Determining Skid Resistance Needs on Horizontal Curves for Different Levels of Precipitation

Srinivas R. Geedipally, Ph. D., P.E.
(Corresponding Author)
Associate Research Engineer
Texas A&M Transportation Institute,
110 N. Davis Dr., Suite 101, Arlington, Texas 76013
Email: Srinivas-G@tti.tamu.edu

Subasish Das, Ph.D.
Associate Transportation Researcher
Texas A&M Transportation Institute
3135 TAMU, College Station, TX 77843
Email: s-das@tti.tamu.edu

Michael P. Pratt, P.E., P.T.O.E.
Assistant Research Engineer
Texas A&M Transportation Institute
3135 TAMU, College Station, TX 77843
Email: m-pratt@tti.tamu.edu

Dominique Lord, Ph.D.
Professor, Zachry Department of Civil Engineering
Texas A&M University, College Station, TX 77843, United States
Email: d-lord@tamu.edu

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ABSTRACT

Horizontal curves are a major cause of crashes that lead to fatal and serious injuries. Much research has been conducted on the safety implications of geometric and traffic characteristics of curves. Variables describing curve geometry and speed have been incorporated into safety prediction methodologies. However, relatively less research has been conducted on the effects of pavement friction and weather data on safety. The objective of this study is to develop a methodology for determining the pavement friction needs for different levels of precipitation. To accomplish the study objective, rural two-lane, and four-lane undivided and divided horizontal curve data from Texas were used. Safety prediction models were developed that includes traffic and geometric characteristics, skid number, and annual precipitation rate. These models were then used to develop the guidelines for assessing the safety performance of a curve of interest by accounting for curve geometry, pavement skid resistance, and exposure to the wet-weather conditions that are most relevant for considerations of skid resistance. For the purpose of conducting a planning-level analysis to identify candidate sites for pavement friction treatments, researchers developed the thresholds based on the combined effect of skid number and annual precipitation variables. Researchers also provided skid number thresholds for high priority sites for two example locations that experience significantly different levels of annual precipitation.

Keywords: Horizontal Curves, Skid Resistance, Pavement maintenance, Annual Precipitation, Safety Performance Functions, Crash Modification Factors

INTRODUCTION

Horizontal curves are a necessary part of the highway system, but statistics have consistently shown that curves represent significant safety concerns. These concerns arise from the increased driver workload associated with traversing a curve, driver errors such as failing to detect a curve or judge its sharpness correctly, and the possibility of obtaining inadequate side friction supply from the tire-pavement interface in inclement weather conditions. Statistics have consistently shown that the crash rate on horizontal curves is significantly greater than that on tangent roadway segments of similar character. This trend may be caused by drivers failing to detect the presence of a curve or attempting to negotiate the curve at unsafe speeds.

Pavement-related treatments are one option to reduce the number of crashes experienced at horizontal curves. These treatments must be implemented judiciously due to their cost but have the potential to improve safety at lower cost than geometric improvements such as curve straightening, and with greater effectiveness than control-device treatments such as installing delineators or chevrons. Pratt et al. (*1*) provided the costs and service life of pavement-related treatments. Implementation of these treatments must be prioritized carefully to spend limited funds where they would yield the greatest benefit in terms of reduction in the number of crashes and injuries and fatalities prevented.

Much research has been conducted on the safety implications of geometric and traffic characteristics of curves. Variables describing curve geometry and speed have been incorporated into safety prediction methodologies. However, relatively less research has been conducted on the effects of pavement friction and weather condition on safety. This study developed safety prediction models to quantify the relationship between curve crash frequency and characteristics such as radius, lane width, shoulder width, skid number, and annual precipitation rate. These models allow the assessment of the safety performance of a curve of interest by accounting for curve geometry, pavement skid resistance, and exposure to the wet-weather conditions that are most relevant for considerations of skid resistance.

BACKGROUND

This section presents some general background information to help support this paper.

Side Friction Demand and Supply

AASHTO's *A Policy on Geometric Design of Highways and Streets* (*Green Book*) states that the design of horizontal curves should be based on a proper relationship between speed, curvature, superelevation rate, and side friction demand (*2*). The *Green Book* offers the following equation to describe the relationship between these variables:

$$f_D = \frac{v^2}{gR} - \frac{e}{100} \tag{1}$$

where:

- f_D = side friction demand (lateral acceleration divided by g).
- v = vehicle speed, ft/s.
- g = gravitational constant (= 32.2 ft/s^2).
- R = curve radius, ft.
- e = superelevation rate, percent.

This equation is referred to as the "point-mass model" or the "simplified curve formula." It shows that the side friction demand f_D of a vehicle traveling at speed v increases as curve radius R or superelevation rate e decrease. For design purposes, the *Green Book* recommends side friction factors that represent driver comfort limits. These factors are used to determine an appropriate curve radius and superelevation rate for the roadway's design speed.

The design side friction factors in the Green Book are lower than the side friction supply f_S provided in the worst-case combination of worn tires and wet pavement. In other words, vehicles traveling at a speed not exceeding the design speed should be able to traverse the curve safely.

In the design process, curve design safety can be assessed in terms of "margin of safety," which is defined as the difference between side friction demand and side friction supply at the given vehicle speed. If the side friction demand exceeds the side friction supply available to the vehicle, a sliding failure will occur. As Equation 1 shows, vehicle speed and curve geometry affect side friction demand. Tire-pavement interface properties such as tire tread condition, pavement texture, and presence of water or solid contaminants on the pavement surface all affect side friction supply.

Various methods can be used to measure surface friction at horizontal curve sites where side friction supply is believed to be inadequate. The side friction supply can then be subtracted from the side friction demand to obtain the curve's margin of safety. An inadequate margin of safety can indicate the need to increase side friction supply through the provision of surface treatment, and also indicate the amount of side friction supply increase that would be needed. It would then be necessary to identify a surface treatment that could provide the needed increase in side friction supply.

Wet Weather Crashes

Weather-related crashes are those that occur in the presence of rain, sleet, snow, fog, wet pavement, snowy/slushy pavement, and/or icy pavement. Weather acts through visibility impairments, precipitation, high winds, and temperature extremes to affect driver capabilities, vehicle performance (i.e., traction, stability, and maneuverability), pavement friction, and roadway infrastructure. These impacts can increase crash risk and severity. Several studies have been conducted on driver behavior and crash during rainfall or snowfall. Examination of free-flow speeds on curved highway sections in rural New York State illustrated that drivers did not reduce speeds sufficiently on curves during wet-pavement conditions (*3*). The investigators concluded that drivers did not recognize that pavement friction is lower on wet pavement as compared with dry pavement.

In a study of crashes during and after rain events in Calgary and Edmonton, Canada (*4*), investigators concluded that crash risk during rainfall was 70 percent higher than crash risk under clear, dry conditions. In an assessment of weather and seasonal effects on highway crashes in California (*5*), the weather was found to be a major factor. On very wet days, the crash frequency was twice the rate on dry days.

Jackson and Sharif (*6*) used fatal crash data and geospatial analysis to examine the temporal and spatial distribution of rain-related fatal crashes in Texas from 1982 to 2011. The data obtained from the Fatality Analysis and Reporting System (FARS) was used to identify spatial clustering patterns of rain-related fatal crashes and their correlation with rainfall and to compare them to spatial patterns of other crashes. Study results suggest that rain is a contributor to crashes in few counties but at less than 95 percent confidence in some of the wetter counties. The authors recommended that these counties should be the focus of further research and detailed analysis to identify underlying crash contributing factors.

Mayora and Pina (*7*) analyzed 10 years of crash data from two-lane rural roads on the Spanish National Road System and estimated a skid threshold. This study collected crash data from over 1,085 miles of rural two-lane roadways with skid resistance values. The results showed that pavement friction improvement yielded significant reductions in wet-pavement crash rates averaging around 68 percent. The results confirmed the importance of maintaining adequate levels of pavement friction to safeguard traffic safety. The authors also reported the crash rate for different alignments and showed that roadways with curves have higher crash rates than roadways with tangent in wet conditions.

Buddhavarapu et al. (*8*) attempted to establish a relationship between crash severities on horizontal curves and pavement surface condition indices. This study used two TxDOT maintained databases: (a) Crash Record Information System (CRIS) data, and (b) Pavement Management Information System (PMIS) data. These two data sets are linked using data fields such as crash location and crash year to create an assimilated database. The combined data set contains information pertaining to 22,199 crashes that occurred on a total of two-lane horizontal curves during 2006–2009. Five different pavement condition indices were used for analysis: (a) Skid Index, (b) Distress Index, (c) Ride Index, (d)

International Roughness Index (IRI), and (e) Condition Index. This study used an ordered probit response model structure for severity modeling. The findings are:

- Skid number was poorly correlated with crash injury severity on two-lane horizontal curves.
- The Distress Index and IRI were found to have a statistically significant effect on crash injury severity.

Najafi et al. (*9)* used New Jersey crash data and pavement condition data to develop regression models to examine the effect of friction on the rate of wet- and dry-condition vehicle crashes for various types of urban roads. The findings showed that friction is not only associated with the rate of wet-condition vehicle crashes, but it also influences the rate of dry condition vehicle crashes.

A before-after examination of wet-weather crashes and pavement friction on several rural highway types was conducted by Blackburn et al. (*10*). They derived the relationship between skid number and wet-pavement crash rate. As expected, wet-weather crash rates are highly influenced by pavement friction.

Given the importance of pavement friction, it is important to understand what friction is need for different levels of precipitation.

DATABASE DEVELOPMENT

The database development involved two major tasks: 1) integration of crash and road-related data, 2) integration of weather station data.

Integration of Crash and Road-related Data

The database assembled for developing the regression models consisted of a set of similar horizontal curves. The horizontal curve information was extracted from the Texas Reference Marker System (TRM) Geo-Hini database for the year 2012. The Geo-Hini database contains geometrics for all curves on all highways in the state. Each curve is given a unique curve identifier number, and the beginning and ending milepoints of each curve are located through a given reference marker and curve length from that marker. Only normal curves (i.e., curves that deflect at a constant rate and do not have spiral transitions) that are ≥ 0.1 miles in length were considered in this analysis.

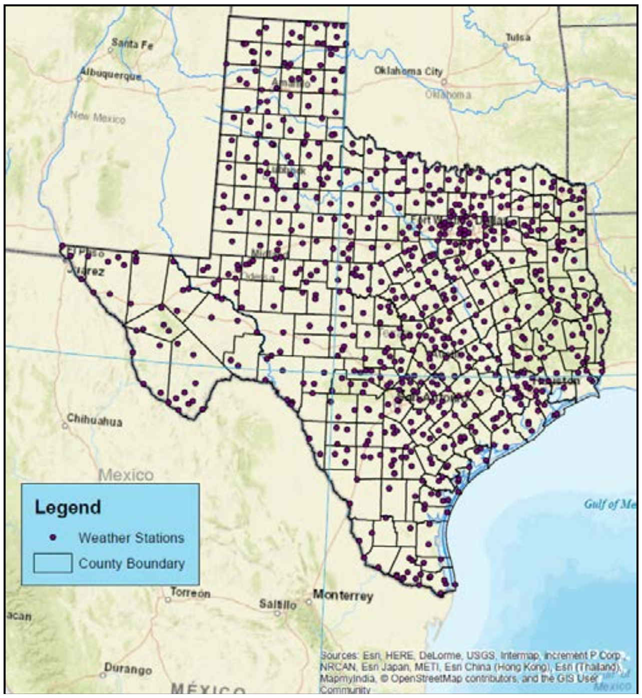
The horizontal curve database was combined with TxDOT's Road-Highway Inventory Network Offload (RHiNo) database using the control section numbers and milepoints. Variables extracted from the RHiNo database included average daily traffic (ADT), truck percentage, shoulder widths, lane width, median width, and the number of lanes. Only those sites that have at least 400 vehicles per day were considered in this study.

Pavement data were obtained from the Pavement Management Information System (PMIS) database for the years 2012 to 2016. Researchers retrieved crash data for the years 2012–2016 from the CRIS database. These data consisted of information describing the date and location of the crash, severity, and weather conditions. Since it is widely recognized that property damage only (PDO) crash counts vary widely on a regional basis due to significant variation in reporting threshold, only those crashes that are associated with injury or fatality were considered in this analysis. The following four crash severity levels were used: fatal (K), incapacitating injury (A), non-incapacitating injury (B), and possible injury (C).

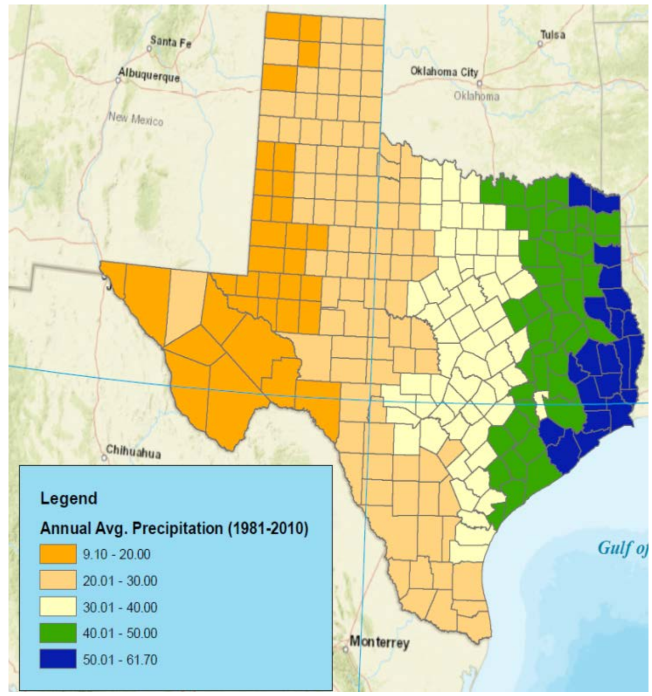
Integration of Weather Station Data

The term "climate normal" is used in a broad sense to refer to a full suite of products issued by the National Oceanic and Atmospheric Administration (NOAA) that describes climatological conditions with 30-year averages and other statistics (*11*). For example, the precipitation normal in January for a station would be computed by taking the average of the 30 January values of monthly average precipitations from 1981 to 2010. Each of the 30 monthly values was in turn derived from averaging the daily observations of precipitation for the station. These data provide users with many tools to understand typical climate conditions for thousands of locations across the United States. Meteorologists and climatologists regularly use NOAA climate normal data for placing recent climate conditions into a historical context. This standardized data set is suitable for showing the precipitation trends over specific regions like counties or districts.

The researchers used two 30-year climate normal data sets (1971–2000 and 1981–2010) and tabulated annual precipitation rates by county. Figure 1a shows the locations of the weather stations that are included in the analysis. Figure 1b illustrates the annual average precipitation rate (in.) by county using the NOAA 1981–2010 climate normal data set. The trend shows that the west regions experience less amount of precipitation than the eastern regions.



a. Weather stations in Texas



b. Annual precipitation (in.) by county

Figure 1 Weather stations and annual precipitation rate (in.) by county (1981–2010 NOAA normal).

Once the crash, road-related, and weather data were collected for each horizontal curve, the data were combined using control section number and milepoints. Separate databases were built for curves on two-lane highways, four-lane undivided highways, and four-lane divided highways. Table 1 presents the summary statistics of the variables used for SPF development. The lower and upper quartiles of skid number were computed as 36 and 57 for two-lane rural highways, 30 and 49 for four-lane undivided rural highways, and 30 and 45 for four-lane divided rural highways. The mean and standard deviation of skid number variable are not provided for legal reasons. The database assembled for calibration included crash frequency over a five-year period. The crash data were separated into two categories:

- All wet-weather-related crashes.
- Run-off-road (ROR) wet-weather-related crashes.

Table 1 Summary Statistics for Horizontal Curve SPF Development

Variable	Two-Lane			Four-Lane Undivided			Four-Lane Divided		
	Range	Mean (SD)*	Total	Range	Mean (SD)*	Total	Range	Mean (SD)*	Total
Curve Length (Miles)	0.05–0.99	0.14 (0.09)	5961	0.1–0.92	0.21 (0.1)	151	0.1–0.99	0.27 (0.16)	416.7
ADT (Vehicles/day)	10–14765	1038 (1332)	--	475–26587	7133 (4731)	--	727–63935	14400 (10370)	--
Average Lane Width (ft)	5.5–16	10.97 (1.0)	--	10.5–15	11.9 (0.8)	--	11–15.5	12.0 (0.34)	--
Average Inside Shoulder Width (ft)	--	--	--	--	--	--	0–13	4.57 (1.68)	--
Average Outside Shoulder Width (ft)	0–17	3.3 (5.7)	--	0–13	3.9 (3.5)	--	0–16	9.68 (1.92)	--
Radius (ft)	106–28633	2869 (2954)	--	169–24548	4326 (3303)	--	127–29982	6977 (5168)	--
Maximum Speed (Miles/hour)	30–75	60.1 (8.0)	--	30–75	65.0 (10.6)	--	35–85	72.8 (6.3)	--
Annual Precipitation (inches)	9.1–63.1	38.5 (11.3)	--	13.2–63.1	37.63 (10.4)	--	9.1–70.4	36.9 (10.4)	--
All Crashes	0–11	0.13 (0.5)	5546	0–5	0.51 (0.86)	486	0–21	1.27 (1.93)	1950
All Wet-Weather Crashes	0–9	0.02 (0.15)	733	0–4	0.10 (0.36)	65	0–15	0.30 (0.86)	458

*SD: standard deviation

REGRESSION MODELING

The data set used in this study contains some variables that vary by year. In such situations, cross-sectional modeling framework may not identify realistic patterns in the data variables. Panel data modeling is a different modeling approach that is recommended when the variables are observed over time. The panel data models allow the safety effects of changing variables to be quantified more precisely when independent variable value is measured for each site for each year. In this particular data set, in addition to ADT, skid number and precipitation rate are known to change notably between years, as skid number degrades over time and precipitation varies naturally. In this study, the researchers repeated the site for each year and the variables ADT, skid number, and precipitation are unique for each year. Panel data modeling has the following advantages (*12*):

- From the statistical perspective, the increase in number of observations leads to higher degree of freedom and less collinearity, which in turn improves the parameter estimation accuracy.
- It will allow researchers to test whether more simplistic specifications are appropriate.
- The panel models can be used to analyze some specific questions, such as change in the variable effect over time, that cannot be answered with cross-sectional modeling.

As discussed by Lord and Persaud (*13*), analyzing time-series or panel data in this manner can create temporal or serial correlation. Random effects models and those estimated using the generalized estimating equations (GEE) can be used for handling serial correlation (*13*). However, after further investigation, it was determined that the serial correlation had a minimal impact on the modeling results. Hence, to simplify the modeling effort, the models were estimated using the generalized linear models (GLMs).

An important characteristic associated with the development of statistical relationships is the choice of the functional form linking crashes to the covariates. For this work, the functional form is as follows:

$$\mu_i = L \times y \times e^{\beta_0} \times F^{\beta_1} \times CMF_1 \times \ldots \times CMF_k \quad (2)$$

where:

μ_i = estimated annual number of crashes per mile.
L = segment length, mi.
y = number of years of crash data, years.
F = traffic volume, vehicles per day.

The coefficients of the regression models were estimated using the Statistical Analysis Software program (*14*). The Akaike Information Criterion (AIC) statistics were used to assess the model goodness-of-fit. Only variables that had a large influence on the predicted values were included in the models.

Modeling Results—Two-Lane Horizontal Curves

Table 2 summarizes the parameter estimates associated with the calibrated SPFs for horizontal curves on two-lane highways. The list of variables presented in Table 2 reflects the findings from several preliminary regression analyses where different combinations of variables were examined. The list that is presented represents the variables that are significant in the model, while also having coefficient values that are logical and constructs that are theoretically defensible and properly bounded.

Table 2 Parameter Estimation for Two-Lane Highway Curves

Variable	All Crashes		Wet Weather Crashes	
	Estimate	Std. err.	Estimate	Std. err.
Intercept	−7.439	0.246	−10.108	0.782
LN (ADT)	0.760	0.027	0.841	0.072
Curve Radius	0.356	0.050	--	--
Lane Width	−0.064	0.025	--	--
Shoulder Width	−0.040	0.009	−0.058	0.021
Skid Number	−0.009	0.002	−0.038	0.005
Annual Prec.	0.014	0.002	0.031	0.007
Dispersion	0.585	0.073	0.277	0.121
AIC	16326		3023	

Note: -- = calibration coefficient is highly insignificant

The annual crash frequency for horizontal curves on two-lane highways is obtained by combining Equation 2 with the coefficients in Table 2 as follows:

$$\mu = L \times y \times e^{-7.439} \times F^{0.760} \times CMF_R \times CMF_{LW} \times CMF_{SW} \times CMF_{SK} \times CMF_{AP} \quad (3)$$

with:

$$CMF_R = 1 + 0.356(0.147V)^4 \frac{(1.47V)^2}{32.2R^2} \quad (4)$$

$$CMF_{LW} = e^{-0.064(LW-12)} \quad (5)$$

$$CMF_{SW} = e^{-0.040(SW-8)} \quad (6)$$

$$CMF_{SK} = e^{-0.009(SK-40)} \quad (7)$$

$$CMF_{AP} = e^{0.014(AP-30)} \quad (8)$$

where:

μ = estimated number of crashes per year per mile.
CMF_R = horizontal curve radius crash modification factor.
CMF_{LW} = lane width crash modification factor.
CMF_{SW} = shoulder width crash modification factor.
CMF_{SK} = skid number crash modification factor.
CMF_{AP} = annual precipitation crash modification factor.
R = curve radius, ft.
V = regulatory speed limit, mph.
LW = lane width, ft.
SW = shoulder width, ft.
SK = skid number.
AP = annual precipitation rate, in.

The annual wet-weather crash frequency for horizontal curves on two-lane highways can be estimated by the following equation:

$$\mu = L \times y \times e^{-10.108} \times F^{0.841} \times CMF_{SW} \times CMF_{SK} \times CMF_{AP} \quad (9)$$

with:

$$CMF_{SW} = e^{-0.058(SW-8)} \quad (10)$$

$$CMF_{SK} = e^{-0.038(SK-40)} \quad (11)$$

$$CMF_{AP} = e^{0.031(AP-30)} \quad (12)$$

Figure 2 shows the fit of the all crash model for two-lane horizontal curves. This figure compares the predicted and observed crash frequency in the calibration database. The data were sorted by ADT and combined into 45 groups. Each data point shown in Figure 2 represents the total predicted and total observed crash frequency in a particular group. In general, the data shown in the figure indicate that the model provides an unbiased estimate of expected crash frequency.

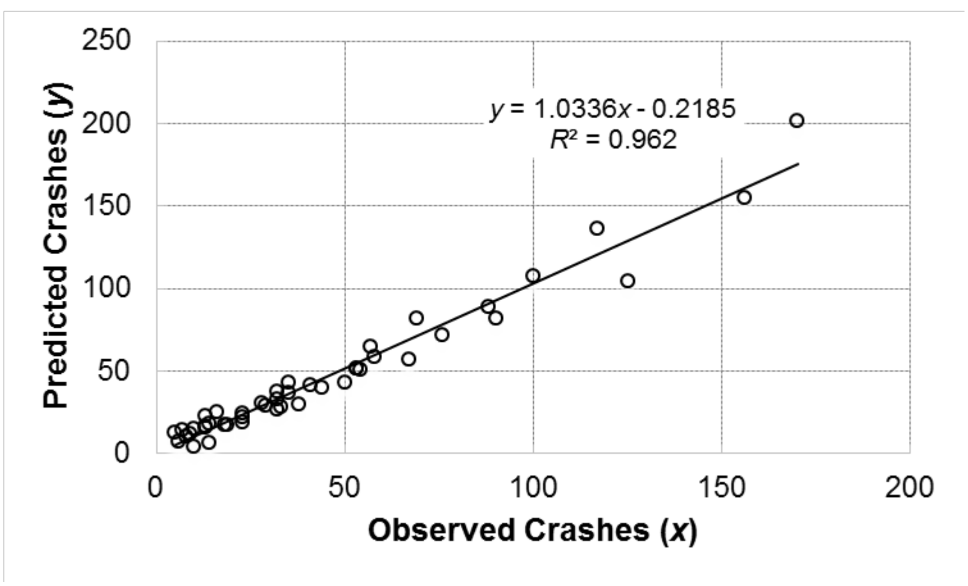


Figure 2 Observed versus predicted crashes (two-lane horizontal curves).

Modeling Results—Four-Lane Horizontal Curves

Table 3 summarizes the parameter estimates associated with the calibrated SPFs for horizontal curves on four-lane undivided and divided highways. The list of variables reflects the findings from several preliminary regression analyses where different combinations of variables were examined. The list represents the variables that provided the best fit to the data, while also having coefficient values that are logical and constructs that are theoretically defensible and properly bounded.

Table 3 Parameter Estimation for Four-Lane Highway Curves

Variable	Undivided				Divided			
	All Crashes		Wet Weather Crashes		All Crashes		Wet Weather Crashes	
	Estimate	Std. err	Estimate	Std. err	Estimate	Std. err	Estimate	Std. err
Intercept	−5.158	1.052	−7.097	2.445	−8.088	0.536	−9.843	1.161
LN(ADT)	0.484	0.115	0.491	0.267	0.843	0.055	0.838	0.119
Inside Shoulder Width	NA	NA	NA	NA	−0.063	0.024	--	--
Curve Radius	0.505	0.194	0.689	0.502	--	--	--	--
Skid Number	−0.007	0.005	−0.034	0.013	−0.004	0.003	−0.0274	0.007
Annual Prec.	--	--	--	--	0.003	0.003	0.0140	0.007
Dispersion	4.192	5.089	1.186	2.636	2.388	0.511	0.676	0.215
AIC	1381		387		4767		1637	

Note: NA= not applicable; -- = calibration coefficient is highly insignificant

The annual crash fatal-and-injury frequency for horizontal curves on four-lane undivided highways is obtained by combining Equation 2 with the coefficients in Table 3 as follows:

$$\mu = L \times y \times e^{-5.158} \times F^{0.484} \times CMF_R \times CMF_{SK} \quad (13)$$

with:

$$CMF_R = 1 + 0.505(0.147V)^4 \frac{(1.47V)^2}{32.2R^2} \quad (14)$$

$$CMF_{SK} = e^{-0.007(SK-40)} \quad (15)$$

The annual wet-weather crash frequency for horizontal curves on four-lane undivided highways can be estimated by the following equation:

$$\mu = L \times y \times e^{-7.097} \times F^{0.491} \times CMF_R \times CMF_{SK} \quad (16)$$

with:

$$CMF_R = 1 + 0.689(0.147V)^4 \frac{(1.47V)^2}{32.2R^2} \quad (17)$$

$$CMF_{SK} = e^{-0.034(SK-40)} \quad (18)$$

The annual crash frequency for horizontal curves on four-lane divided highways is obtained by combining Equation 2 with the coefficients in Table 3 as follows:

$$\mu = L \times y \times e^{-8.088} \times F^{0.843} \times CMF_{ISW} \times CMF_{SK} \times CMF_{AP} \quad (19)$$

with:

$$CMF_{ISW} = e^{-0.063(ISW-4)} \quad (20)$$

$$CMF_{SK} = e^{-0.004(SK-40)} \quad (21)$$

$$CMF_{AP} = e^{0.003(AP-30)} \quad (22)$$

where:

CMF_{ISW} = inside shoulder width crash modification factor.

ISW = inside shoulder width, ft.

The annual wet-weather crash frequency for horizontal curves on four-lane divided highways can be estimated by the following equation:

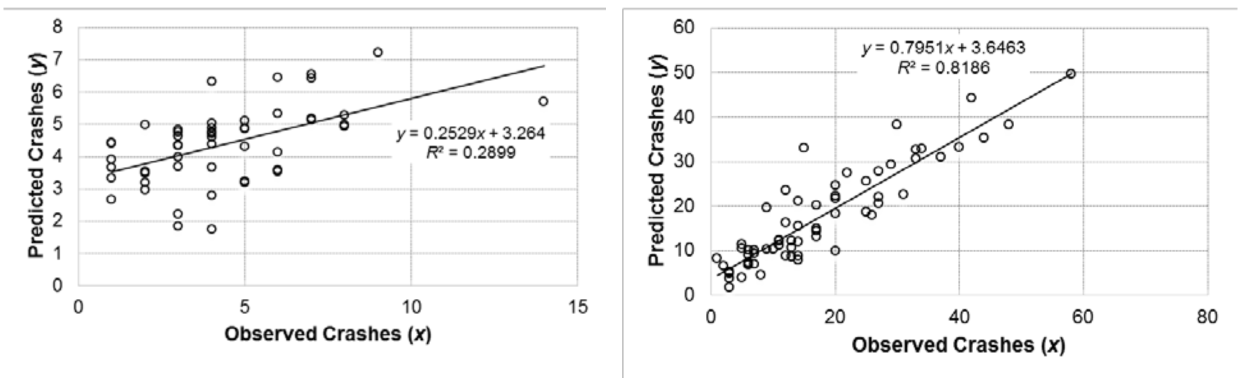
$$\mu = L \times y \times e^{-9.843} \times F^{0.838} \times CMF_{SK} \times CMF_{AP} \tag{23}$$

with:

$$CMF_{SK} = e^{-0.0274(SK-40)} \tag{24}$$

$$CMF_{AP} = e^{0.014(AP-30)} \tag{25}$$

Figure 3 shows the fit of the all crash model for four-lane undivided and four-lane divided horizontal curves. Figure 3a and Figure 3b compares the predicted and observed crash frequency in the calibration database for four-lane undivided and four-lane divided highways respectively. The data were sorted by ADT and combined into 50 groups for undivided highways and into 64 groups for divided highways. Each data point shown in Figure 3 represents the total predicted and total observed crash frequency in a particular group. The data shown in the Figure 3 indicate that the model may provide a biased estimate of expected crash frequency on undivided highways, whereas an unbiased estimate of expected crash frequency on divided highways.



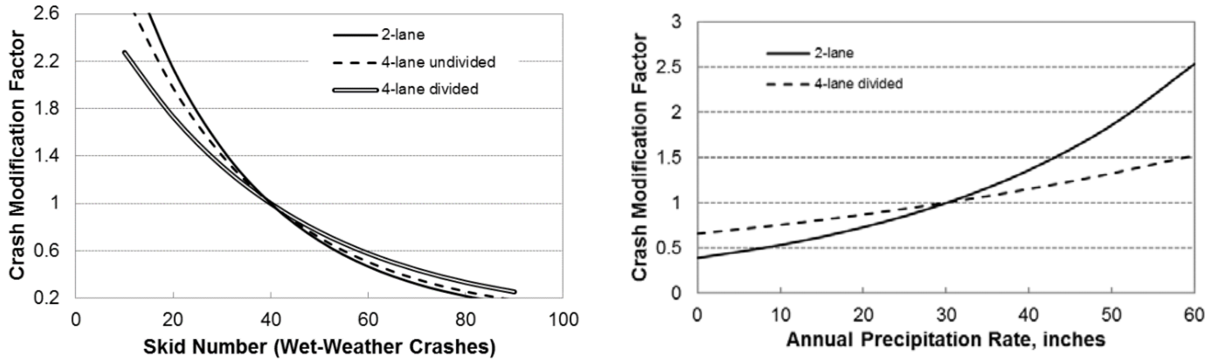
a) Undivided Highways

b) Divided Highways

Figure 3 Observed versus predicted crashes (four-lane horizontal curves).

DISCUSSION AND CONCLUSIONS

Figure 4 plots the skid number CMFs (Equations 11, 18, and 24) and annual precipitation (Equations , and) CMFs for the wet-weather crashes. The skid number CMF was found to be statistically significant for all highway types and the influence of skid resistance is much more notable for wet-weather crashes than all crashes together. The skid number CMF trends were similar across the different highway types. The annual precipitation CMF for four-lane undivided highways was not found to be statistically significant, mainly due to the small sample size. Thus, the comparison of annual precipitation CMF is shown for two-lane and four-lane divided highways only. For both highway types shown, higher annual precipitation results in an increase in wet-weather crashes, with a much more notable increase on two-lane highways compared to four-lane divided highways.



a. Skid Number CMF **b. Annual Precipitation CMF**

Figure 4 Skid number and annual precipitation CMFs for wet-weather crashes.

The safety trends shown by the CMFs for skid number and annual precipitation rate can be combined and applied to jurisdictions of interest. The wet-weather CMFs for skid number and annual precipitation rate for rural two-lane highways (Equations 11 and 12, respectively) are combined as follows:

$$CMF_{sk|ap} = CMF_{sk}CMF_{ap} = e^{-0.038(SK-40)}e^{0.031(p-30)} \quad (26)$$

$$SK = 0.816p - 26.316ln\left(CMF_{sk|ap}\right) + 15.526 \quad (27)$$

The $CMF_{sk|ap}$ quantity represents the proportional change in crash frequency that occurs in wet-weather conditions given the specified skid number. This quantity also represents the potential reduction in wet-weather crashes that can be achieved through the provision of increased skid resistance. For a given annual precipitation rate, the provision of higher skid resistance would mitigate the increase in crashes that can be attributed to wet weather.

The authors examined the distribution of the $CMF_{sk|ap}$ quantity across two-lane highway curves statewide using a methodology similar to that described by Long et al. (*15*). This methodology is summarized as follows:

1. Generate a list of the state's roadway sections, sorted in ascending order of skid number.
2. Determine the cumulative distribution of crash counts across the roadway sections.
3. Determine the cumulative distribution of lane-mileage across the roadway sections.
4. For each skid number value from 0 to 100, compute a crash rate ratio (CRR) as the total crashes for the skid number (from step 2) divided by the total lane-mileage for the skid number (from step 3).
5. Define threshold CRR values to indicate whether a roadway section of interest should be considered for a pavement friction treatment.

Long et al. (*15*) defined the CRR thresholds in the second column of Table 4 based on the input of an Expert Working Group consisting of pavement expert practitioners within Texas Department of Transportation (TxDOT). The CRR values are interpreted as follows:

- CRR ≥ 3: Consider short-term treatment action to improve skid resistance.
- 2 ≤ CRR < 3: Conduct detailed project-level testing to determine if a treatment to improve skid resistance is needed.
- 1 ≤ CRR < 2: Vigilance is recommended to identify possible issues with skid resistance and crash frequency.
- CRR < 1: Improving skid resistance may have little effect on reducing crash frequency.

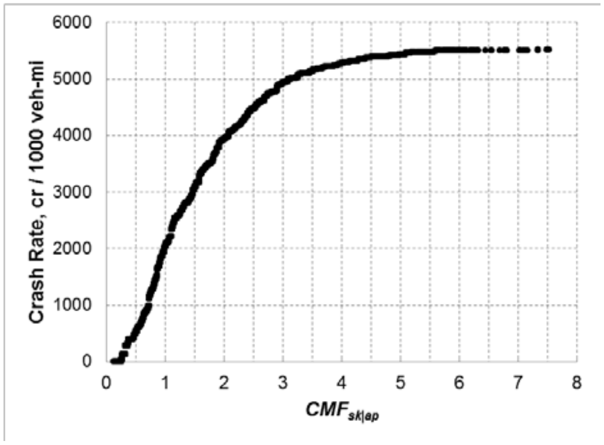
Table 4 CRR and Skid Resistance Thresholds (Source: *15*).

Skid Resistance Level	Corresponding CRR Value	Suggested Threshold *SK* value	
		All Crashes	Wet-Weather Crashes
SK_1	3	14	17
SK_2	2	28	29
SK_3	1	74	74

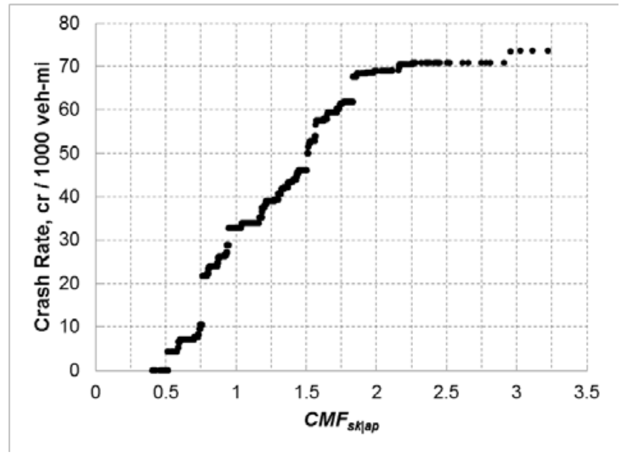
Long et al. (*15*) acknowledged that their guidance can be augmented by incorporating weather data into the methodology, since pavement friction treatments have the greatest effect on wet-weather crashes. Based on these findings and recommendations, the researchers examined the distribution of the $CMF_{sk|ap}$ quantity across Texas' rural highway curves. Figure 5 shows crash rate (in terms of crashes per 1000 vehicle-miles) as a function of the $CMF_{sk|ap}$ quantity. This trend was developed using the same set of curves that comprised the safety model calibration data set. The crash rate is used as the *y*-axis variable to account for both crashes and exposure (i.e., volume and length) and plotted after sorting the curves in ascending order of $CMF_{sk|ap}$. The $CMF_{sk|ap}$ quantity accounts for both skid resistance and wet weather exposure. Due to the smaller sample size of curves for four-lane highways, the trends are not as clearly defined as that for two-lane highways. However, all three figures show a general trend of increasing $CMF_{sk|ap}$ values as crash rate increases. This trend is intuitive because wet-weather crashes are expected to increase as exposure to wet weather increases or skid resistance decreases.

Hence, for the purpose of conducting a planning-level analysis to identify candidate sites for pavement friction treatments, the researchers recommend the thresholds documented in Table 5. These thresholds are identified based on the key breaking points on the preceding distributions (Figure 5) and extension of the judgment of the Expert Working Group that advised Long et al. (*15*). For all three roadway types, the first threshold is $CMF_{sk|ap}$ = 1. The second threshold is $CMF_{sk|ap}$ = 2.5 for two-lane highways and 1.5 for four-lane highways, based on the knees of the distribution plots. The third threshold is $CMF_{sk|ap}$ = 4 for two-lane highways and $CMF_{sk|ap}$ = 2 for four-lane highways. The thresholds are described as follows:

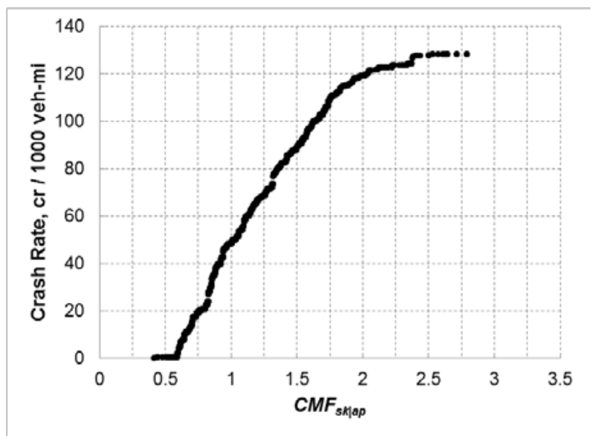
- If a curve has a $CMF_{sk|ap}$ value below the first threshold (1 or less), its skid resistance is likely high enough to mitigate crash risk in wet-weather conditions.
- If a curve has a $CMF_{sk|ap}$ value between the first and second thresholds, it may represent an elevated risk for wet-weather crashes, so it should be monitored. If actual crash data reveal an elevated number of wet-weather crashes at the curve, or if the curve is located on a roadway section that is on the WSCRP location report for the district, it should be analyzed further to determine the potential benefit of a pavement friction treatment.
- If a curve has a $CMF_{sk|ap}$ value between the second and third thresholds, it should be analyzed further to determine the potential benefit of a pavement friction treatment.
- If a curve has a $CMF_{sk|ap}$ value above the third threshold, it should be considered a high priority for implementation of a pavement friction treatment.



a) Two-Lane Highways



b) Four-Lane Undivided Highways



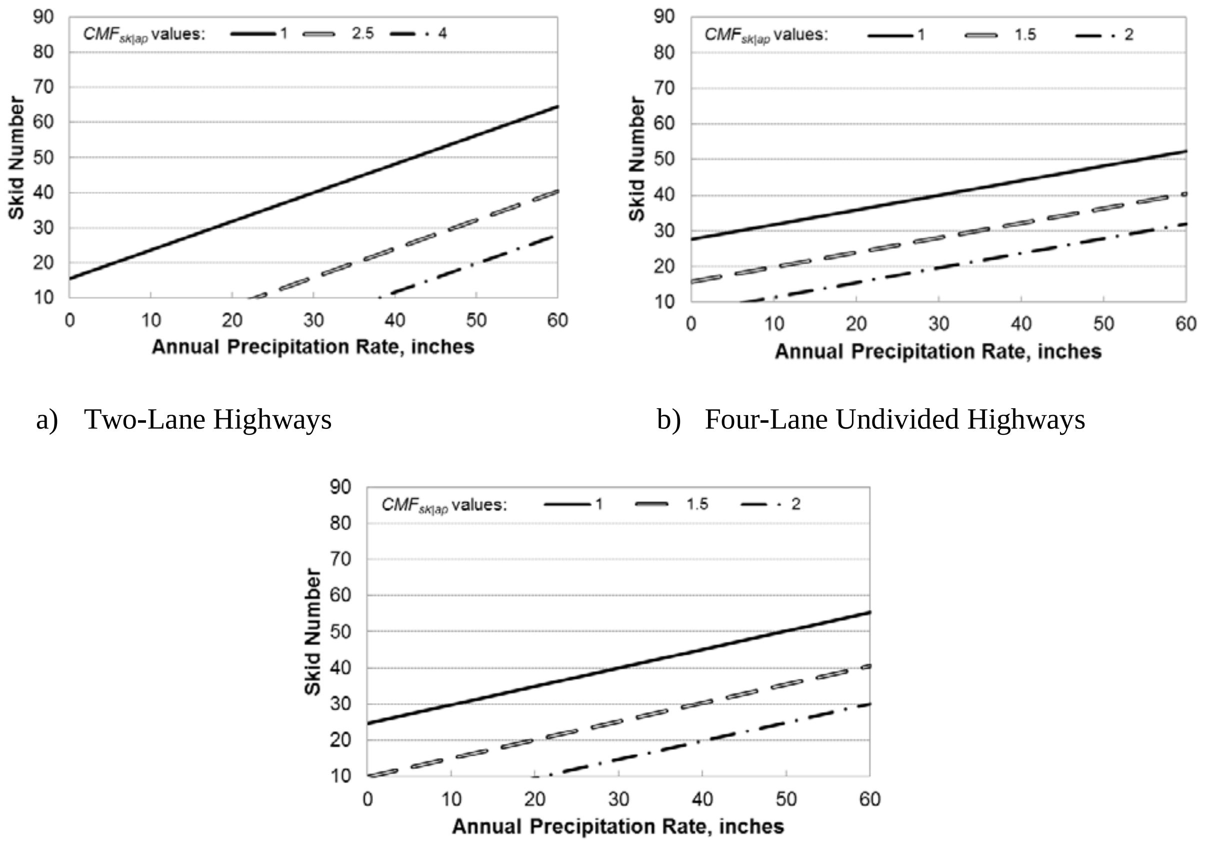
c) Four-Lane Divided Highways

Figure 5 Distribution of Combined CMF Values and Crash-to-Length Ratios.

Table 5 Recommended Combined CMF Thresholds.

Description	**Combined CMF Range by Roadway Type**		
	2-Lane	**4-Lane Undivided**	**4-Lane Divided**
Friction treatments will not likely yield cost-effective wet-weather crash reduction	$CMF_{sk\|ap} \leq 1$	$CMF_{sk\|ap} \leq 1$	$CMF_{sk\|ap} \leq 1$
Monitor the curve for elevated wet-weather crash frequency	$1< CMF_{sk\|ap} \leq 2.5$	$1< CMF_{sk\|ap} \leq 1.5$	$1 < CMF_{sk\|ap} \leq 1.5$
Conduct a detailed analysis to determine potential benefit of a friction treatment	$2.5 < CMF_{sk\|ap} \leq 4$	$1.5 < CMF_{sk\|ap} \leq 2$	$1.5 < CMF_{sk\|ap} \leq 2$
The curve is a high-priority location for a friction treatment	$CMF_{sk\|ap} > 4$	$CMF_{sk\|ap} > 2$	$CMF_{sk\|ap} > 2$

Figure 6 shows a nomograph that represents Equation 27 plotted with $CMF_{sk|ap}$ values of 1, 2.5, and 4. Since an annual precipitation CMF could not be developed for four-lane undivided highways, the nomograph represents a combination of the skid number CMF for four-lane undivided highways and the annual precipitation CMF for four-lane divided highways. The four regions on the nomograph represent the four thresholds and their descriptions in Table 5. The nomograph provides a visual tool that allows the analyst to consider both variables (skid number and annual precipitation rate) that are needed to determine the $CMF_{sk|ap}$ value and evaluate the curve. As shown, a curve is more likely to be identified as a priority for pavement friction treatment if its skid number is low and/or if its annual precipitation rate is high. The contour lines for four-lane highways have smaller slopes than the lines for two-lane highways, suggesting that skid resistance has less of an influence on wet-weather crash frequency on four-lane highways compared to two-lane highways. Much of this difference is attributable to the differences in the annual precipitation CMFs for these two roadway types.



a) Two-Lane Highways

b) Four-Lane Undivided Highways

c) Four-Lane Divided Highways

Figure 6 Combined Skid Number and Annual Precipitation Rate Nomograph.

In addition to the combined CMF values shown in the nomographs, it is important to consider the total number of wet-weather crashes predicted at curves of interest. Wet-weather crash frequency can be estimated using the SPFs described by Equations 9, 16, and 23. The following observations are made based on the expected crashes estimated from the SPFs:

- For typical two-lane highway curves, such as those on FM roads, traffic volumes are sufficiently low that the total predicted number of wet-weather crashes is small and so these curves are a low priority for pavement friction treatments.

- Higher-volume curves, such as those on state or U.S. highways, will experience a larger number of wet-weather crashes, such that pavement friction treatments are more likely to be beneficial on these curves.
- Curves on four-lane highways (both divided and undivided) are also more likely to experience notable numbers of wet-weather crashes, so these curves are more likely to benefit from pavement friction treatments.

Table 6 shows skid number values that correspond with the high-priority threshold $CMF_{sk|ap}$ values and the annual precipitation rates for two example locations. Curves with skid numbers below those in Table 6 would be considered high priority in these locations. The skid number thresholds suggest that Location A, which experiences low precipitation, pavement friction treatments are likely to be cost-beneficial only curves with very low skid numbers. Conversely, in Location B, which experiences high precipitation, pavement friction treatments are likely to be cost-beneficial on many curves.

Table 6. Skid Number Thresholds for High-Priority Sites in Selected Locations.

Roadway Category	Skid Number Threshold (Annual Precipitation Rate)	
	Location A (15 in./yr)	Location B (60 in./yr)
Two-lane highways	Negligible	28
Four-lane undivided highways	13	32
Four-lane divided highways	7	30

This analysis is precise within the chosen data aggregation period of one year. Safety prediction models developed for annual crash prediction can mask the safety effects of variables that fluctuate within a year, such as precipitation rate, so the analyst must consider the fluctuation that may occur within the year. There is a need to explore functional forms of crash prediction methods using representing short-term roadway conditions to better account for these variables and understand short-term fluctuations in highway safety performance.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm the contribution to the paper as follows: study conception and design: Michael Pratt, Srinivas Geedipally, and Subasish Das; data collection: Srinivas Geedipally, Subasish Das, and Michael Pratt; analysis and interpretation of results: Srinivas Geedipally, Michael Pratt, Subasish Das, and Dominique Lord; draft manuscript preparation: Srinivas Geedipally, Subasish Das, Michael Pratt, and Dominique Lord. All authors reviewed the results and approved the final version of the manuscript.

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