

Article

Modeling the Severity of Crashes in Rainy Weather by Driver Gender and Crash Type

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Abstract

Rainy weather conditions can have significant impact on the severity and frequency of traffic crashes. This study investigated factors that influence the severity of vehicle crashes during rainy weather in California. Data from 23,242 rain-related crashes in California were taken from the Highway Safety Information System (HSIS) database. The data was divided into 12 groups based on driver gender (male and female) and crash type (six categories: rear-end, hit object, sideswipe, overturned, head-on, and broadside). Each group was assigned a logistic regression model for crash severity (Property Damage Only (PDO) vs. injuries or fatalities (NotPDO)) yielding 12 models for various combinations of driver gender and crash types. Results indicate that factors such as the number of vehicles involved, vehicle manufacturing year, annual average daily traffic (AADT), road topography, season of crash, number of lanes, and driver age group all significantly influenced crash severity across various scenarios. These findings provide detailed insights into how various factors contribute to crash severity in different scenarios, allowing policymakers to develop targeted interventions. Policymakers can utilize the findings of this study to implement targeted measures in areas with high frequencies of specific crash types, particularly during adverse environmental conditions.

Keywords: crash severity; traffic safety; rainy weather crashes; logistic regression; HSIS data



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1. Introduction

Traffic crashes represent a persistent and significant global public health challenge, resulting in millions of fatalities, injuries, and disabilities each year [1]. In the United States, these incidents are a leading cause of death, particularly among young and middle-aged individuals, highlighting the critical need for effective mitigation strategies [2]. California, with its high population density and heavy traffic volume, faces particularly acute

challenges in managing road safety, making it a key region for targeted research [3]. A thorough analysis of the factors that influence crash occurrence and severity is therefore essential for developing effective, tailored interventions.

Weather conditions are well-established contributors to traffic accidents, with rainy weather posing an especially significant risk. Recent data from the National Highway Traffic Safety Administration [NHTSA] (2022) indicates that adverse weather conditions account for a significant proportion of crashes, with rain being a particularly common factor [4]. This highlights the importance of understanding the underlying mechanisms that increase accident risk and severity during rainy conditions [5]. Weather-related accidents are more likely to result in severe outcomes than those that occur in clear conditions, making this a critical area of focus [6]. Additionally, the increased mental and physical effort required while driving in adverse weather has been shown to compromise driver performance and safety [7].

Numerous factors have been identified as influencing crash severity in adverse weather. These include reduced visibility, changes in road surface friction, and heightened driver stress [8,9]. Peak traffic hours, unsafe driving behaviors, and even the lack of seatbelt use have been linked to greater crash severity in rainy conditions [6]. While roadway characteristics, such as wet surfaces and narrow segments, increase the risks of severe collisions, particularly in head-on crashes [10,11]. Furthermore, some studies have investigated the impacts of specific weather events, such as heavy rain, on crash risk [12]. Similarly, motorcycle crash studies have shown that temporal and seasonal variations (e.g., time-of-day and season combinations) play a critical role in shaping crash severity outcomes, highlighting the complex interactions between environment and driver behavior [13]. However, these studies often examine such factors in isolation, limiting our understanding of their complex interplay.

Individual driver characteristics, particularly gender, also influence crash dynamics. Research suggests that female drivers may sustain more severe injuries in certain crashes compared to their male counterparts [14–16]. Moreover, older female drivers are more likely to suffer severe injuries during adverse weather conditions, demonstrating a need for nuanced analyses that consider both gender and age-related factors [17–19]. In addition to the influence of gender, crash type is a substantial determinant of severity. Studies highlight the vulnerability of motorcyclists in multi-vehicle collisions during rain, and others focus on the increased risks associated with different collision types, such as rear-end, sideswipe, and head-on crashes, under wet conditions [20,21]. Recent disaggregated modeling of rear-end collisions further demonstrates that driver sex, age, area type, and lighting conditions significantly affect injury severity, underscoring the importance of incorporating demographic and environmental heterogeneity in crash severity research [22]. These patterns underscore the need to account for demographic and environmental heterogeneity in severity analyses.

Recent studies continue to investigate how traffic exposure, weather conditions, and crash characteristics interact to influence injury outcomes. For instance, one study using a correlated random parameters logit model with heterogeneity in means showed that real-time weather conditions significantly shift the risk of injury severity, while traffic volume can have a mitigating effect [23]. Another study identified persistent sex-based differences in injury risk even after accounting for vehicle mass and crash configuration, suggesting that some disparities remain despite controls [24]. Additional evidence suggests that weather conditions influence the severity of injuries in truck-involved crashes [25] and that sex-based differences vary significantly across different types of crashes [26].

While extensive research has examined the individual impacts of driver gender, crash type, and environmental factors, a significant gap remains in understanding their combined

effects under high-risk conditions such as rainy weather. Comprehensive reviews (e.g., [8]) confirm that the general link between weather and crashes has been widely studied; however, dominant approaches often rely on aggregated models in which weather is treated as just one of many predictors for a general crash population. This tendency, along with studies that focus on specific crash types without adequately controlling for gender or environmental factors [27] or examine gender differences without considering crash types and road conditions [28], assumes stability across contexts and overlooks crucial interactions. Consequently, we still lack evidence on how crash type relates to driver gender in rainy conditions and which crash types disproportionately affect different gender groups.

The novelty of this study lies in directly challenging that aggregated paradigm. Rather than asking the broad question, “What is the effect of rain on crash severity?”, we ask the more actionable one: “Given that it is raining, how do the determinants of crash severity differ across scenarios jointly defined by driver gender and crash type?” By adopting a stratified analytical framework, we move beyond average effects to uncover hidden heterogeneity in risk patterns and identify high-risk scenarios and their contributing factors, thereby enabling targeted, evidence-based interventions.

Previous studies have acknowledged the role of adverse weather but often incorporate it as one of many independent variables within a single comprehensive model. While informative, this approach assumes that the effects of other critical factors—such as driver characteristics, vehicle type, or road geometry—remain consistent across clear and rainy conditions. Such assumptions may mask important interactions and lead to generalized findings that lack situational specificity.

Accordingly, this research departs from the traditional approach by defining rainy weather as the scope condition for the entire analysis. By isolating the high-risk environment of rain-related crashes and employing a stratified design that disaggregates data into 12 scenarios based on driver gender and crash type, we reveal how the significance of risk factors changes across specific contexts. This framework provides a more granular understanding of crash severity, moving beyond “what” factors are significant to “for whom” and “under what collision type”.

Therefore, the purpose of this study is to fill this gap by examining the combined effects of driver gender, crash type, and environmental factors on crash severity in rainy weather in California. Using Highway Safety Information System (HSIS) data and stratified binary logistic regression, the study addresses policy-relevant questions, such as whether pavement type (PCC vs. AC) differentially affects severity for male and female drivers in head-on crashes, or whether older drivers face greater risk in sideswipe crashes during rain. The findings will provide transportation agencies with evidence to create targeted, data-driven interventions and educational campaigns for specific driver groups, ultimately supporting safer and more efficient safety policies during adverse weather conditions.

Given our policy-oriented goal of achieving interpretable, scenario-specific effects, we employ stratified binary logistic regression, which provides transparent odds ratios for each predictor while avoiding the black-box complexity of machine-learning models and the parameter proliferation required by mixed logit models.

A detailed methodology follows, describing the HSIS dataset and the binary logistic regression approach. Next, we define all study variables (dependent and independent). The Results section reports findings from 12 stratified models, identifying significant predictors of crash severity by driver gender and crash type. The Conclusion synthesizes key findings, notes limitations, and offers targeted policy recommendations.

2. Materials and Methods

2.1. Research Framework

The overall research framework, from data extraction to final analysis, is visually summarized in Figure 1. This flowchart illustrates the step-by-step process employed in the study. The process begins with the extraction of data from the California HSIS, which is then filtered to isolate crashes that occur under rainy weather conditions. Subsequently, the filtered dataset is stratified based on two key criteria: driver gender (male/female) and six distinct crash types. This stratification yields 12 subgroups, for each of which a separate binary logistic regression model is developed. Each model utilizes a set of predictors (independent variables) to analyze crash severity (the dependent variable), which is defined as property damage only (PDO) versus Injury/Fatality (NotPDO). The final output is the identification of significant predictors for each specific scenario, providing targeted insights for developing effective infrastructure, policy, and educational safety interventions.

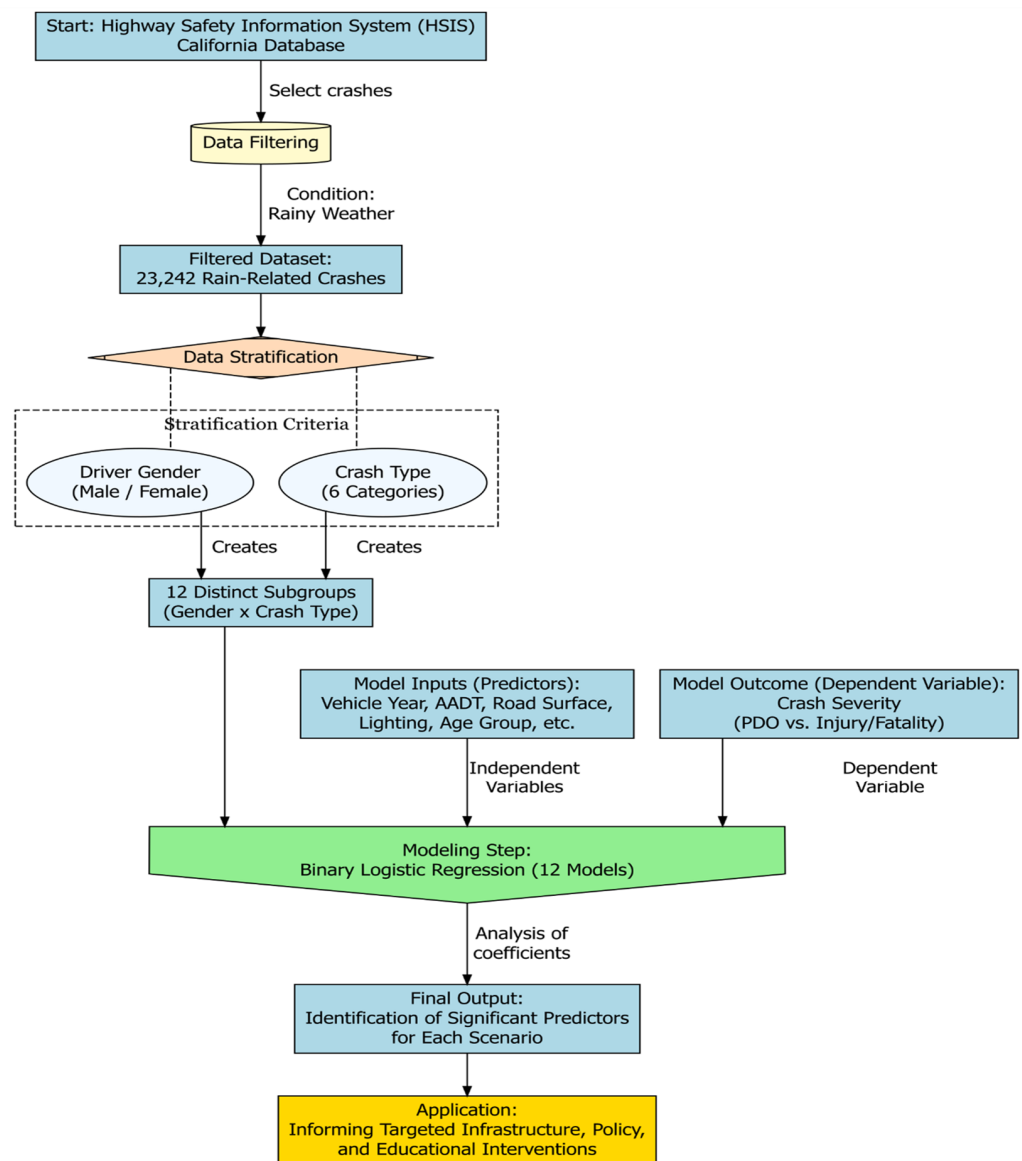


Figure 1. Conceptual framework of the research methodology.

2.2. Binary Logistic Regression

Binary Logistic Regression is a statistical method that predicts or explains binary outcomes. It is used in various fields where linear regression is not suitable. This technique is used when the dependent variable is inherently binary, with only two possible values. The objective of binary logistic regression is therefore to estimate the probability that an instance belongs to a specific category, given one or more predictors [29]. The Binary Logistic Regression model is expressed mathematically as:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}} \quad (1)$$

In this formula, $P(Y = 1|X)$ represents the probability that the dependent variable Y equals 1 given the independent variables X . The terms $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients that represent the relationship between the independent variables and the log-odds of the outcome [30]. The logistic function converts the linear combination of input variables into a probability value ranging from 0 to 1, making it suitable for classification problems, risk assessment, and decision-making with dichotomous outputs [31]. Because of the model's interpretability and flexibility, which enable the modeling of both nominal and interval independent variables, it has received a lot of attention from researchers [32].

In this study, Binary Logistic Regression was used to analyze crash severity in relation to the driver's gender and the type of crash. The data were divided into 12 subgroups based on two genders and six types of crash: Rear-End, Hit Object, Sideswipe, Overturned, Head-On, and Broadside. In the context of each group, a logistic regression analysis was used to model crash severity, with PDO and NotPDO as the two outcome categories.

This approach is ideal for this analysis for several reasons. First, the binary logistic regression model is well-suited to the scale of outcome variables PDO and NotPDO [33]. Second, by developing separate models for each gender-crash type combination, we can capture variations in the effects of various inputs on crash severity across each category. This stratified approach provides greater precision and targeted insights than a single, overall model. Likewise, logistic regression can analyze both categorical and continuous predictors, making it suitable for analyzing various factors associated with the occurrence of crashes [34]. Finally, logistic regression does not require normality of predictor distributions, making it more accurate for analyzing real-world crash data, where distributions are typically not normal [35].

The selection of binary logistic regression was a strategic choice guided by the primary objective of this study, which is to produce interpretable and actionable insights for safety practitioners and policymakers. While alternative methods like machine learning (e.g., Random Forest, Gradient Boosting) may yield higher predictive accuracy, they often operate as black boxes, making it difficult to quantify the specific impact of individual predictors. In contrast, the coefficients and odds ratios generated by logistic regression provide a clear and direct measure of how each factor influences the likelihood of a severe crash, which is essential for evidence-based decision-making.

Furthermore, regarding heterogeneity, rather than relying on more complex models such as mixed or random-parameters logit to capture unobserved differences, we address heterogeneity explicitly through full data stratification. We estimate 12 separate models, one for each gender-crash type combination, so that every parameter can vary freely across scenarios. This design is intentional, not redundant: our objective is not a single parsimonious predictor but a systematic comparison of risk patterns across distinct subgroups. A single model, even with numerous interaction terms, would average effects and obscure nuanced (and sometimes opposing) influences across contexts. The stratified framework en-

hances transparency and policy relevance, and we synthesize the findings in an integrated heatmap that summarizes the outcomes of all 12 models.

The evaluation criteria for goodness of fitting logistic regression models in this study include Deviance, AIC, McFadden R^2 , R^2 ML, R^2 CU, and AUC. The following summarizes the evaluation criteria.

- Deviance: A reduction in Deviance indicates an improvement in model fit. Models with lower Deviance values are considered to have a better fit to the data.
- Akaike Information Criterion (AIC): AIC is used for model comparison. Lower AIC values indicate a better model fit, while being simpler.
- McFadden R^2 : This criterion assesses the overall quality of the model. Higher McFadden R^2 values indicate a better fit.
- R^2 ML and R^2 CU: These two criteria are also used to evaluate the quality of model fit. R^2 ML is based on maximum likelihood, and R^2 CU is calculated based on the Cox-Snell criterion. Higher values indicate a better fit.
- Area Under the ROC Curve (AUC): The AUC is a metric used to evaluate the model's ability to correctly identify different classes. AUC values range from 0.5 (random) to 1 (perfect discrimination). Higher AUC values indicate better model performance.

2.3. HSIS Data

The HSIS is a database that contains motor vehicle crash data, roadway characteristics, and traffic statistics from various states of the United States of America [36]. The primary purpose of HSIS is to facilitate highway safety research and provide data on traffic crashes to address safety issues. The collected data encompasses a wide range of crashes, roadways, and traffic variables that are crucial for identifying safety risks and designing interventions to reduce the number of crashes and fatalities.

The selection of the HSIS database was deliberate, as its unique characteristics make it particularly suitable for achieving the objectives of this research. Firstly, HSIS provides high-quality, integrated data that links crash records with detailed roadway characteristics (e.g., surface type, topography) and traffic volume inventories (e.g., AADT). This linkage is crucial for a comprehensive, multifaceted analysis and is often lacking in standalone crash databases. Secondly, the database offers richness in its variables, containing the specific and well-defined data points required for our stratified analysis, including weather conditions, manner of collision, and detailed driver demographics. Finally, the large sample size of crash records available for California ensures that even after filtering for rainy conditions and stratifying into 12 subgroups, each subgroup retains a sufficient number of observations for a statistically robust regression analysis, which would not be feasible with a smaller, less comprehensive dataset.

California has participated in the HSIS program since 1991. It has provided a considerable amount of high-quality data, improving the system's functionality [36]. The HSIS dataset for California is quite extensive, consisting of inventories of roadways and intersections, crash characteristics, and vehicle involvement specifics [36]. The HSIS dataset for California has been refined over the years with the goal of enhancing both data quality and accessibility.

California presents a particularly compelling context for studying rain-related crashes. The state's Mediterranean climate is characterized by long dry seasons followed by distinct wet periods. This pattern often leads to the first flush phenomenon, where initial rainfall mixes with accumulated oil and road debris, creating exceptionally slick pavement conditions [37]. Furthermore, because rainfall is relatively infrequent in much of California, rain events produce marked operational impacts, lower speeds and capacity, and higher headways, indicating region-specific responses to wet conditions, which has been linked to a disproportional

tionate increase in crash frequency during rainfall events. This unique environmental and behavioral context makes California a critical region for this analysis [38].

It is essential to note that this analysis is based on data from California, a state with distinct climate patterns, traffic culture, and roadway infrastructure, and therefore, the findings may not be directly generalizable to other regions. However, this focused approach allows for a detailed, context-specific case study that can serve as a valuable benchmark for similar research elsewhere.

The WEATHER1 variable in the HSIS dataset was used to filter for crashes under rainy conditions. It is important to note that this variable is categorical (Raining) and does not provide further granularity regarding the intensity of the rain (e.g., light, moderate, heavy). Therefore, the analysis encompasses all crashes recorded under this general weather condition.

As presented in Table 1, which includes 20 randomly selected records, the data prepared for this research pertains to crashes that occurred in California during rainy weather between 2015 and 2017. These crashes are categorized as “PDO”, meaning property damage only, and “NotPDO”, for other crashes with injuries or fatalities. Other valuable information in the dataset includes time of day, weather conditions, and the type of road surface at the time of the crash. It also provides information on the number of vehicles, the number of lanes, and the type of road surface.

Table 1. Twenty Random Records from the Prepared Dataset from HSIS.

Driver Sex	Vehicle Year	Hour Class	Severity	Light	No. Vehicles	No. Lanes	Surface Type	Terrain	AADT	Rural/Urban	Season	Crash Type	Age Group
M	2000–2005	5	PDO	Dark	2	+8	PCC	F	125k–175k	U	Winter	Hit_Object	25–65
F	2000–2005	3	PDO	Dark	3	+8	PCC	F	+250k	U	Spring	Rear_End	25–65
F	+2015	5	PDO	Dark	3	+8	PCC	F	+250k	U	Winter	Rear_End	25–65
F	+2015	2	NotPDO	Daylight	2	–5	AC	R	–125k	U	Winter	Rear_End	25–65
M	2010–2015	3	NotPDO	Dark	+3	+8	PCC	F	175k–250k	U	Fall	Sideswipe	25–65
F	–2000	2	NotPDO	Daylight	1	6–7	AC	F	–125k	U	Fall	Hit_Object	+65
M	+2015	4	PDO	Daylight	2	+8	AC	R	–125k	R	Spring	Broadside	–25
F	+2015	4	NotPDO	Daylight	1	–5	AC	R	–125k	R	Fall	Hit_Object	25–65
F	2005–2010	2	NotPDO	Daylight	2	–5	AC	F	–125k	R	Fall	Rear_End	+65
M	2000–2005	4	PDO	Daylight	3	–5	AC	R	–125k	U	Spring	Sideswipe	25–65
M	2010–2015	3	PDO	Dark	3	+8	AC	F	175k–250k	U	Spring	Rear_End	25–65
M	2000–2005	5	PDO	Dark	1	–5	AC	F	–125k	R	Fall	Hit_Object	–25
F	2000–2005	5	NotPDO	Daylight	2	–5	AC	F	–125k	U	Winter	Sideswipe	25–65
F	–2000	2	PDO	Daylight	2	–5	AC	M	–125k	R	Fall	Sideswipe	25–65
M	2005–2010	1	PDO	Dark	1	+8	PCC	R	–125k	R	Winter	Hit_Object	25–65
F	2010–2015	5	PDO	Dark	2	+8	PCC	F	175k–250k	U	Winter	Rear_End	25–65
M	–2000	4	PDO	Daylight	2	+8	PCC	F	175k–250k	U	Winter	Rear_End	25–65
M	2005–2010	4	PDO	Dark	1	+8	PCC	M	–125k	U	Winter	Hit_Object	–25
M	+2015	4	PDO	Dark	2	+8	PCC	F	+250k	U	Winter	Sideswipe	25–65
M	–2000	2	PDO	Daylight	3	6–7	AC	R	–125k	U	Winter	Broadside	25–65

Moreover, Table 2 displays the frequency of each level of the variables used in the research. For instance, Table 2 indicates that there are 8168 observations where the driver’s gender is female (F) and 15,074 observations where the driver’s gender is male (M). The table also displays the frequency of each severity level, road surface type, light condition, number of vehicles involved, number of lanes, terrain, Annual Average Daily Traffic (AADT), urban-rural classification, and season.

Table 2. Frequency of Each Level of Variables for the Prepared Dataset.

Variable	Frequency						
Driver Sex	F: 8168	M: 15,074					
Vehicle Year	–2000: 3466	2000–2005: 5216	2005–2010: 5922	2010–2015: 5631	+2015: 3007		
Hour Class	1: 3736	2: 6561	3: 3299	4: 4274	5: 5372		
Severity	NotPDO: 8544	PDO: 14,698					
Light	Dark: 11,420	Daylight: 11,822					
No. Vehicles	1: 6430	2: 11,936	3: 3606	+3: 1270			
No. Lanes	–5: 7104	6–7: 4131	+8: 12,007				
Surface Type	AC: 10,042	PCC: 13,200					
Terrain	F: 14,707	M: 2467	R: 6068				
AADT	–125K: 9910	125k–175k: 4050	125k–175k: 4050	175k–250k: 6265	+250k: 3017		
Rural/Urban	R: 4164	U: 19,078					
Season	Fall: 4607	Spring: 5431	Summer: 734	Winter: 12,470			
Crash Type	Broadside: 2028	Rear End: 8975	Hit Object: 6517	Sideswipe: 4316	Head On: 600	Overturned: 806	
Age Group	–25: 5584	25–65: 16,417	+65: 1241				

The HOUR Class variable was created to categorize the time of the crash into five distinct periods, capturing different traffic patterns throughout the day. The classes are defined as follows:

- Class 1: Early Morning (00:01–06:00)
- Class 2: Midday (10:01–16:00)
- Class 3: Night (20:01–24:00)
- Class 4: Morning Peak (06:01–10:00)
- Class 5: Evening Peak (16:01–20:00)

3. Results

This section presents the results of fitting logistic regression models to analyze the severity of crashes in rainy weather, using various combinations of driver gender and crash types. The evaluation criteria for goodness of fit include Deviance, AIC, McFadden R², R²ML, R²CU, and AUC. Table 3 summarizes the goodness-of-fit criteria for logistic regression models of crash severity in rainy weather, by gender and crash type.

Table 3. Goodness of Fit Evaluation Criteria for Logistic Regression Models.

Model	Driver Sex	Crash Type	<i>n</i>	Deviance	AIC	McFadden R ²	R ² ML	R ² CU	AUC
1	M	Rear_End	5536	7180.411	7204.411	0.006	0.008	0.011	0.559
2	M	Hit_Object	4311	5288.738	5308.738	0.018	0.022	0.031	0.576
3	F	Rear_End	3439	4555.068	4569.068	0.007	0.009	0.012	0.559
4	M	Sideswipe	2940	3215.336	3243.336	0.047	0.053	0.077	0.638
5	F	Hit_Object	2206	2884.048	2918.048	0.019	0.025	0.034	0.583
6	F	Sideswipe	1376	1670.868	1688.868	0.010	0.012	0.018	0.565
7	M	Broadside	1327	1803.142	1823.142	0.020	0.027	0.036	0.597
8	F	Broadside	701	957.696	969.696	0.009	0.013	0.017	0.558
9	M	Overturned	563	763.230	775.230	0.021	0.029	0.038	0.572
10	M	Head_On	397	450.951	470.951	0.137	0.164	0.225	0.709
11	F	Overturned	243	309.678	317.678	0.030	0.039	0.053	0.571
12	F	Head_On	203	228.520	258.520	0.145	0.174	0.238	0.748

Rear-End crash models for male and female drivers have lower McFadden R² values (0.006 and 0.007) and AUC (0.559). This indicates a weak fit for these models. These results could be attributed to the complexity and high variability of factors that affect Rear-End collisions.

Models for Hit_Object crashes for both genders have slightly higher McFadden R² and AUC values compared to other models (0.018 and 0.576 for males, 0.019 and 0.583 for females). This indicates a relatively better fit for these models.

Notable McFadden R² (0.047) and AUC (0.638) values are found in Sideswipe crashes model for males. These results suggest a relatively good fit in identifying the severity of Sideswipe crashes. The McFadden R² and AUC values are slightly lower (0.010 and 0.565) for females.

The greatest McFadden R² and AUC values are found in models for Head-On collisions for both male and female drivers (0.145 and 0.748 for women, 0.137 and 0.709 for males). This indicates a better fit and higher accuracy of these models in identifying severity.

Models for Broadside crashes demonstrate moderate performance. Male drivers have a McFadden R² of 0.020 and an AUC of 0.597, while female drivers have lower values (0.009 and 0.558, respectively). This suggests that the model predicts Broadside crash severity more accurately for male drivers compared to female drivers.

The models for Overturned crashes perform similarly for both genders, with a slightly better result for female drivers. Male drivers have a McFadden R² of 0.021 and an AUC of 0.572, while female drivers have values of 0.030 and 0.571, respectively. This indicates a

moderate fit for both genders, with a slightly better performance in predicting Overtaken crash severity for female drivers.

The results of the goodness-of-fit evaluation for the logistic regression models indicate that the model’s accuracy and performance vary depending on the combinations of driver gender and crash types. Models for Head-On crashes perform best for both genders, while models for Rear-End crashes need improvement. These analyses can serve as a basis for developing strategies to improve road safety during rainy weather conditions.

Table A1 in the Appendix A presents the results from 12 logistic regression models used to analyze the severity of crash types.

To provide a comprehensive and intuitive summary of the findings from the 12 logistic regression models, a heatmap of the coefficient estimates was generated (Figure 2). This visualization allows for the direct comparison of predictor effects across all scenarios. Each row corresponds to an explanatory variable, and each column to a specific model. The color scale indicates the sign and magnitude of the coefficient estimates (red = positive effect, blue = negative effect, white ≈ zero), while non-significant predictors ($p > 0.05$) are marked with a cross (×). This graphical representation facilitates the identification of overarching patterns, variable consistency, and context-dependent effects that would be difficult to discern from tabular data alone.

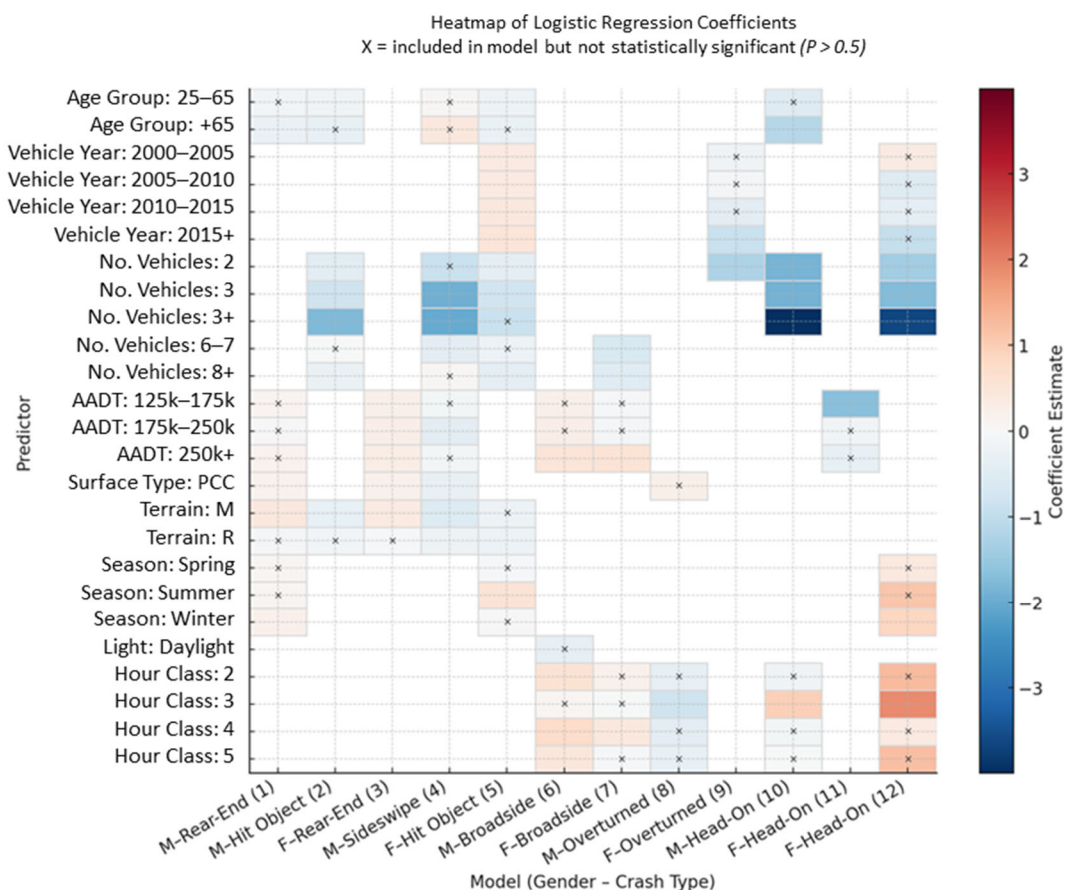


Figure 2. Heatmap of regression coefficients for crash severity.

Model 1 (Male, Rear-End Crash): The results of the first model indicate that road surface type (Surface Type: PCC) and road topography (Terrain: M) have a positive and significant effect on crash severity. Additionally, the season of occurrence (Season: Winter) and driver age group (Age Group: +65) have significant effects. These findings suggest that road conditions and the season of occurrence can impact crash severity.

Model 2 (Male, Hit Object Crash): In the second model, the number of vehicles involved (No. Vehicles: 2, No. Vehicles: 3, and No. Vehicles: +3) has a negative and significant effect on crash severity. Also, road topography (Terrain: M) and driver age group (Age Group: 25–65) have a significant impact. These findings suggest that an increase in the number of vehicles involved, along with the type of topography, can lead to a decrease in crash severity.

Model 3 (Female, Rear-End Crash): The third model's findings indicate that road surface type (Surface Type: PCC) and road topography (Terrain: M) have a positive and significant effect on crash severity. Additionally, daily traffic volume (AADT: 125k–175k, AADT: 175k–250k, and AADT: +250k) has a significant impact. These findings indicate that road conditions and traffic volume can affect crash severity.

Model 4 (Male, Sideswipe Crash): The fourth model shows that the number of vehicles involved (No. Vehicles: 3 and No. Vehicles: +3) has a negative and significant effect on reducing crash severity. This model also accounts for road surface type (PCC) and road topography (Terrain: M and Terrain: R). The results show that concrete roads and flat areas can help reduce crash severity.

Model 5 (Female, Hit Object Crash): In the fifth model, vehicle manufacturing year (Vehicle Year) and number of vehicles involved (No. Vehicles: 2 and No. Vehicles: 3) have a significant impact on crash severity. Newer vehicles (with a more recent manufacturing year) are less likely to be involved in severe crashes due to improved safety technologies. Similarly, an increase in the number of vehicles involved is associated with a decrease in crash severity.

Model 6 (Male, Broadside Crash): In the sixth model, the time of crash occurrence (Hour class) and ambient light (Light) have a significant impact on crash severity. Crash severity is higher at night (Hour class: 4 and Hour class: 5) and in poor lighting conditions (Light: Daylight). These results show that lighting conditions and the time of crash occurrence can have a significant impact on crash severity.

Model 7 (Female, Broadside Crash): The results show that the number of road lanes (No. Lanes: 6–7 and No. Lanes: +8) and the time class of crash occurrence (Hour class: 4) have a significant effect on crash severity. More lanes and nighttime crashes are associated with increased crash severity. These findings indicate that roads with more lanes and specific time conditions can lead to increased crash severity. Additionally, daily traffic volume (AADT) contributes to an increase in crash severity.

Model 8 (Male, Overturned Crash): The time class of crash occurrence (Hour class: 3) has a negative and significant effect on crash severity. This indicates that midday crashes are less severe. Additionally, road surface type (Surface Type: PCC) has a significant effect on reducing crash severity. These results show that concrete roads can help reduce crash severity.

Model 9 (Female, Overturned Crash): The vehicle manufacturing year (Vehicle Year: +2015) and the number of vehicles involved (No. Vehicles: 2) have negative and significant effects on crash severity. Newer vehicles have improved safety technologies, and crashes involving fewer vehicles are less severe.

Model 10 (Male, Head-On Crash): In the tenth model, the time class of crash occurrence (Hour class: 3) and the number of vehicles involved (No. Vehicles: 2, No. Vehicles: 3, and No. Vehicles: +3) have a significant effect on crash severity. While midday Crashes involving fewer vehicles are less severe.

Model 11 (Female, Head-On Crash): The results show that daily traffic volume (AADT: 125k–175k) has a negative impact on crash severity. This suggests that reducing roadway traffic volumes has a substantial impact on reducing crash severity.

Model 12 (Female, Head-On Crash): In the twelfth model, the time class of crash occurrence (Hour class: 2, Hour class: 3, Hour class: 5) and the number of vehicles involved (No. Vehicles: 2, No. Vehicles: 3, and No. Vehicles: +3) have significant effects on crash severity. Crash occurrences during nighttime hours and those involving fewer vehicles are associated with decreased crash severity. Additionally, the season of occurrence (Season: Winter) has a positive and significant effect on crash severity.

4. Discussion

This study employed a stratified modeling approach to identify the nuanced factors that influence crash severity during rainy weather. The results, summarized visually in Figure 2, not only identify significant predictors but also highlight their high degree of context-dependency. Some of the key findings are as follows:

The results show that crashes with multiple vehicles are consistently associated with reduced severity compared to single-vehicle crashes. Both No. Vehicles: 2 and No. Vehicles: 3 were significant in five of the twelve models, with negative coefficients, while No. Vehicles: 3+ displayed the strongest reductions. This suggests that crashes involving more vehicles tend to distribute the crash energy across multiple impacts, thereby lowering the severity of individual injuries. Prior studies have similarly reported that chain-reaction or multi-vehicle crashes are associated with less severe outcomes because impact forces are distributed across multiple vehicles [39,40]. Moreover, such crashes often occur under congested, lower-speed conditions.

Vehicle Manufacturing Year (Vehicle Year): The effect of vehicle model year on crash severity was inconsistent. Although newer vehicles (2015 and later) are expected to reduce injury severity through advanced safety features, the results show mixed outcomes, with coefficients ranging from negative to positive across different models. In some cases, newer vehicles were associated with slightly higher odds of severe outcomes, which may reflect risk compensation, where drivers take greater risks due to a perceived sense of safety, or the greater likelihood of newer vehicles being used on higher-speed facilities [41,42].

Time of Crash (Hour class): The timing of a crash showed a significant influence on injury severity. Nighttime crashes were generally associated with more severe outcomes, reflecting the combined effects of reduced visibility, fatigue, and a higher likelihood of risky behaviors such as impaired driving. Morning and evening peaks also showed positive associations with severity in some subgroups, suggesting that congestion does not always mitigate crash outcomes when high exposure and aggressive driving behaviors are present. These results are consistent with earlier findings that adverse conditions such as rain and low visibility increase crash severity in multivehicle events [10] and that precipitation-related crashes, especially under poor visibility, elevate both crash frequency and severity [6]. More recent analyses also reinforce that real-time weather and temporal variations interact to significantly influence crash severity outcomes [23].

Type of Road Surface (Surface Type): PCC was significant in three models, with one negative and two small positive coefficients, indicating no consistent advantage over AC. The effects were modest, suggesting surface type is a secondary factor in severity outcomes. This aligns with recent findings that skid resistance, rather than pavement type itself, is the more critical determinant of injury severity under wet conditions [43].

Annual Average Daily Traffic (AADT): The strongest effect in results appears at the very highest volumes. $AADT \geq 250,000$ was significant in three models, consistently yielding positive coefficients, indicating higher injury severity. A likely mechanism is the combination of short headways, greater speed variability, and complex operations (such as weaving/heavy-vehicle mix), which compresses reaction time and increases impact

energy [44]. By contrast, mid-range volumes (e.g., 125k–175k) trend lower or mixed, pointing to a non-linear volume–severity relationship.

Ambient Light (Light): Lighting conditions did not emerge as significant predictors of injury severity in this study. The Daylight indicator (with dark conditions as the baseline) was not statistically significant in any model. This contrasts with prior evidence linking low-light conditions to higher severity [6,23], suggesting that in these models, the effects of lighting are largely absorbed by other covariates.

Road Topography (Terrain): The rolling terrain showed a slight reduction in severity, with small negative effects observed in two models. Mountain terrain appeared in four models, with mixed and near-zero coefficients, indicating a minimal systematic impact. Previous studies, however, report higher severity on mountainous roads due to steep grades, sharp curves, and limited sight distance [45]. The difference may be because variables such as AADT and crash type already capture much of the risk usually attributed to topography.

Season of Crash (Season): Seasonal effects appeared in only a few models. Summer was significant in one model, and Winter in two models, both with positive coefficients, indicating a slight increase in severity. The limited presence and modest effect sizes suggest that the season itself is not a strong predictor; rather, its influence likely reflects associated factors such as weather, daylight hours, and surface conditions.

Number of Lanes (No. Lanes): Lane count showed consistent negative effects at the higher categories. Roadways with 6–7 lanes were significant in two models, and those with 8 or more lanes were significant in three models, all of which were associated with reduced severity compared to the baseline. This may reflect that wider roads often operate at lower effective speeds under congestion, and crash energy is more dispersed across multiple lanes. Prior studies have also found that multilane facilities are linked with lower injury severity due to similar operational characteristics [46].

Driver Age Group (Age Group): Both 25–65 and 65+ were significant in two models each, with negative coefficients (larger in magnitude for the 65+ group), indicating lower severity compared to the ≤ 24 group. This concentrates higher severities among the youngest drivers, while middle-aged and older drivers show lower severity in these models. Prior work similarly reports elevated risk for young drivers and shows that age effects attenuate once crash type, exposure, and speed environment are controlled [47,48].

The multifaceted nature of crash severity, as highlighted by this research, calls for a similarly multifaceted approach to policy development. Severity is highest on very high-exposure corridors ($\text{AADT} \geq 250,000$), so network operations need to emphasize speed harmonization and variable limits, ramp metering, queue warning, and stronger weaving and merge control on these links. Because higher lane counts (6–7 and 8+) are associated with lower severity, preserving cross-section quality, such as shoulders, separation, and lane discipline, as well as active speed management, needs to be prioritized over capacity expansion, framed as a safety measure.

Findings by crash configuration suggest that countermeasures should focus on preventing the most severe outcomes. Since multi-vehicle crashes are generally less severe, policies need to focus on the most injurious patterns: single-vehicle, head-on, and rollover crashes. Key countermeasures include median and roadside barriers, centerline and shoulder rumble strips, curve speed management, and improved delineation with high-friction spot treatments at high-risk locations. Where the models indicate increased risk by hour class, operations need to be timed accordingly, with targeted enforcement, quick incident response, and speed management during those times.

With respect to road users and vehicles, the younger age group carries the highest severity. Education and enforcement efforts should be targeted at young drivers through

refinements to graduated licensing, telematics-based feedback, and location-focused campaigns near schools and universities. Vehicle model year effects are mixed, which implies that technology alone does not guarantee lower severity. Incentives for active safety features, such as automatic emergency braking, electronic stability control, and lane departure warning, need to be paired with behavioral programs and real-time operational strategies on high-exposure corridors, and their effectiveness needs to be validated through ongoing evaluation.

5. Conclusions

This study employed stratified logistic models, stratified by driver gender and crash type, to investigate factors associated with injury severity in rainy conditions. The results show clear, context-dependent patterns rather than uniform effects. Crashes involving multiple vehicles were consistently less severe than single-vehicle events, with two- and three-vehicle crashes being significant in several models, and crashes involving three or more vehicles showing the strongest reductions. Very high exposure was the most consistent risk signal: facilities with an annual average daily traffic of 250,000 or above were linked to higher severity, whereas higher lane counts, six to seven and eight or more, were associated with lower severity. Seasonal indicators appeared only sparingly, and vehicle model year effects were mixed.

These findings point to targeted operational and engineering responses. On very high-volume corridors, network operations need to emphasize speed harmonization, ramp metering, queue warning, and stronger weaving and merge control. To mitigate the most severe outcomes, countermeasures should prioritize single-vehicle, head-on, and overturn crashes through the use of median and roadside barriers, centerline and shoulder rumble strips, curve speed management, and enhanced delineation at high-risk sites. Education and enforcement efforts should focus on the youngest drivers, who exhibit the highest severity, through refinements to graduated licensing, telematics-based feedback, and location-focused campaigns near schools and universities. Given the mixed model year results, incentives for active safety technologies should be paired with behavioral programs and real-time operational strategies on high-exposure links, and their benefits should be verified through ongoing evaluation.

Overall, policy making needs to concentrate on the conditions where the models provide the strongest and most reliable signals: very high traffic exposure, lane configuration that supports safe operations, prevention of the most severe crash types, and risk among the youngest drivers. Focusing resources on these leverage points offers the clearest path to practical reductions in crash severity during rainy weather.

While this study offers valuable insights, several limitations should be acknowledged. Our analysis is based on data from California (2015–2017), which may limit its applicability to other regions with different traffic patterns, road conditions, and weather. Additionally, our definition of “rainy weather” was constrained by the categorical nature of the HSIS data. Future studies could achieve a more nuanced understanding by integrating granular meteorological data to explore the differential effects of light versus heavy rainfall on crash severity. Unobserved variables, such as specific driver behaviors or vehicle maintenance, which are not captured in the HSIS database, may also influence the results. The broad categorization of crash types and our binary outcome measure (PDO vs. NotPDO) limit our ability to analyze subtle patterns and injury severities. Future research could address these points by utilizing data from diverse geographic regions and employing advanced statistical methods, such as machine learning algorithms. Incorporating more driver-specific information through surveys or direct observation studies, analyzing injury severity as a

continuous outcome, and conducting longitudinal studies to evaluate policy effectiveness would further advance our understanding of crash severity during rainy conditions.

Finally, a key methodological consideration is the potential for temporal instability in the estimated parameters. By pooling data from 2015 to 2017, our models implicitly assume that the relationships between predictor variables and crash severity are stable over this period. However, a significant body of literature demonstrates that the effects of various factors can change over time due to shifts in vehicle technology, driver behavior, economic conditions, or policy [49,50]. A formal statistical investigation of temporal instability for each of our 12 subgroups was beyond the scope of this study. Nonetheless, we acknowledge this as a limitation and suggest that it represents a critical point for future research. Future work could apply appropriate statistical tests to explore how these scenario-specific risk patterns evolve over longer time horizons.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Detailed Regression Model Results

Table A1. Summary of Logistic Regression Models Examining Factors Influencing Crash Severity in Rainy Weather.

Model	Term	Estimate	Std. Error	Statistic	p-Value
1	(Intercept)	0.409	0.099	4.115	0.000
	Surface Type: PCC	0.184	0.062	2.973	0.003
	Terrain: M	0.430	0.132	3.262	0.001
	Terrain: R	−0.085	0.067	−1.259	0.208
	AADT: 125k–175k	0.123	0.085	1.454	0.146
	AADT: 175k–250k	0.011	0.076	0.150	0.881
	AADT: +250k	0.160	0.091	1.749	0.080
	Season: Spring	0.081	0.085	0.950	0.342
	Season: Summer	0.078	0.169	0.464	0.643
	Season: Winter	0.191	0.074	2.581	0.010
	Age Group: 25–65	−0.134	0.071	−1.882	0.060
Age Group: +65	−0.252	0.126	−2.002	0.045	
2	(Intercept)	1.230	0.095	12.923	0.000
	No. Vehicles: 2	−0.458	0.096	−4.746	0.000
	No. Vehicles: 3	−0.811	0.203	−4.002	0.000
	No. Vehicles: +3	−1.765	0.332	−5.310	0.000
	No. Lanes: 6–7	−0.027	0.107	−0.257	0.797
	No. Lanes: +8	−0.278	0.083	−3.332	0.001
	Terrain: M	−0.314	0.104	−3.015	0.003
	Terrain: R	−0.151	0.079	−1.903	0.057
	Age Group: 25–65	−0.173	0.075	−2.312	0.021
	Age Group: +65	−0.312	0.176	−1.774	0.076

Table A1. Cont.

Model	Term	Estimate	Std. Error	Statistic	p-Value
3	(Intercept)	0.176	0.073	2.395	0.017
	Surface Type: PCC	0.210	0.078	2.684	0.007
	Terrain: M	0.356	0.162	2.200	0.028
	Terrain: R	−0.044	0.085	−0.521	0.603
	AADT: 125k–175k	0.229	0.102	2.239	0.025
	AADT: 175k–250k	0.250	0.096	2.609	0.009
	AADT: +250k	0.283	0.114	2.475	0.013
4	(Intercept)	2.648	0.623	4.250	0.000
	No. Vehicles: 2	−0.891	0.610	−1.460	0.144
	No. Vehicles: 3	−1.911	0.615	−3.106	0.002
	No. Vehicles: +3	−2.013	0.631	−3.191	0.001
	No. Lanes: 6–7	−0.431	0.163	−2.644	0.008
	No. Lanes: +8	0.049	0.181	0.272	0.786
	Surface Type: PCC	−0.306	0.099	−3.087	0.002
	Terrain: M	−0.542	0.174	−3.120	0.002
	Terrain: R	−0.208	0.104	−2.005	0.045
	AADT: 125k–175k	−0.116	0.158	−0.733	0.463
	AADT: 175k–250k	−0.422	0.165	−2.566	0.010
	AADT: +250k	−0.095	0.184	−0.518	0.604
Age Group: 25–65	0.034	0.112	0.306	0.760	
Age Group: +65	0.427	0.225	1.900	0.057	
5	(Intercept)	0.674	0.175	3.845	0.000
	Vehicle Year: 2000–2005	0.366	0.141	2.594	0.009
	Vehicle Year: 2005–2010	0.355	0.136	2.616	0.009
	Vehicle Year: 2010–2015	0.427	0.149	2.864	0.004
	Vehicle Year: +2015	0.520	0.200	2.600	0.009
	No. Vehicles: 2	−0.397	0.143	−2.780	0.005
	No. Vehicles: 3	−0.796	0.309	−2.574	0.010
	No. Vehicles: +3	−0.879	0.499	−1.761	0.078
	No. Lanes: 6–7	−0.244	0.135	−1.814	0.070
	No. Lanes: +8	−0.391	0.113	−3.470	0.001
	Terrain: M	−0.245	0.140	−1.751	0.080
	Terrain: R	−0.248	0.104	−2.393	0.017
	Season: Spring	−0.032	0.134	−0.238	0.812
	Season: Summer	0.550	0.263	2.094	0.036
Season: Winter	0.004	0.117	0.032	0.975	
Age Group: 25–65	−0.219	0.096	−2.288	0.022	
Age Group: +65	−0.261	0.257	−1.013	0.311	
6	(Intercept)	0.383	0.204	1.872	0.061
	Hour class: 2	0.582	0.296	1.965	0.049
	Hour class: 3	0.083	0.227	0.364	0.716
	Hour class: 4	0.743	0.288	2.580	0.010
	Hour class: 5	0.464	0.230	2.020	0.043
	Light: Daylight	−0.373	0.210	−1.778	0.075
	AADT: 125k–175k	0.232	0.167	1.392	0.164
	AADT: 175k–250k	0.276	0.147	1.878	0.060
AADT: 250k+	0.518	0.187	2.764	0.006	
7	(Intercept)	0.236	0.172	1.370	0.171
	Hour class: 2	0.195	0.178	1.097	0.273
	Hour class: 3	−0.017	0.206	−0.081	0.936
	Hour class: 4	0.422	0.201	2.096	0.036
	Hour class: 5	−0.041	0.192	−0.216	0.829
	No. Lanes: 6–7	−0.638	0.184	−3.477	0.001
	No. Lanes: +8	−0.496	0.214	−2.317	0.021
	AADT: 125k–175k	−0.055	0.208	−0.264	0.792
	AADT: 175k–250k	−0.085	0.216	−0.393	0.694
AADT: +250k	0.555	0.262	2.118	0.034	

Table A1. Cont.

Model	Term	Estimate	Std. Error	Statistic	p-Value
8	(Intercept)	0.112	0.281	0.398	0.690
	Hour class: 2	−0.365	0.296	−1.234	0.217
	Hour class: 3	−0.818	0.337	−2.424	0.015
	Hour class: 4	−0.430	0.320	−1.345	0.179
	Hour class: 5	−0.332	0.312	−1.065	0.287
	Surface Type: PCC	0.234	0.154	1.525	0.127
9	(Intercept)	0.340	0.201	1.691	0.091
	Vehicle Year: 2000–2005	−0.175	0.247	−0.709	0.478
	Vehicle Year: 2005–2010	−0.077	0.265	−0.290	0.772
	Vehicle Year: 2010–2015	−0.423	0.302	−1.400	0.161
	Vehicle Year: +2015	−0.894	0.363	−2.462	0.014
	No. Vehicles: 2	−1.232	0.480	−2.566	0.010
10	(Intercept)	1.622	0.482	3.365	0.001
	Hour class: 2	−0.161	0.361	−0.446	0.656
	Hour class: 3	0.959	0.396	2.419	0.016
	Hour class: 4	−0.113	0.407	−0.278	0.781
	Hour class: 5	−0.007	0.388	−0.018	0.986
	No. Vehicles: 2	−1.858	0.432	−4.302	0.000
	No. Vehicles: 3	−1.900	0.547	−3.473	0.001
	No. Vehicles: +3	−3.991	0.737	−5.418	0.000
	Age Group: 25–65	−0.529	0.277	−1.910	0.056
Age Group: +65	−1.148	0.527	−2.178	0.029	
11	(Intercept)	−0.380	0.159	−2.399	0.016
	AADT: 125k–175k	−1.657	0.634	−2.613	0.009
	AADT: 175k–250k	−0.131	0.363	−0.360	0.719
	AADT: +250k	−0.313	0.633	−0.495	0.621
12	(Intercept)	−0.620	0.850	−0.730	0.466
	Vehicle Year: 2000–2005	0.332	0.533	0.623	0.533
	Vehicle Year: 2005–2010	−0.526	0.562	−0.935	0.350
	Vehicle Year: 2010–2015	−0.381	0.558	−0.683	0.494
	Vehicle Year: +2015	−0.958	0.665	−1.442	0.149
	Hour class: 2	1.256	0.696	1.804	0.071
	Hour class: 3	1.896	0.758	2.502	0.012
	Hour class: 4	0.351	0.753	0.466	0.642
	Hour class: 5	1.216	0.707	1.720	0.085
	No. Vehicles: 2	−1.385	0.529	−2.621	0.009
	No. Vehicles: 3	−1.717	0.727	−2.362	0.018
	No. Vehicles: +3	−3.618	1.175	−3.078	0.002
	Season: Spring	0.403	0.499	0.807	0.420
	Season: Summer	1.096	0.600	1.825	0.068
Season: Winter	0.853	0.419	2.038	0.042	

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