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Research Article

Analysis of Nonsevere Crashes on Two- and Four-Lane Urban and Rural Highways: Effects of Wet Pavement Surface Condition

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This study examines the effects of wet pavement surface conditions on the likelihood of occurrences of nonsevere crashes in two- and four-lane urban and rural highways in Alabama. Initially, sixteen major highways traversing across the geographic locations of the state were identified. Among these highways, the homogenous routes with equal mean values, variances, and similar distributions of the crash data were identified and combined to form crash datasets occurring on dry and wet pavements separately. The analysis began with thirteen explanatory variables covering engineering, environmental, and traffic conditions. The principal terms were statistically identified and used in a mathematical crash frequency models developed using Poisson and negative binomial regression models. The results show that the key factors influencing nonsevere crashes on wet pavement surfaces are mainly segment length, traffic volume, and posted speed limits.

1. Introduction

According to FHWA report [1], 12.6 percent of the total accidents for the ten-year period between 2000 and 2009 in the United States occurred on wet roadway pavement condition with insufficient pavement friction. Based on this report, until 2009, eight states have implemented successful and formal wet weather crash program to reduce the crash associated with wet pavement skidding. These states were California, Florida, Kentucky, Maryland, Michigan, New Jersey, New York, and Virginia. The procedures followed by each state to identify and mitigate wet crash locations were different. For instance, State of California uses the statistical relationship to evaluate the number of crashes required for significance average wet crash rate and identify wet weather crash locations based on Poisson's distribution one-tail test for 99.5 percent confidence interval. The statistical analysis considers the average number of crashes, ADT, the length of the highway segment under consideration (typically 0.2 mile), analysis period, the percentage of the wet time, and weather condition. In the State of Florida, wet weather crashes locations were identified using five years of crash data. For a site to be considered as wet weather crash location, out of a minimum of four wet weather crashes, at least 25% are due to wet weather or 50 percent of the crashes in that specific segment for the last five years have to be wet weather-related. In the State of Virginia, a location is classified as a potential wet accident hotspot (PWAH), if a minimum of three wet weather crashes were reported with at least 20 percent of which were more than the ratio for all roads in the area. Kentucky adopts a minimum of eight crashes, and at least 35 percent of the crashes in that location were wet pavement related crashes. In New York State, a location is designated as wet weather crash location if a minimum of six (in rural locations) and ten (urban areas) wet weather crashes with a minimum of 35 percent of the crash are in the specific segment for at least two years.

2. Literature Review

The impact of wet pavement on highway crash involves the drivers' behavior and condition, the vehicle, pavement surface, environmental and geometric characteristics of the road,

travel speed, visibility, the drivers' behavior, and other conditions. The relationship between these factors and integration of these variable makes wet pavement related crash a complex problem to solve [2, 3]. El Halim et al. [2] reported the results of four statistical models: exponential, logarithmic, power-based, and linear based models. The variables considered included regions, collision severity classes (fatal, injury, and property damage), pavement surface (dry, ice, snow, and wet), environment (clear, drifting snow, fog, freezing rain, rain, snow, and wind), visibility (clear, fog, rain, and snow), and roadway location (intersection, mainline, off the road, and shoulder). Based on the findings of the analysis, one model which was used to best fit the data for one of the road surface conditions may result in low correlation for the other variables. For instance, the logarithmic model was found to best fit wet surface condition with an R^2 value of 0.822 whereas exponential model best fits dry and snow road surface conditions with R^2 values of 0.855 and 0.900, respectively [2]. Recently, Leard and Roth [4] studied the impacts of snowfall, rainfall, and temperature on the three types of accidents: property damage only (PDO), injury, and fatality were analyzed. A Poisson regression model was used to predict the frequency of PDO weather-related accidents, injuries, and fatalities; and a linear probability model was used to model the relationship between weather variation and fatality rates. To account for deferred travel arrangements, the model included lag variables for weather and temperature. Based on the regression results, there was about a 97% increase in PDO accidents during the coldest day as compared with 50°F temperature. Similarly, it was found that a 3 cm rainfall and snowfall of 3 cm per day increases the PDO accident by 18.8% and 43.3%, respectively, as compared with days without rainfall event.

Using a five-year data from 2004 to 2009 obtained from Wisconsin DOT (Department of Transportation) crash database, Jung et al. [5] used negative binomial regression and sequential logistic regression for statistical modeling of crash frequency and crash severity, respectively. The study found that high rainfall and less sunlight in winter, the existence of off-ramp, and change in left lane width increased multivehicle crash. On the other hand, it was shown that wet pavement crash decreased due to the drivers paying more attention as a result of low visibility during strong wind and rainfall. It was also reported that rainfall crash severity is low on Mondays and Fridays due to commuting peak hour traffic which makes the driver more cautious as well. However, Levine et al. [6] reported that, in Honolulu, low accident rates were reported on Fridays.

Dense-graded pavements and wider roadway sections were reported to be more favorable to produce hydroplaning-crashes [7]. To reduce wet pavement crashes, Florida Department of Transportation limits the maximum number of lanes in one direction with a cross slope in one direction to three lanes. If the design requires wider than three lanes in one direction, the cross slope of the inner lane will be toward the median. The hydroplaning related crash analysis was based on the data obtained from the Florida Department of Transportation Crash Analysis Reporting System (CARS) database. The roadway sections considered were sections with "standing water." During peak hours, the driving speed was usually low which reduces the chances of a hydroplaning crash. Based on this study, during light rainfall (≤0.025 cm/hr) with visibility of 1500 ft, for a free-flow speed of 70 mph, the speed reduction reported was in the range of 1.4 mph to 6.4 mph. During heavy rainfall, for FFS and visibility, the speed reduction reported ranges from 3.7 mph to 20.3 mph. As a result, the analysis excludes the off-peak period crash data. Wet weather crash data at intersections, on curves and superelevated sections, were not considered due to other contributing factors to crash. The analysis was made to determine the correlation of wet weather crashes to pavement conditions (rutting, cracks, International Roughness Index), pavement surfaces (open graded friction course, dense-graded asphalt, Portland cement concrete, and dense-graded asphalt concrete), and interlane hydroplaning potential of multilane facilities. The study concluded the following: (i) the impact of pavement rutting and cracks in weather-related crash is insignificant; (ii) the International Roughness Index (IRI) of the pavement surface was found to have a significant impact on wet weather crash [7]; (iii) on multilane highways, in general, the higher the travel speed in any lane, the higher the hydroplaning related crash; and (iv) the hydroplaning related crash on dense-graded asphalt surface for two- and three-lane highway was higher than the crash rate on Portland cement concrete.

Another work by Villiers et al. [8] in cooperation with the State of Florida DOT, used a driving simulator for evaluating drivers behavior to hydroplaning and recommended the safe speed limits during rainfall events for two categories of rainfall: light intensity rainfall (0.025-0.635 cm/hr) and heavy rainfall (rainfall intensity ≥0.635 cm/hr). The study was conducted on six Florida highway sections with 55 mph or higher posted speed limit and segments close to airport locations where rainfall data from NOAA's rain gauge stations could be utilized. They found that heavy rain which reduces visibility was the prime cause of operating speed reduction. Based on the study, the average speed reductions due to light and heavy rainfall were 2 mph and 5 mph, respectively. During nighttime rainfall events, 8 mph drop in speed was reported.

Chan et al. [9] used the 2006 Tennessee accident database collected from 55 mph posted speed limit divided interstates to calibrate regression models to predict the relationship between crash frequency and pavement conditions (mainly pavement distress) in the State of Tennessee for daytime, nighttime, different weather conditions (normal and rainy), peak hour, and nonpeak hour accidents. The variables used in the negative binomial regression model were rut depth (RD), present serviceability index (PSI), and IRI. The results found that only 20% of the accidents occur during rainy weather condition and about 77% of the accidents happened during normal weather condition, and IRI and PSI were found to be key predictive factors.

Another possible factor which influences traffic accident on wet pavements is pavement skid resistance. To determine the quantitative relationship between pavement skid resistance and crash risk, Wu et al. [10] used a method called Crash

Rate Ratio (CRR) and developed CRR-SN model (curve), which could be used at the network level. They claimed that the CRR-SN has several benefits over the general regression models. Some of the advantages mentioned include ease of model calibration and a better quantitative relationship between skid resistance and crash risk for the data. Several earlier studies reported that there was a clear relationship between rainfall intensity and traffic volume. As the rainfall intensity increases, the traffic volume tends to decrease [11]. The report indicated a reduction of 1.86 and 2.16 percent in traffic volume on rainy days in winter and spring, respectively. At nighttime the reduction in traffic volume in winter and spring was 0.87 and 2.91 percent. Levine et al. [6] suggested that rainfall traffic increases accidents which were not only due to the weather but also as a result of the fluctuations on the daily traffic accident count resulting from the interaction between the weather and traffic volume, and other variables such as weekday versus holiday were influencing factors. One interesting finding by the team was that the interaction effect between the rainfall and the time of the day, specifically the afternoons, elevates the crash count. Another finding by the same team was that, in Honolulu, Hawaii, more accidents occurred on Fridays and Saturdays than the other days of the week. However, the observation on Fridays does not agree with another study by Jung et al. [5], which claimed that Mondays and Fridays had the lowest crash rate in Wisconsin.

One of the other factors elevating traffic accidents during rainfall is visibility. As the rainfall intensity increases, the drivers' visibility decreases, which in turn increases the crash risk [12–15]. Based on these studies, the influence of rainfall intensity on drivers' visibility was associated with the water film on the windshield [16], the condition of the wipers, and splash from one vehicle to another. The other major factor reducing the visibility of the drivers was the interaction between rainfall intensity and vehicle speed [13]. Traffic accidents were found to be significantly higher on the first day of rainfall occurring after a prolonged period of dry weather [11, 17]. One of the reasons suggested was the existence of road grime accumulated on the pavement surface, which created a slippery surface. Sudden onset of rainfall especially on the first day of the rainfall event significantly increased the traffic accident count as compared with the second and third day of the rainy days [6].

Negative binomial regression model has been extensively used in traffic safety studies. However, recent studies suggest that Generalized Warning (GW) model, which is based on Generalized Warning distribution [18] outperforms the traditional negative binomial model in terms of providing both a better fit and information on crash variances. On the other hand, Ma et al. [19] compared the adequacy of Tobit model with hurdle models developed using Poisson, Gamma, Weibull, and lognormal distributions. The study found that the lognormal hurdle model with flexible scale parameter is superior to the other models. More recently, Ye et al. [20] proposed seminonparametric (SNP) Poisson model which accounts for unobserved heterogeneity in crash data. Using ten years of crash data collected from California rural roads, the authors suggested that the overall performance of SNP-Poisson model is better than the traditional negative binomial model. The remainder of the paper is organized as follows. The next section covers a review of the literature on traffic safety modeling and crash contributing factors, followed by the methodologies adopted for extracting and preparation of dataset used for crash analysis and the investigation of the effects of wet pavement surface conditions on traffic accidents. Next, the Results and Discussion presents the results of the statistical analysis with the discussions. Finally, the key findings of the research are summarized and concluding remarks are provided.

3. Methodology

The study area covers a wide range of locations in the State of Alabama. For model formulation and comparison of crash rates recorded during normal weather condition (dry pavement) with crash rate occurring on wet pavement surface condition, the crash record of the State of Alabama route system, ranging from 2010 to 2014, was extracted from Critical Analysis Reporting Environment (CARE) managed by the Center for Advanced Public Safety (CAPS) at the University of Alabama and was used. The selected segments represent different geographic locations and counties in the State, excluding intersection areas, bridge locations, and ramps. The crash data from CARE have a detailed information on the location, day of the week, time of the day, speed limit, surface condition of the pavement (wet, dry), visibility, the number of vehicles involved, if the accident was at intersection or not, the distance from intersection, and more. However, it does not include information on the traffic volume, roadway data like horizontal and vertical curvatures, superelevation, and pavement roughness conditions. Other variables, including AADT (annual average daily traffic), the percentage of trucks, IRI, pavement rutting, grade, and cross slope were linked to the CARE data. After combining the two datasets, explanatory factors essentially considered for further analysis were filtered. The scope of this study was to analyze the nonsevere crashes on two- and four-lane urban and rural highways in Alabama. With this in mind, the data were prepared as follows. As the majority of the crashes occurred on two- and four-lane rural and urban highway segments, the data for these sections were filtered, excluding three-, five-, and six-lane crash data. The crash data recorded on freeway segments and at intersections were also excluded from the analysis.

The number of crash counts within the segments were converted to crash rates using AADT and vehicles-miles-traveled (VMT) for each roadway segment using the Federal Highway Administration guideline [21]: $R = (C \times 10^8)/(AADT \times 365 \times N \times L)$; and $VMT = AADT \times 365 \times L$. Here, R is roadway crashes rate for the segment expressed as crashes per 100 million vehicle- miles of travel; C is crash count for the segment; N is number of years of data; and L is length of roadway segment.

Analysis of individual highways and tests of homogeneity of the routes for combining the crash data of individual highways have rarely been reported in the literature. To create a homogenous highway section, Cafiso and Graziano [22] and Thomas [23] used the comparison of the mean values

of individual segments. The approach used t-test statistics to determine the statistical significance of the differences between the mean values of the adjacent highway segments. The highway segments with statistically insignificant differences in the mean values were aggregated and used for further analysis. In this study, the approach adopted was to combine the crash data of the homogenous segments and examine the statistical significance of each of the categorical variables independently across the dummy coded groups. These included the number of lanes (two versus four), the significance of urban versus rural sections of the segments under considerations, the lighting (dark or light), and weather (rainfall or normal) condition. Initially, sixteen rural and urban state highways (AL 001 to AL 017, except AL 011) representing the major geographic locations of the State of Alabama were selected. Since the crash data for three-, five-, and six-lane urban and rural highways were insignificant as compared with the two- and four-lane highways, these crash data were excluded from the analysis. Here it is well understood that highways with different roadway geometric features and traffic characteristics may yield similar crash rates. However, the variables such as the traffic volume, the geometric design elements of the highways, and the environmental factors considered in the modeling and analysis of the individual segments considered, where the crash rates were observed, were assigned corresponding to each data point within the individual segment length. The relationship between the explanatory variables and the crash rates for each data point is estimated using their respective explanatory factors as independent variables in the negative binomial regression model.

In order to identify the homogenous highways with similar characteristics in terms of homogeneity of variances, equality of means, and similarity in distribution of the data, the crash data were tested with respect to the following three null (H_o) and alternate (H_1) hypotheses. (1) H_o: the mean crash rates for each highway were the same; H1: at least one of the highways was different; (2) H_o: the variances of the highways were equal; H1: at least one of the highways had different variance; (3) H_o: the distributions of crash rates were the same across the highways; H1: at least one highway had different distribution of the crash rate. Equality of means of the crash rates across the sixteen highways was tested using Welch's test followed by Games-Howell simultaneous test for differences of means (*post hoc* test). As the data were not normally distributed, a test of homogeneity of variances was performed using nonparametric Levene's test. Independent samples Kruskal-Wallis test was used to test the similarity of the distributions of the crash data across the different highways.

Initially, fourteen candidate engineering, environmental, and traffic conditions influencing the crash rates were identified. The variables selected include segment length, AADT, TADT (truck average daily traffic), grade, IRI, rut depth, macrotexture, cross slope, number of lanes, posted speed limit, urban/rural designation of the segment, and weather (rainfall/normal), lighting (dark/light), and pavement surface condition (wet/dry). To determine the impact of the categorical variables and ascertain the significance of the differences in the means, variances, and distributions of the crash rates across the categories of the individual variable, statistical tests were performed with respect to the null and alternate hypothesis described above. For the crash rates whereby the categories of the variable were statistically significant, the categorical variables were retained by assigning dummy codes 0 and 1. For the crash rates which were not statistically significantly different across the assigned categories, it is suggested that there was no need to include the variable as a predictive variable. The categorical variables used to test the crash rates across the categories include urban versus rural sections, two lanes versus four lanes, dark versus light, rainfall versus normal weather, dry versus wet pavement conditions.

Traffic crash data are characterized as count data mostly following overdispersion distribution [24, 25]. To address the overdispersion of the count data, mixed-Poisson regression model such as a negative binomial or Poisson-gamma model whereby the mean of the Poisson follows a gamma distribution is widely utilized. Due to this, the mixed-Poisson regression model such as negative binomial regression model (a mixture of Poisson-gamma distribution) has been widely used for analyzing highway crashes [25–28]. However, there were cases where crash data follow an underdispersed distribution. For such distribution and when the sample mean of the distribution is low, the negative binomial model performs poorly as well [26]. For the negative binomial distribution described by the parameter, μ, the mean of the distribution is given by $\ln(\mu_i) = \beta_0 + \sum_j x_{ij}\beta_j + \varepsilon$ [25, 26]. The models developed were evaluated by using goodness-of-fit tests including, Deviance, Log Likelihood, Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC).

4. Results and Discussions

Using the tests outlined in the methodology section, for dry and wet pavement conditions, out of the sixteen highways initially considered, eight and ten of the highways, respectively, were found to be homogenous and are not found to be statistically significantly different in their mean values, variances, and distributions of the crash rates (Tables 1 and 2). Hence, the homogenous highways shown in these tables were combined to form two different datasets one representing the dry pavement crashes and another one representing wet pavement accidents. To combine the dry and wet pavement crashes, the common six routes from each group were selected (Table 3) and dummy coded to identify the dry and wet pavement crashes forming a single crash dataset for the aggregate data. Based on both Shapiro-Wilk (S-W) and Kolmogorov-Smirnov (K-S) tests of normality, all the crash rate at the individual and combined routes were not normally distributed at a significance level of $\alpha = .001$. Similar descriptive analyses and test of normality of the crash data across the categorical variables were performed for dry and wet weather and aggregate datasets and presented in Tables 4, 5, and 6, respectively.

To determine whether crash rates across the categorical variables were significantly different or not, statistical tests including tests of homogeneity of variances, equality of

Table 1: Descriptive statistics of the nonsevere crash rates occurring on dry pavement surfaces and tests of normality for the selected eight routes.

Route ID	Length (mi)	‡N	Mean	St. Dv.	Normality Test		
					Skewness	Kurtosis	*Sig.
AL 001	353	420	481	694	2.751	8.940	0.001
AL 005	198	161	364	551	3.698	21.575	0.001
AL 006	240	172	375	509	2.813	10.802	0.001
AL 008	218	141	371	456	2.381	7.048	0.001
AL 010	231	122	345	579	4.327	22.885	0.001
AL 012	232	170	368	545	3.133	11.862	0.001
AL 016	77	84	480	695	2.730	9.350	0.001
AL 017	347	178	357	522	4.424	28.303	0.001
¥Combined	1896	1448	405	592	3.223	13.629	0.001

*Significance level for both S-W and K-S tests, with the level of significance <0.01. ¥All routes combined. ‡Number of segments.

Table 2: Descriptive statistics of the nonsevere wet-weather crash rates and tests of normality for the ten selected routes.

Route ID	Length (mi)	N	Mean	St. Dv.	Normality Test		
					Skewness	Kurtosis	Sig.
AL 001	353	408	64	81	1.529	1.784	0.001
AL 003	374	347	70	85	1.217	0.577	0.001
AL 004	192	101	75	88	1.000	0.008	0.001
AL 005	198	152	67	91	1.468	1.294	0.001
AL 006	240	161	50	69	1.830	3.924	0.001
AL 010	231	131	59	82	1.667	2.213	0.001
AL 012	232	170	55	79	1.624	2.036	0.001
AL 014	218	135	69	77	1.189	0.944	0.001
AL 015	227	98	69	84	1.215	0.971	0.001
AL 016	77	69	69	94	1.424	1.101	0.001
Combined	2342	1772	68	82	1.417	1.341	0.001

Table 3: Descriptive statistics of the nonsevere aggregate (dry and wet) crash rates and tests of normality for the ten selected routes.

Route ID	Length (mi)	N	Mean	St. Dv.	Normality Test		
					Skewness	Kurtosis	Sig.
AL 001	353	774	164	224	2.051	4.290	0.001
AL 005	198	296	157	238	2.261	5.202	0.001
AL 006	240	317	154	226	2.233	5.161	0.001
AL 010	231	244	141	197	2.131	4.745	0.001
AL 012	232	325	145	206	2.347	6.419	0.001
AL 016	77	142	181	262	1.799	2.529	0.001
Combined	1331	2098	157	224	2.149	4.750	0.001

Table 4: Descriptive statistics of the nonsevere crash rates occurring on dry pavement surfaces across the categorical variables and tests of normality for the selected eight routes.

Variable		N	Mean	St. Dv.	Skewness	Kurtosis	Sig.
Rural/Urban	Rural	712	278	439	4.922	31.890	0.001
	Urban	736	527	688	2.496	8.285	0.001
No. of Lanes	Two	732	422	610	4.092	25.215	0.001
	Four	716	386	573	2.672	8.533	0.001
Lighting	Dark	434	332	440	2.866	10.970	0.001
	Light	1014	435	644	3.113	12.255	0.001
Weather	Cloudy	293	412	648	3.973	20.168	0.001
	Clear	1155	403	577	2.944	10.889	0.001

Table 5: Descriptive statistics of the nonsevere wet-weather crash rates across the categorical variables and tests of normality for the selected ten routes.

Variable		N	Mean	St. Dv.	Skewness	Kurtosis	Sig.
Rural/Urban	Rural	810	56	73	1.606	2.341	0.001
	Urban	962	72	87	1.253	0.678	0.001
No. of Lanes	Two	936	60	80	1.458	1.545	0.001
	Four	836	69	85	1.371	1.126	0.001
Lighting	Dark	642	57	77	1.544	1.876	0.001
	Light	1130	68	85	1.347	1.076	0.001
Weather	Rain	1412	64	82	1.433	1.415	0.001
	No Rain	360	66	84	1.364	1.100	0.001

Table 6: Descriptive statistics of the nonsevere aggregate crash rates across the categorical variables and tests of normality for the ten selected routes.

Variable		N	Mean	St. Dv.	Skewness	Kurtosis	Sig.
Surface Cond.	Dry	1032	262	273	1.293	1.126	0.001
	Wet	1066	54	71	1.455	1.462	0.001
Rural/Urban	Rural	1022	133	180	2.326	7.048	0.001
	Urban	1072	179	256	1.890	3.024	0.001
No. of Lanes	Two	1084	167	235	2.088	4.193	0.001
	Four	1010	145	210	2.210	5.466	0.001
Lighting	Dark	683	137	196	2.281	5.816	0.001
	Light	1411	166	235	2.071	4.238	0.001
Weather	Rain	864	55	74	1.613	2.459	0.001
	No Rain	1230	228	262	1.509	1.829	0.001

means, and similarity in distributions across the categories were performed. For the crash rates which were not statistically significantly different, the result suggested that the particular categorical variable did not have any influence on the likelihood of the occurrences of crashes and hence needs to be excluded from further analysis. For those significantly different, the variable was retained, dummy coded, and used as categorical variables in the mathematical models.

In terms of evaluating the crash rate with respect to equality of mean, homogeneity of variances, and similarity in distribution across each of the categorical variables, we can see that for the accidents occurring on dry pavements (Table 7) the crashes that occurred on two-lane highways were found to have similar distribution (p-value=0.007) and significantly different means (p-value=0.927) and inhomogeneous variances (p-value=0.246). Similarly, the mean, variances, and distributions of crashes occurring during clear and cloudy weather conditions were not significantly different with p-values of 0.981, 0.829, and 0.814, respectively. However, the mean, variances, and the distributions of the crashes occurring in rural and urban sections of the highway segments and across the lighting condition (light versus dark) were significantly different, which warrants dummy coding and the inclusion of these categorical variables in statistical modeling. This indicates that the mean values, the variances, and the distributions of the crashes occurring during dark time driving was significantly different from the crashes occurring during nighttime driving with no lighting condition.

For crashes that occurred on wet pavement surfaces (Table 8), the mean, variances, and distributions of crashes occurring during rainfall condition and normal weather conditions were not significantly different with p-values of 0.573, 0.686, and 0.788, respectively. However, the mean, variances, and the distributions of the crashes that occurred in rural and urban sections of the highway segments and across the lighting condition (light versus dark) were significantly different, which suggests dummy coding and the inclusion of these categorical variables in statistical modeling. Test of homogeneity of variances across the number of lanes showed that the variances of crashes across the two- and four-lane highways were not significantly different (p-value = 0.305). However, the mean and distribution of the data across the categories were significantly different with a p-value of 0.029 and 0.004, respectively. This result also suggests the inclusion of a number of lanes as an explanatory variable in the model. The crash rate across the category of lighting, on the other hand, was found to be significantly different with respect to the variances (p-value = 0.021), the mean (p-value = 0.001), and the distribution (p-value = 0.008). The variances, the means, and the distribution of the crash rates across the categories of weather (rainfall versus normal weather condition) were not found to be significantly different, suggesting that the inclusion of this categorical variables was not necessary.

For the aggregate dataset consisting of dry pavement and wet weather crashes the mean, variances, and distributions of the crash data across the pavement surface conditions (wet

Table 7: Test for equality of mean, homogeneity of variances, and similarity in distribution of the dry pavement crashes across the categorical variables.

Variables		Levene's Test	Welch's Test	Kruskal-Wallis Test	Games-Howell Test
Rural/Urban	Test Stat.	70.430	67.450	49.500	8.210
	P-Value	0.001	0.001	0.001	0.001
No. of Lanes	Test Stat.	0.010	1.350	7.150	1.160
	P-Value	0.927	0.246	0.007	0.246
Lighting	Test Stat.	10.430	12.400	3.100	3.520
	P-Value	0.001	0.001	0.078	0.001
Weather	Test Stat.	0.000	0.050	0.060	0.220
	P-Value	0.981	0.829	0.814	0.820

Table 8: Test for equality of mean, homogeneity of variances, and similarity in distribution of the wet pavement crashes across the categorical variables.

Variables		Levene's Test	Welch's Test	Kruskal-Wallis Test	Games-Howell Test
Rural/Urban	Test Stat.	21.160	17.440	8.610	4.180
	P-Value	0.001	0.001	0.003	0.001
No. of Lanes	Test Stat.	1.050	4.800	8.510	2.190
	P-Value	0.305	0.029	0.004	0.028
Lighting	Test Stat.	5.350	17.440	6.730	2.720
	P-Value	0.021	0.001	0.008	0.007
Weather	Test Stat.	0.320	0.160	0.070	0.400
	P-Value	0.573	0.686	0.788	0.686

and dry) were all found to be significantly different at 0.001 level (Table 9). This warrants the inclusion of the pavement surface condition as a categorical variable in the model. Across the rural-urban designation of the segments and the lighting conditions, the means and variances appeared to be significantly different, but the distributions of the crash rates were similar. However, Games-Howell post hoc tests suggested that the pairs of the crash data across these categories belong to different groups. This again suggested the inclusion of these categorical variables in the model. Similarly, the crash rates across the number of lanes and weather were found to be significantly different.

The results of the final negative binomial models developed using the key variable identified were shown in Table 10. For wet pavement condition, the principal variables influencing the likelihood of occurrences of crashes were segment length (p-value = 0.001), AADT (p-value = 0.002), TADT (p-value = 0.001), and posted speed limits (p-value = 0.01). Other highway design parameters such as number of lanes, pavement cross slope, grade, IRI, rutting depth, and macrotexture of the pavement surfaces of the highway segments studied were not found to have significant impact on the occurrences of crashes on wet pavement surfaces, which agreed well with previous work by Li et al. [29]. The urban-rural designation of the segments, weather, and lighting conditions were not also the key factors associated with the crashes recorded on wet pavement surfaces.

For the aggregate dataset consisting of crashes recorded on both dry and wet pavement surfaces, it appeared that pavement surface condition (B=-1.624 and IRR = 0,197) was one of the significant factors (p-value =0.001) for the crash occurrence. The results of the analysis suggested that the likelihood of occurrences of the crash on wet pavement surface was 80.3 percent less than on dry pavement surfaces. Some of the possible explanations for this are as follows: (1) short exposure time on wet pavement as compared with dry pavement condition within a year; (2) drivers change in travel plan due to bad weather condition, which alters the traffic volume and reduces the likelihood of occurrences of accidents; (3) reduction in driving speed due to rainfall, visibility, and other factors associated with inclement weather conditions [7]; and (4) the case when the weather condition is not conducive and drivers tend to take appropriate precautions to avoid crashes [5, 30].

For the aggregate dataset, the key factors influencing traffic accidents were segment length, AADT, TADT, posted speed limits, and the pavement surface conditions all at a significance level of 0.001. As can be seen, the increase in segment length and AADT values increased the likelihood of occurrences of crashes. But, the more the number of heavy trucks on the segments is, the higher the posted speed limits decrease the likelihood of occurrences of crashes on the segments. For every unit increase in TADT (B = -0.035, IRR = 0.966) there was a likelihood of 3.4 percent decrease in the crash rate, which agrees with previous reports by Ma et al. [19] and Usman et al. [31]. Similarly, for every unit increase in the posted speed limit (B=-0.014, IRR=0.987) along the study segments, the crash rate reduces by 1.3 percent. This

Table 9: Test for equality of mean, homogeneity of variances, and similarity in distribution of the aggregate crashes across the categorical variables.

Variables		Levene's Test	Welch's Test	Kruskal-Wallis Test	Games-Howell Test
Pavement Surf. Cond.	Test Stat.	555.250	558.790	430.090	23.640
	P-Value	0.001	0.001	0.001	0.001
Rural/Urban	Test Stat.	33.140	22.330	1.580	4.730
	P-Value	0.001	0.001	0.209	0.001
No. of Lanes	Test Stat.	2.210	4.800	7.900	2.190
	P-Value	0.137	0.029	0.005	0.028
Lighting	Test Stat.	8.820	9.050	3.440	3.010
	P-Value	0.003	0.003	0.064	0.003
Weather	Test Stat.	381.900	478.790	293.590	21.880
	P-Value	0.001	0.001	0.001	0.001

Table 10: Estimated parameters for nonsevere crashes on two- and four-lane rural and urban highways using the significant variables.

Parameter	Wet-Pavement Crash			Aggregate Crash		
	Estimate	Sig.	IRR	Estimate	Sig.	IRR
Constant	4.74	0.001	114.3	6.112	0.001	451
Seg. Length	0.347	0.001	1.415	0.279	0.001	1.322
AADT	0.000021	0.002	1.000	0.00002	0.001	1.000
TADT	-0.044	0.001	0.957	-0.035	0.001	0.966
Speed Limit	-0.016	0.01	0.984	-0.014	0.004	0.987
Surface Cond.						
Wet=1	_	_	_	-1.624	0.001	0.197
Dry=0						
Disp. Coeff.	5.23			4.00		
Goodness-of-Fit Statistics						
AIC	15084			21350		
BIC	15117			21390		
LL	-7536			-10668		
Dev./DF	1.02			1.11		

DF=degree of freedom.

complies with the result suggested by Choi et al. [32]. Prior studies showed that, during heavy rainfall, the drivers tend to reduce their operating speed in the ranges from 3.7 mph to 20.3 mph [7]. During light and heavy rainfall, for a free-flow speed of 70 mph, the speed reduction reported was in the range of 1.4 mph to 6.4 mph and the range from 3.7 mph to 20.3 mph, respectively. This reduction in driving speed below the posted speed limits along the study segments could be one possible factor for the reduction of the chances of wet weather crash along the segments with higher posted speed limits. Rainfall intensity also has a relationship with traffic volume which is one of the influencing factors for traffic accidents. As the rainfall intensity increases, the traffic volume tends to decrease by 1.86 and 2.16% in winter and spring, respectively [11]. This is another potential factor for the lower crash rates on wet pavement surfaces as compared with the dry surface condition.

Based on the results shown in Table 10, a negative binomial model for nonsevere crashes that occurred on wet pavement (CR_w) as well as for the aggregate data consisting of both the crashes that occurred on dry and wet pavements (CR_a) per 100 million VMT can be represented by the following regression equations:

$$CR_w = \exp(4.74 + 0.347\ SL + 2.1x10^{-5}\ AADT - 0.044\ TADT - 0.016\ PSL).$$

$$CR_a = \exp(6.112 + 0.279\ SL + 2x10^{-5}\ AADT - 0.035\ TADT - 0.014\ PSL + 0.0\ DRY - 1.624\ WET).$$

Here, SL is segment length, PSL is posted speed limit, DRY is dry pavement surface, and WET is wet pavement surface.

The models developed were evaluated by using goodness-of-fit tests including Deviance, Log Likelihood, Akaike's Information Criterion (AIC), and the Bayesian Information Criterion (BIC). To assess the relative improvements of the models, the AIC and the deviance values of both the negative binomial model (NBM) and Poisson regression model (PRG) models (not shown here) for crashes occurring only on wet pavements (degree of freedom, DM=1767) and the aggregate crash data (DF=2088) were compared. The model with a smaller value of AIC indicates better model to approximate

the statistical fit to the crash rates [25]. The AIC and deviance values show sizeable drop indicating that, in both crashes, the negative binomial models show significant improvements over the Poisson models fitting the crash involvement rates on wet pavement surfaces as well as for the aggregate dataset including the crashes on dry and wet pavement surface conditions.

5. Conclusions

In this paper, the effect of wet pavement surface conditions on the likelihood of occurrences of nonsevere crashes in two- and four-lane urban and rural highways in Alabama was analyzed. The significance of fourteen explanatory variables including segment length, AADT, TADT, grade, IRI, rut depth, macrotexture, cross slope, number of lanes, posted speed limit, urban/rural designation of the segment, weather, lighting, and pavement surface condition was tested. The principal terms were statistically identified and used in a mathematical crash frequency models developed using negative binomial regression models. The performance of the models developed was evaluated using the goodness-of-fit test statistics such as AIC, BIC, Deviance, and Log Likelihood ratio tests. As can be seen from the goodness-of-statistics values, the negative binomial regression model developed for wet pavement condition has superior prediction power than the model developed using the aggregate dataset. The results show that the key factors influencing nonsevere crashes on wet pavement surfaces were mainly segment length, traffic volume, and posted speed limits. For the aggregate dataset consisting of dry and wet pavement crashes, the principal variables were segment length, AADT, TADT, posted speed limits, and the pavement surface conditions. In both models, geometric design elements such as grade, cross slope, and number of lanes of the highways and the urban-rural classification of the highways were not the critical factors contributing to the likelihood of occurrences of crashes. The results of the study will benefit stakeholders engaged in transportation safety in the State of Alabama.

Data Availability

The pavement, geometric elements of the highway, and the traffic volume data used to support the findings of this study were supplied by the Alabama Department of Transportation and cannot be made freely available.

Disclosure

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Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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