.6%
Rear-end collision	19.2%	14.2%
Sideswipe collision	5.2%	3.7%
Other multiple-vehicle collision	2.7%	2.7%
Total multiple vehicle collision	29.6%	30.7%
TOTAL CRASHES	**100.0%**	**100.0%**

Table 6. Statistical summary of the *CMFs*.

CMF	Description	Type of road element							
		Horizontal Curves				Tangents			
		Min.	Max.	Mean	St. Dev.	Min.	Max.	Mean	St. Dev.
CMF_{1r}	Lane width	1	1.1173	1.044	0.02789	1	1.1173	1.044	0.028
CMF_{2r}	Shoulder width and type	1.031	1.1321	1.066	0.02789	1.024	1.1321	1.066	0.02821
CMF_{3r}	Horizontal curves	1	10.059	1.795	1.36664	1	1	1	0
CMF_{4r}	Superelevation	1	1	1	0	1	1	1	0
CMF_{5r}	Grades	1	1	1	0	1	1	1	0
CMF_{6r}	Driveway density	1	2.8943	1.271	0.36885	1	72.788	1.693	3.76648
CMF_{7r}	Centerline rumble strips	1	1	1	0	1	1	1	0
CMF_{8r}	Passing lanes	1	1	1	0	1	1	1	0
CMF_{9r}	Two-way left-turn lanes	1	1	1	0	1	1	1	0
CMF_{10r}	Roadside design	1	1.1429	1.059	0.07002	1	1.1429	1.057	0.06964
CMF_{11r}	Lighting	1	1	1	0	1	1	1	0
CMF_{12r}	Automated speed enforcement	1	1	1	0	1	1	1	0

Table 7. Calibration factor for North Carolina.

Type of road segment	Sample-size	Calibration factor			
		Minimum	Maximum	Mean	St. Deviation
Horizontal curves	90%	1.472	1.725	1.578	0.066
	80%	1.405	1.776	1.573	0.089
	70%	1.294	1.780	1.568	0.121
	60%	1.344	1.798	1.559	0.137
	50%	1.284	1.870	1.582	0.168
Tangents	90%	1.088	1.228	1.163	0.036
	80%	0.993	1.291	1.158	0.081
	70%	0.926	1.330	1.143	0.093
	60%	0.979	1.333	1.157	0.095
	50%	0.886	1.371	1.142	0.143
All	90%	1.264	1.396	1.344	0.033
	80%	1.248	1.441	1.342	0.053
	70%	1.269	1.435	1.350	0.048
	60%	1.206	1.513	1.339	0.067
	50%	1.169	1.539	1.335	0.094

Table 8. Calibration factors in North Carolina.

Name of the model	Description
$HSM_{Findley\ et\ al.}$	Equation 5 with calibration factors proposed by Findley et al. (2012): • Calibration factor for horizontal curves: 1.33 • Calibration factor for tangents: 1.00
$HSM_{Smith\ et\ al.}$	Equation 5 with calibration factors proposed by Smith et al. (2017): • Calibration factor for Coast: 1.78 • Calibration factor for Mountain: 0.78 • Calibration factor for Piedmont: 1.21
$HSM_{new,\ type}$	Equation 5 with calibration factors proposed in this research for each type of road segment (Table 7): • Calibration factor for horizontal curves: 1.57 • Calibration factor for tangents: 1.15
$HSM_{new,\ all}$	Equation 5 with calibration factor proposed in this research for all types of road segments (Table 7): • Calibration factor: 1.34

Table 9. Parameters of goodness of fit.

(a) Aggregated analysis				
Model	MAD	RMSE	CURE plot (AADT)*	CURE plot (L)**
HSM$_{\text{Findley et al.}}$	1.622	2.487	61.02%	50.85%
HSM$_{\text{Smith et al.}}$	1.615	2.252	45.76%	35.59%
HSM$_{\text{new, type}}$	1.683	2.490	16.95%	8.47%
HSM$_{\text{new, all}}$	1.715	2.489	35.59%	27.12%
(b) Disaggregated analysis – Horizontal curves				
Model	MAD	RMSE	CURE plot (AADT)*	CURE plot (L)**
HSM$_{\text{Findley et al.}}$	0.451	0.748	43.43%	67.14%
HSM$_{\text{Smith et al.}}$	0.448	0.748	65.71%	72.57%
HSM$_{\text{new, type}}$	0.472	0.754	1.71%	58.57%
HSM$_{\text{new, all}}$	0.451	0.748	42.29%	67.14%
(c) Disaggregated analysis – Tangents				
Model	MAD	RMSE	CURE plot (AADT)*	CURE plot (L)**
HSM$_{\text{Findley et al.}}$	0.262	0.570	41.33%	8.80%
HSM$_{\text{Smith et al.}}$	0.283	0.565	9.87%	17.07%
HSM$_{\text{new, type}}$	0.271	0.571	12.00%	5.60%
HSM$_{\text{new, all}}$	0.288	0.584	9.07%	13.60%

*Percentage of CURE plot out of the limits for traffic volume
** Percentage of CURE plot out of the limits for road segment length