

Article

Statistical and Spatial Analysis of Large Truck Crashes in Texas (2017–2021)

Khondoker Billah ¹, Hatim O. Sharif ^{2,*}  and Samer Dessouky ² 

¹ Department of Civil Engineering, East West University, Aftabnagar, Dhaka 1212, Bangladesh; khondoker.billah@ewubd.edu

² School of Civil and Environmental Engineering and Construction Management, University of Texas at San Antonio, San Antonio, TX 78249, USA; samer.dessouky@utsa.edu

* Correspondence: hatim.sharif@utsa.edu; Tel.: +1-210-458-6478

Abstract: Freight transportation, dominated by trucks, is an integral part of trade and production in the USA. Given the prevalence of large truck crashes, a comprehensive investigation is imperative to ascertain the underlying causes. This study analyzed 2017–2021 Texas crash data to identify factors impacting large truck crash rates and injury severity and to locate high-risk zones for severe incidents. Logistic regression models and bivariate analysis were utilized to assess the impacts of various crash-related variables individually and collectively. Heat maps and hotspot analysis were employed to pinpoint areas with a high frequency of both minor and severe large truck crashes. The findings of the investigation highlighted night-time no-passing zones and marked lanes as primary road traffic control, highway or FM roads, a higher posted road speed limit, dark lighting conditions, male and older drivers, and curved road alignment as prominent contributing factors to large truck crashes. Furthermore, in cases where the large truck driver was determined not to be at fault, the likelihood of severe collisions significantly increased. The study's findings urge policymakers to prioritize infrastructure improvements like dual left-turn lanes and extended exit ramps while advocating for wider adoption of safety technologies like lane departure warnings and autonomous emergency braking. Additionally, public awareness campaigns aimed at reducing distracted driving and drunk driving, particularly among truck drivers, could significantly reduce crashes. By implementing these targeted solutions, we can create safer roads for everyone in Texas.

Keywords: large truck; severe crashes; logistic regression; fatalities; bivariate analysis



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1. Introduction

The road network in the United States has substantially improved freight movement efficiency over the past few decades. Freight transportation aids the activities associated with the production and trade of goods and materials by efficiently moving the goods and making the raw materials available in time [1]. In the United States, trucks contributed to 67% and 69% of the total freight transportation in 2007 and 2013, respectively [2]. Different types of trucks are being operated on roadways, and the quantity and type of cargo and duration of travel determine the type of truck to be used for the freight. The United States Department of Transportation (USDOT) stated that the dominance of trucks in freight transportation is estimated to continue in the future [3]. In addition to being autonomous, future trucks are expected to communicate among themselves as well as with the infrastructure, increase the productivity and safety of transport, and lower fuel consumption [4]. Considering the escalating economic losses, fatalities, and injuries linked to large truck crashes, trucking companies and other entities responsible for constructing, operating, and maintaining transportation infrastructure are growing increasingly concerned [5–7].

1.1. Statistics of Large Truck Crashes and Economic Impact

Large trucks increase cargo capacity per trip and help to increase economic productivity in the process. Fewer truck trips due to increased cargo capacity result in lesser fuel emissions and reduced transportation and fuel costs [8]. The proportion of large trucks in overall motor vehicles as well as the total vehicle miles traveled have shown an increasing trend [9]. In 2019, large trucks represented 9% of the total vehicle miles traveled in the United States, while constituting only about 4% of all registered vehicles. Large truck crashes occurring on roadways result in losses of billions of dollars every year [10]. This loss reflects the aggregate economic value of the lifetime costs associated with fatalities, property damage, injuries, and vehicle damage. The total cost of crashes related to commercial vehicles occurring during 2009, 2010, and 2011 in 2012 monetary value were USD 88.0, 94.0, and 94.3 billion, respectively [10]. A 2004 study estimated the average cost of a truck crash to be USD 59,153, while for multiple combination trucks, the average cost was USD 88,483 [11]. As of 2020, the average expense for a commercial truck accident involving a single injury is approximately USD 148,000 [12].

The National Highway Traffic Safety Administration defined a large truck as a commercial or non-commercial vehicle with a gross vehicle weight rating >10,000 lbs [13]. Approximately 159,000 people were injured in 538,000 large truck crashes in 2019, resulting in 5005 fatalities. However, the data show that the majority (71%) of fatalities occurred among occupants of other vehicles, while only 18% of fatalities were among large truck drivers, and the remaining 11% were among non-occupants, such as pedestrians and bicyclists. The substantial difference between the fatality proportion of large truck occupants and other vehicle occupants may result from differences in size, weight, and the type of collision. A relatively higher proportion (81%) of fatalities related to large trucks were crashes involving multiple vehicles. The proportion of drivers associated with DUI-related fatal crashes was substantially lower for large trucks (2%) compared to motorcycles (29%), passenger cars (20%), or light trucks (19%). Compared to other vehicles, the likelihood of large trucks being struck at the rear was almost four times higher. Most of the large truck crashes (41%) occurred when both the large truck and the other crash-involved vehicle were moving straight. In the case of turning crashes, left-turn maneuvers were associated with a substantially greater risk of a crash compared to right-turn maneuvers. When all vehicles associated with crashes are considered, large trucks account for 10% of fatal crash-related vehicles and only 4% of all injury- or property-damage-related vehicles. Interstate roads were associated with about 25% of all fatal large truck crashes. About 57% of fatal crashes related to large trucks occurred in rural land areas, and about 6% of fatal crashes occurred in work zones. On average, about 36% of all fatal large truck crashes occur at night. However, a substantial difference in the proportion of night-time crashes is observed when the weekday/weekend period is considered (28% during weekdays and 61% during weekend nights) [13].

1.2. Literature Review

Several studies have attempted to determine the factors influencing the frequency and severity of crashes involving large trucks. Large truck crash occurrence and injury severity are dependent on several variables, including roadway-, crash-, vehicle-, weather-, and driver-related factors, among others. A study analyzing data from 2010 to 2017 in Los Angeles found that crash severity was significantly affected by the time of day, and crashes where the truck driver was considered to be at fault were significantly linked to severe injuries [14]. Another study analyzing Tennessee state route roadways for the 2006–2010 period concluded that the most significant factors associated with large-truck-related crash frequency are driver age, speed limit, and location type, whereas the most significant factors involving large-truck crash-related injury severity are lighting condition, seat belt usage, and terrain type [15]. Utilizing data from the Fatality Analysis Reporting System (FARS) for the 2010–2015 period, one study identified two-lane undivided roadways, crash types, vehicle count, intersection types, driver impairment, speed limits, and weather conditions

as significant predictors of severe large truck crashes [16]. The annual average daily traffic (AADT) of large trucks, selected road segment length, terrain and median type, lane and shoulder width, land use, lighting condition, degree of horizontal curvature, and posted speed limits were found to be significantly associated with the likelihood of large-truck crash occurrence in a 4-year period study (2004–2007) in Tennessee [17]. Obstructed vision due to a fixed object or fog, following too closely, and running red lights were among the most hazardous factors related to severe large truck crashes in Florida (from 2007 to 2016) occurring on state highways with straight alignment and unpaved shoulders [18]. A study concluded that the significant contributing factors observed in the weekend and weekday periods were mostly different; however, some factors such as young drivers, intersection crashes, at-fault drivers, colliding with fixed objects, rear-end crashes, and crash time significantly affected injury severity irrespective of the period of the week [19]. Another study analyzing the injury severity associated with work zones found that daytime crashes, higher speed limits, no traffic control during access, and crashes on rural principal arterials substantially increased the likelihood of severe crashes [20]. Traffic engineers and roadway designers should adopt better, safer, and more efficient geometric designs and traffic control strategies, as roadway-related variables are more controllable, to assist with reducing specific types of crashes [21].

The influence of driver-related variables on large truck crash-associated injury severity is also substantial. A study utilized data from the Texas Crash Records Information System (CRIS) for the years 2011–2015 employing three tree-based machine learning methodologies, and “impairment due to alcohol or drugs” and “driver fatigue” emerged as the most critical factors linked to large truck crash severity [22]. Another study concluded that distractions among truck drivers, alcohol consumption, and the emotional states of the drivers were significantly correlated with severe large truck crashes [23]. A study conducted in Florida focused on rollover large truck accidents for the 2007–2016 period and concluded that careless driving, speeding, abnormal driving conditions, and vision obstruction increased the likelihood of severe crashes, especially under insufficient lighting conditions [24]. Characteristics like alcohol or drug impairment, seat belt use, and airbag availability significantly influenced injury severity in large truck crash incidents [25]. Cell phone use, lack of attention, failure to provide right of way, and failure to obey traffic rules are some of the factors that increase the probability of a fatal large truck crash [26]. However, no statistically significant difference was observed in crash characteristics and outcomes when large truck crashes involving middle-aged and older drivers were analyzed, but older drivers exhibited increased seat belt use and lesser alcohol use [27].

Researchers have employed various techniques in past traffic safety analyses, such as negative binomial models [28], ordinal probit models [29], heteroskedastic ordered probit models [30], tree-based models [22], generalized ordered approaches [31], zero-inflated hierarchical ordered probit models [32], and random parameter ordered probit models [24]. Logistic regression, widely utilized in prior large truck crash analyses [33–35], can assess associations and control for confounding variable effects [36]. One approach to analyzing the factors affecting the severity and frequency of large truck crashes is data clustering or dividing into sub-groups. The data clustering approach to large truck crashes in Florida for the 2007–2016 period suggested that crash datasets could be sub-grouped into same-direction, opposite-direction, and single-vehicle crash datasets to obtain a better understanding of the effects of contributing factors [37]. The dividing approach of the analysis period on urban freeways in Texas between 2006 and 2010 using different logit models suggests that the contributing factors related to injury severity varied over five periods per day [38]. The effects of variables on large truck crashes can also vary by the period of the week, and one study involving large truck crashes occurring on Los Angeles highways concluded that weekday and weekend crashes should be modeled separately [19].

The association of large truck crash occurrence or severity with crash-related factors might be influenced by the type of large truck crash. A study based in Oregon found

that human factors and driving fatigue increased the risk of minor injury in run-off-road crashes involving large trucks [39]. Another study on Wyoming's mountainous interstates concluded that off-road veering and strong winds heightened the risk of single-truck rollovers, whereas guardrails, median barriers, sharp curves, and adverse weather conditions lowered it [40]. Another Oregon-based study concluded that the influence of the contributing factors to driver injury severity in run-off-road crashes differs based on road type (rural or urban); however, horizontal curves, failure to use a seat belt, and fatigue of the driver increased the severe injury risk irrespective of the land use setting [41]. The use of alcohol or drugs, fatigue, emotional state, time of day, familiarity of the road, distraction, and road alignment are some of the factors that significantly affect lane departure-related large truck crashes [42]. Other studies highlighted the necessity of analyzing large-truck crash-related severe injuries by the party at fault [14,43]. Moreover, the impact of a variable on the severity of a large truck crash may vary based on the geographic location. A study conducted in Alabama determined that certain determinants influencing the severity of injuries sustained in crashes could exhibit significance exclusively within specific crash configurations (either single- or multi-vehicle) or geographical locations (either urban or rural) [44]. The likelihood of fatal crashes is higher for crashes involving two-trailer large trucks compared to those involving single-trailer trucks [30].

1.3. Large Truck Crashes in Texas

Texas is one of the chart-leading states for several types of roadway crashes, and large truck collisions are similarly prevalent. Following the inception of the Strategic Highway Safety Plan (SHSP) in 2006, the Texas Department of Transportation (TxDOT) has implemented multiple strategies to enhance road safety. As the second-largest U.S. state by both size and population, Texas, situated in the South-Central region, spans roughly 268,596 square miles, and had a population exceeding 30 million as of 2022. Texas has some of the biggest cities in the United States by population and has the largest highway networks. In 2019, Texas experienced the highest frequency of fatal crashes (658), and about 12.6% of all fatal crash-related vehicles were large trucks. The percentage of large trucks in Texas is about 13.1% of the total trucks in the United States. Texas leads the chart when death counts of occupants of large trucks (69 occupants in single-vehicle crashes, 77 occupants in multi-vehicle crashes), occupants of other vehicles associated with large truck crashes (433), and non-occupants involved in large truck crashes are considered (73). Large truck crash-related fatalities have been the highest in Texas since 1994 [13].

1.4. Scope of the Study

Considering the substantial contribution of large truck crashes to the annual road traffic incidents in Texas, which result in fatalities, injuries, and economic loss, a detailed investigation into the factors impacting large truck crash severity is of paramount importance. Moreover, a comprehensive examination of the overall patterns of large truck crashes and the identification of locations with notably high concentrations of severe incidents can provide valuable insights for policymaking and efficient resource management. The primary focus of this research encompasses a comprehensive analysis and assessment of the risk elements linked to severe large truck crashes, in addition to investigating the correlation between large truck crashes and the factors associated with large truck crashes in Texas through spatial and statistical analyses. Furthermore, this study also evaluated the variables pertaining to driver behaviors involved in the crashes. The research team thoroughly discussed the safety concerns regarding the high-risk locations and suggested recommendations that incorporate the utilization of existing technologies.

2. Materials and Methods

This study utilized crash data for the study period (2017–2021) from the TxDOT CRIS database, comprising information recorded by the peace officers and including the details of all the traffic crashes that transpired on Texas roadways. As per the Texas Transportation

Code (Section 550.062), reporting to the TxDOT is mandatory for the peace officer if a crash is associated with any injury or death of involved individuals within ten days of the crash incident and involves at least one motor vehicle. Moreover, when “property damage only” crashes surpass the monetary damage value of USD 1000, they are also mandated to be reported to the CRIS.

The CRIS data are organized into distinct categories for each year and contain information pertaining to crash coordinates; lighting and weather conditions; road class; road speed limit; surface conditions; time and day of the crash; and the age, gender, ethnicity, and injury severity of the involved individuals, among numerous other variables. The term “primary person” in this study encompasses drivers of various types of vehicles, including drivers of motor vehicles, bicyclists, and motorcyclists, as well as pedestrians. Each reported crash in the database is assigned a unique identification number, which facilitates the preparation of a comprehensive dataset by merging files from different categories.

The large truck crashes were sorted using the vehicle body information and include truck-, truck tractor-, and semi-trailer-related crashes [45]. The subsets for distraction, driving under the influence of drugs or alcohol, speeding, and lane departure crashes were prepared using the primary contributing factors associated with the crashes. According to the instructions for reporting crashes in Texas, a contributing factor is defined as a circumstance that plays a vital role in the occurrence of a crash, where the absence of that factor would have prevented the crash. If a crash happened because of distractions inside the vehicle, the driver not paying attention, falling asleep or being tired, or using a cell phone while driving, it was labeled as a distracted driving crash. If the crash was due to the driver drinking alcohol or being under the influence of drugs, it was labeled as a DUI (Driving Under the Influence) crash. Crashes caused by not controlling speed, driving too fast, or exceeding speed limits were marked as speeding-related. Finally, if the main reason for the crash was unsafe lane changes or not staying in one lane, the crash was identified as a lane departure crash. In this research, the injuries sustained by primary persons associated with large truck crashes were classified into two distinct categories: KA (i.e., fatal or incapacitating) injuries and KAB (i.e., fatal, incapacitating, or non-incapacitating) injuries. In essence, a KA injury corresponds solely to severe injuries, whereas a KAB injury encompasses any confirmed injury, irrespective of its severity. Distinct datasets and models were created for all large truck crashes and for crashes categorized by the at-fault party.

The selection of variables in this study was based on their significance in relation to crashes, as identified in previous studies [13,46–49]. A comprehensive list of all the variables employed in this investigation is presented in Table 1. In this study, the data processing and statistical analyses were conducted using RStudio software (version 1.3.1073) [50] due to its efficacy and practicality in performing statistical computations and ArcGIS Pro for spatial analyses [51].

Heat map analysis is widely employed for data visualization as it enables the user to represent the magnitudes in two dimensions through colors. The variation in colors can be used for visual cues, aiding observers in perceiving clusters or distributions of crash incidents across space [52]. Heat maps can be broadly categorized as clustered heat maps and spatial heat maps. Clustered heat maps utilize a fixed-cell-size matrix to lay out magnitudes and intentionally sort the rows and columns by considering the columns as discrete phenomena. On the other hand, because the process is continuous and each magnitude’s position is based on its location within the space, spatial heat maps do not require a fixed cell size. In this study, heat maps were generated by employing the kernel density method for density calculation to visualize the distribution of large truck crashes on continuous surfaces [53]. The density estimation for each location utilized the total count of large truck crashes at that location, and the center (i.e., the crash location) was assigned the maximum density value, with density gradually decreasing away from the center [54,55].

Table 1. Description of the study variables.

Num.	Description	Values	Num.	Description	Values
1	Day of Week	Weekend Weekday	9	Intersection Status	Yes No
2	Speed Limit	≤25 mph >25 mph	10	Road Class	Highway/FM Roads City/County/Other Roads
3	Time of Day	8:00 p.m.–6:00 a.m. 6:00 a.m.–8:00 p.m.	11	Gender	Male Female
4	Lighting Cond.	Daylight Dark	12	Ethnicity	Hispanic Non-Hispanic
5	Weather Cond.	Rain Clear/Cloudy	13	Surface Cond.	Wet Dry
6	Road Alignment	Level: Straight/Curve Grade/Hillcrest: Straight/Curve	14	Season	Winter Spring
7	Traffic Control	Marked Lane or No Passing Zone Stop Sign/Signal/Crosswalk/Other			Summer Fall
8	License Class	A/AM B/BM C/CM Unknown	15	Age	≤18 19–64 ≥65

The kernel density estimation utilizes a quartic kernel function, defined as follows:

$$P_2(z) = \begin{cases} 3\pi^{-1}(1 - z^T z)^2 & \text{if } z^T z < 1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where $P_2(z)$ represents the kernel function, and P is the probability density function which is generally radially symmetric unimodal.

The formula below calculates the predicted density at a given (x, y) location:

$$Density = \frac{1}{(radius)^2} \sum_{i=1}^n \left[\frac{3}{\pi} \cdot pop_i \left(1 - \left(\frac{distance_i}{radius} \right)^2 \right)^2 \right] \text{ for } distance_i < radius \quad (2)$$

where i represents the input points or point crashes; pop_i represents the value of the population field for point i ; and $distance_i$ represents the distance between the two points i and (x, y) .

Due to its inability to distinguish between different severity levels, heat map analysis is not appropriate for identifying road sections that are susceptible to severe crashes. In this study, hotspot analysis was used to identify significant spatial clusters of severe (“hot spots”) and non-severe (“cold spots”) crashes using the Getis–Ord G_i^* statistic, which generates an output with a z-score, p -value, and confidence level for each feature, indicating the likelihood of clustering not due to random chance. Conducted under the null hypothesis of Complete Spatial Randomness (CSR), significant clustering or dispersion rejects this hypothesis, evident from the high/low z-scores and small p -values. A False Discovery Rate correction addresses concerns of multiple testing and spatial data dependence. The appropriate choice of search bandwidth in the hotspot analysis is critical. An inappropriately large estimation of search bandwidth may produce overly smooth patterns, making it challenging to distinguish among local hotspot locations. Conversely, selecting a narrow search bandwidth for estimation may produce a spiky density pattern that highlights individual hotspot locations, potentially leading to ineffective clustering. To avoid drawing any erroneous conclusions, this study adopted a “trial and error” approach to address this issue by following the recommendations of previous studies [56–58]. Usually, an effective estimation of search bandwidth can be made by analyzing the spacings among the severe crashes within the extent of the selected area. Closely spaced crash locations would require

a relatively narrow search bandwidth to yield better results, whereas a relatively large search bandwidth would be required for crashes spaced far apart.

Assigning weights to the large truck crashes according to their respective severity levels plays a crucial role in accurately pinpointing hot- and cold spots. While the approach of assigning greater weight to more severe crashes is common, a universally accepted weighting system remains unestablished [59]. For example, the Roads and Traffic Authority (RTA) of New South Wales, Australia, applies severity indices of 3.0 for fatal, 1.8 for serious injury, 1.3 for other injury, and 1.0 for property damage-only crashes [60]. Similarly, another study used severity indices of 5.0 for fatal, 3.0 for serious, and 1.0 for light-injury crashes. [61]. In this study, relatively higher weights were assigned to large truck crashes that resulted in fatal or severe injuries to primary persons to effectively identify road segments with substantially higher risk. The Severity Exposure Index (SI) of a location was calculated using the following equation:

$$SI = 5.0 \times S1 + 3 \times S2 + 1.8 \times S3 + 1.3 \times S4 + S5 \quad (3)$$

where S1 is the aggregate count of fatal crashes; S2 is the aggregate count of incapacitating/serious-injury crashes; S3 is the aggregate count of non-serious-injury crashes; S4 is the aggregate count of possible-injury crashes; and S5 is the aggregate count of no-injury/property damage-only crashes.

The frequencies and proportions of large truck crashes by each variable class provided an initial impression about the correlation between injury severity and standalone variable classes. Bivariate analysis (chi-square test) helped in analyzing the significance of association between the crash severity and standalone variables. However, the chi-square test is unable to control for potential confounding factors, leaving causal relationships uncertain. A study on large truck crashes used a random-parameter ordered probit model and concluded that the injury severity levels are substantially influenced by the cross-interactions between several factors [62]. Logistic regression models were used to find the connections between the crash severity and factors related to the crashes themselves, such as weather, lighting, type of road, traffic control, condition of the road's surface, speed limit, time of day/week/month, and the presence of an intersection, as well as factors related to the people involved, such as their age, gender, and race. The logistic regression models offer several advantages over bivariate analysis, as they allow for the assessment of the effect of a predictor on the severity of large truck crashes while simultaneously controlling for other predictors. Furthermore, logistic regression models are easier to implement, train, and interpret and are extendable to multiple classes without making any assumptions about the distribution of classes.

The overall performance of the logistic regression models was assessed using null and residual deviance values and their respective degrees of freedom. Null deviance evaluates model prediction using only the intercept, while residual deviance assesses prediction accuracy with additional predictors. The disparity between null and residual deviance reflects the model's success in reducing deviance through predictor inclusion. The natural logarithm of the odds was utilized in this study, with the response variable Y being classified as severe (Y = 1) or non-severe (Y = 0), as shown in Equation (4):

$$\text{Logit}(Q) = \ln(Q/1 - Q) = \beta_0 + \beta_1 * Z_1 + \dots + \beta_i * Z_i \quad (4)$$

where Z_i refers to the independent variable, β_i refers to the model coefficient, which directly determines the odds ratio (OR), and Q refers to the probability of severe crashes. The odds ratio quantifies the likelihood of an event occurring in the presence of the independent variable compared to its absence.

3. Results and Discussion

3.1. Spatial Analysis

The assessment of the spatial distribution of large truck crashes utilized a heat map and hotspot analysis (Figures 1–5). The spatial analysis employed the World Geodetic System (WGS 1984, EPSG 4326), with the World Street Map serving as the base map. Predominantly, large truck crashes were concentrated within major cities along major highways. Houston, Dallas–Fort Worth, San Antonio, El Paso, and Austin exhibited the highest concentrations of large truck crashes among all cities. In addition to counties containing these major cities, other counties with notably elevated large truck crash concentrations included Lubbock, Amarillo, Laredo, Brownsville, and Corpus Christi, among others. Most of the severe crash hotspot locations were not located on the major highways.

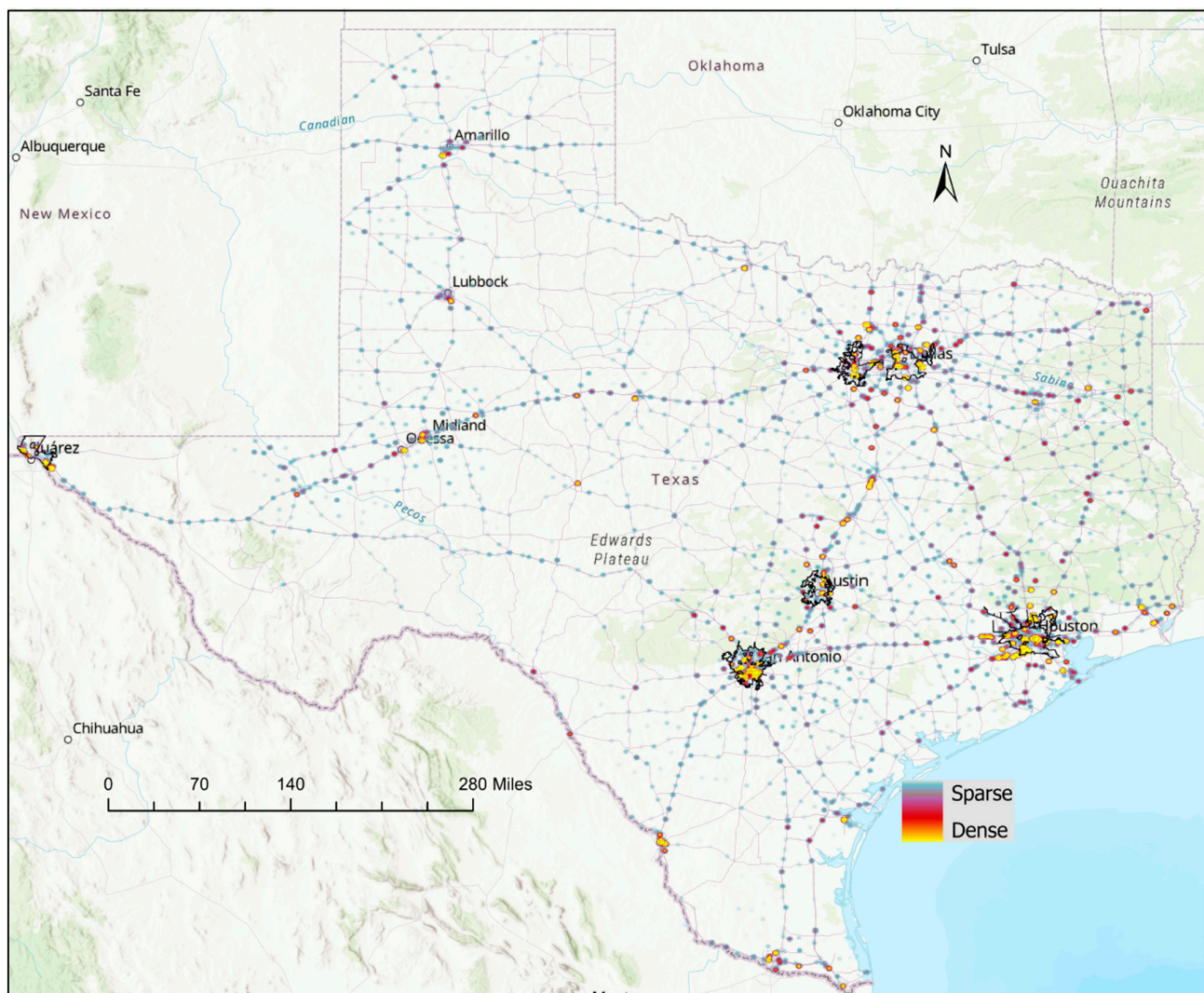


Figure 1. Heat map of large truck crashes in Texas.

While the overall vehicle crashes in Texas were predominantly concentrated in the downtown areas, large truck heat maps show that the crash concentration was high on the outskirts of the major cities, especially crashes at major intersections on the loops surrounding the cities. Notably, in Dallas, a substantial concentration of large truck crashes was observed around the city center. Consistent with prior research, areas with high concentrations of large truck crashes were not identified as high-risk locations for severe crashes, as crashes at these locations were statistically less likely to result in severe outcomes.

High-risk locations were distributed across various road types, with a notable concentration on city streets and farm-to-market (FM) roads.

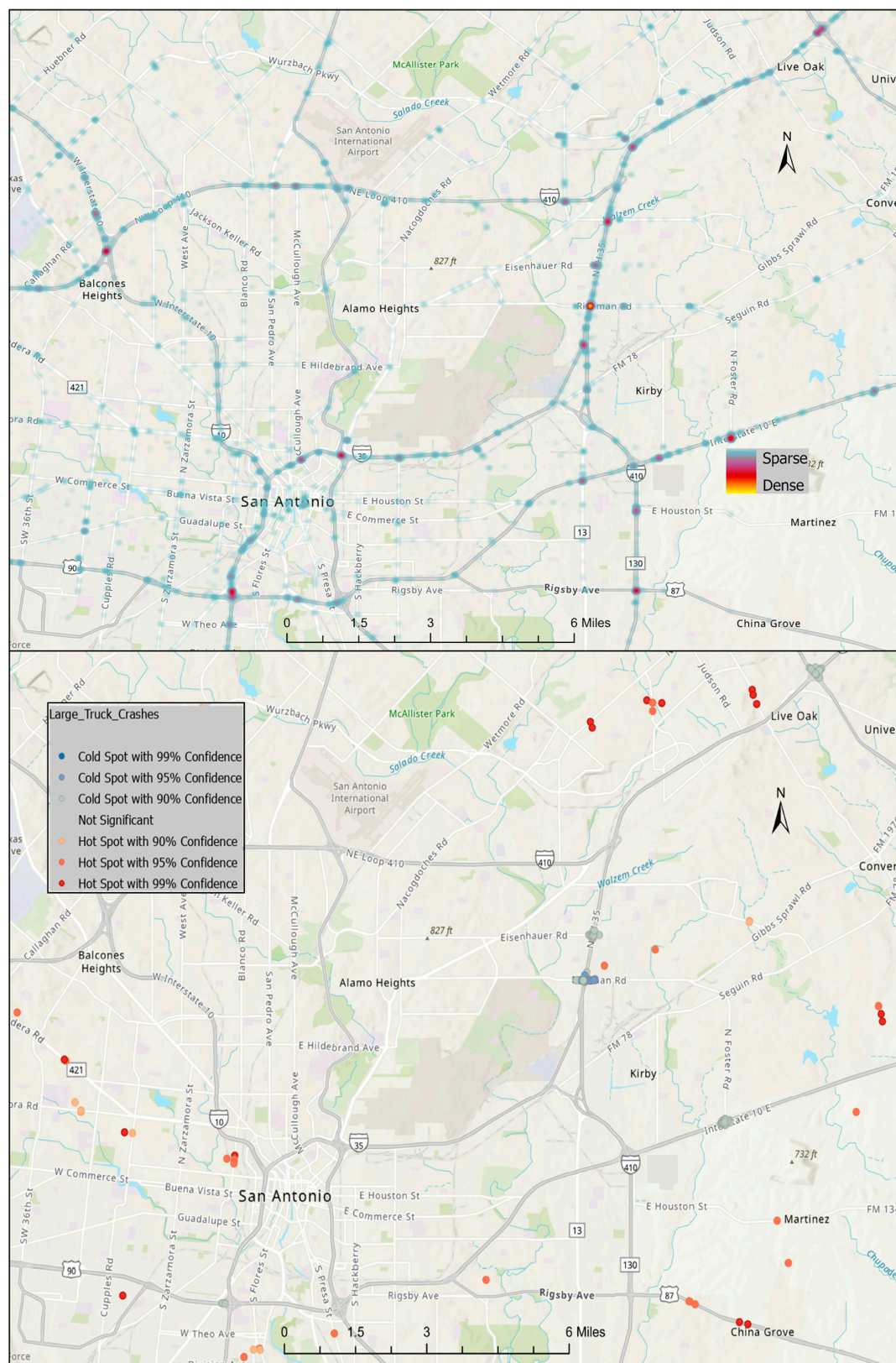


Figure 2. Locations in San Antonio with frequent large truck crashes (**top**) and severe large truck crash hotspots (**bottom**).

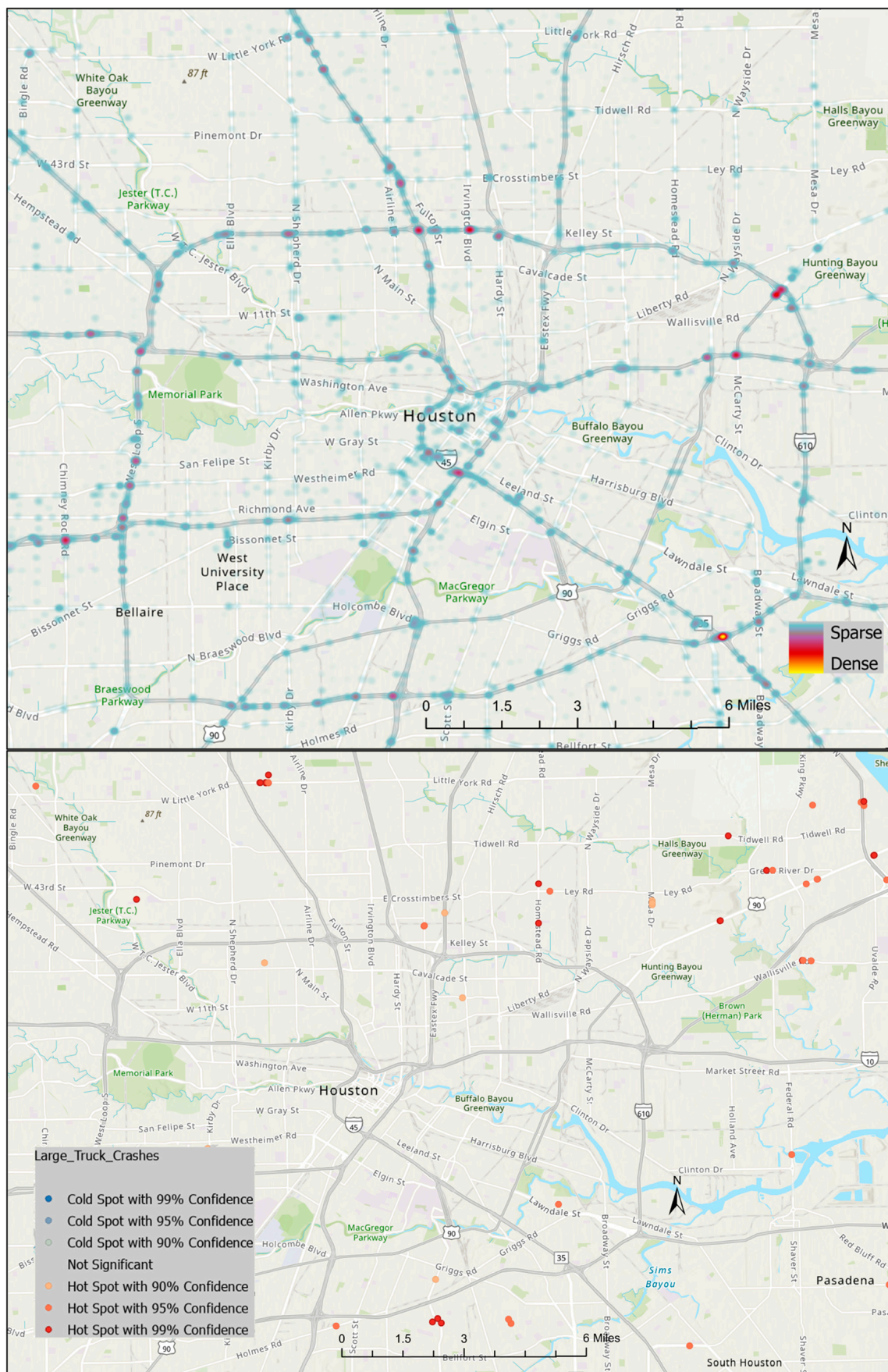


Figure 3. Locations in Houston with frequent large truck crashes (**top**) and severe large truck crash hotspots (**bottom**).

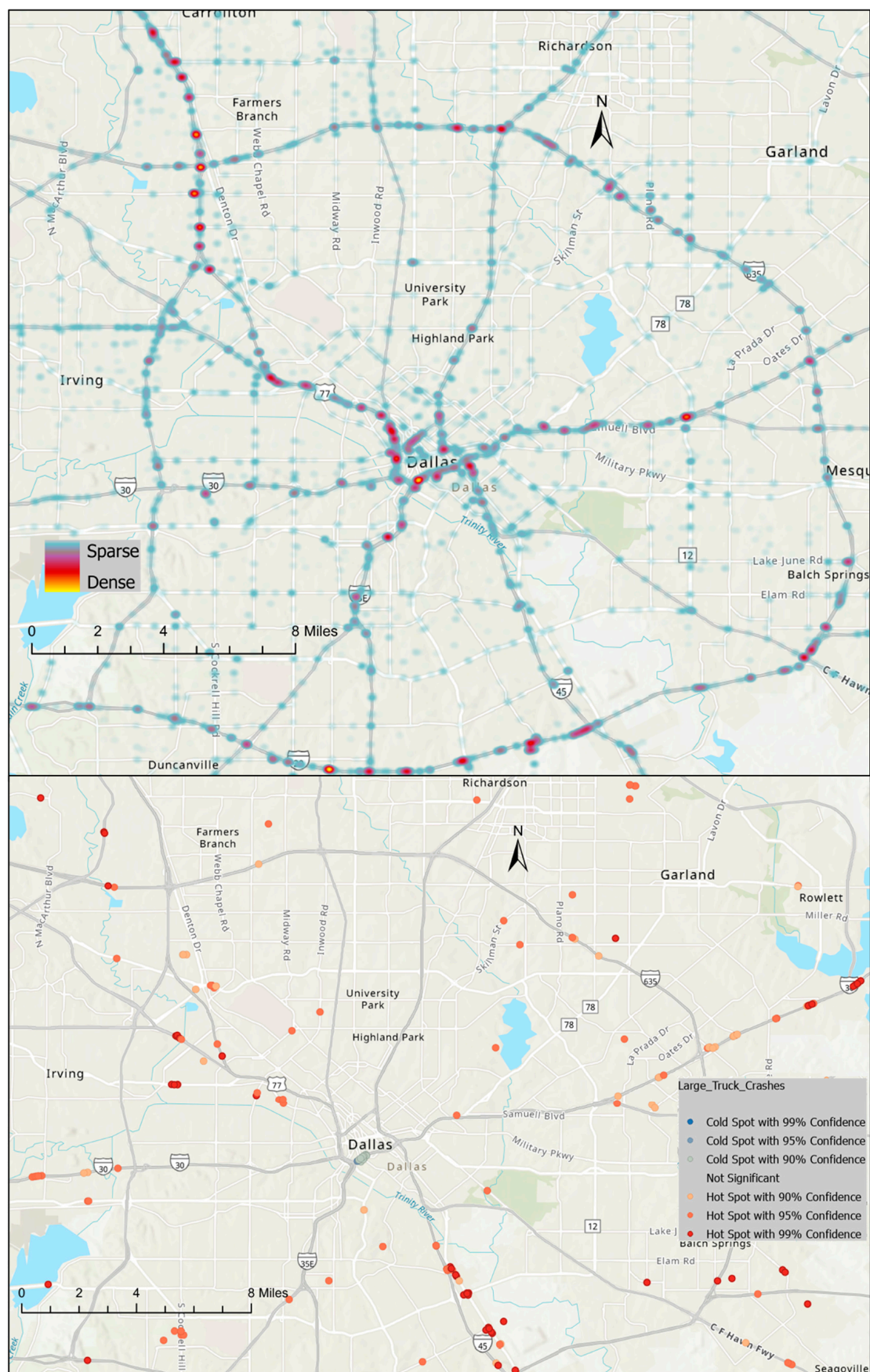


Figure 4. Locations in Dallas with frequent large truck crashes (top) and severe large truck crash hotspots (bottom).

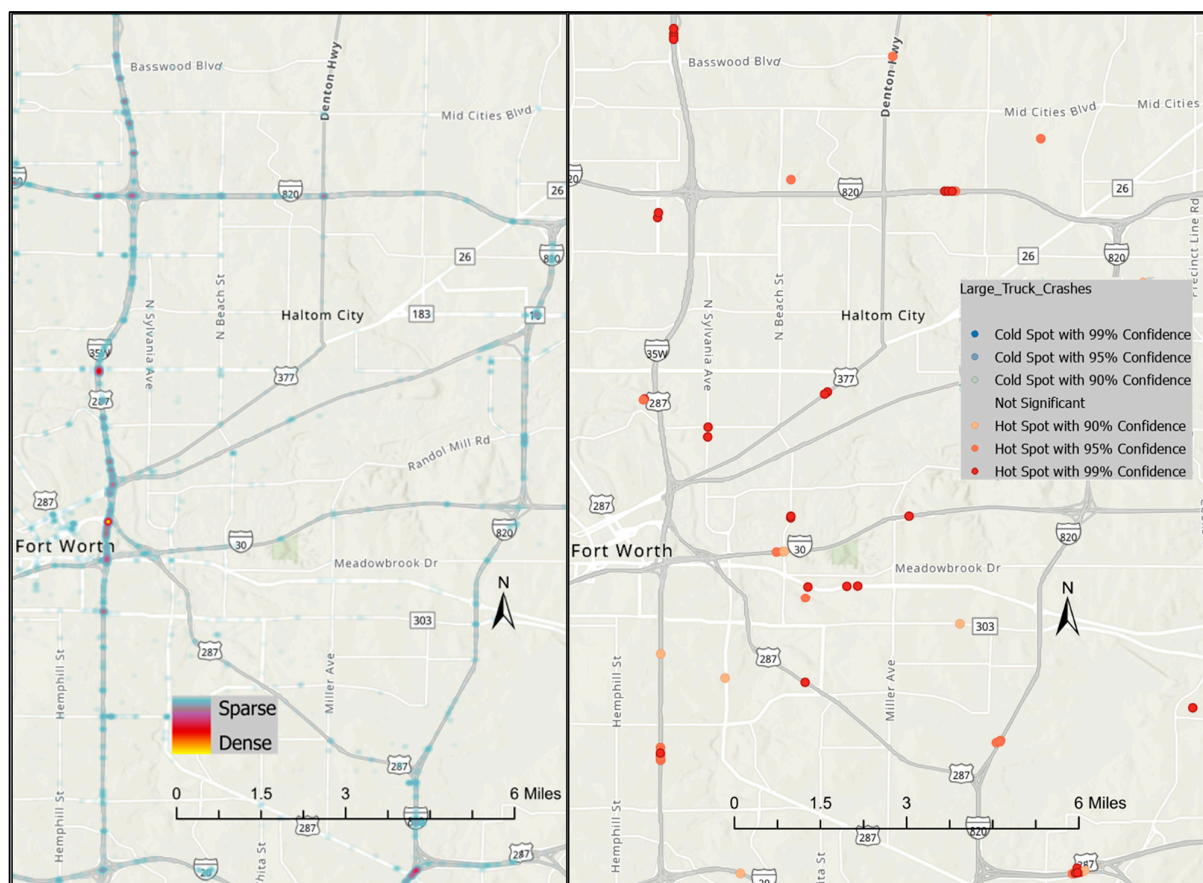


Figure 5. Locations in Fort Worth with frequent large truck crashes (**left**) and severe large truck crash hotspots (**right**).

In San Antonio, intersections along N Interstate 35 with Rd., Walzem Rd., Eisenhower Rd., and Thousand Oaks Dr. exhibited relatively high concentrations of large truck crashes (Figure 2). Specific road segments, such as Toepperwein Rd, O'Connor Rd, and Nacogdoches Rd near N Interstate 35; segments of N Interstate 35 near the junction with Somerset Rd; segments of Somerset Rd between Fischer Rd and Verano Pkwy; and N Colorado St between Leal St and Arbor St, were identified as statistically significant high-risk locations for severe large truck crashes. In Houston, the intersection at Interstate 45 and Loop 610 and the intersection at Highway 90 and Loop 610 had the highest concentration of large truck crashes. Major intersections along Interstate 45 and Loop 610 also experienced relatively more frequent large truck crashes (Figure 3). The hotspots of severe large truck crashes include Veterans Memorial Dr between Turney Rd and Candytuft Ct, E Little York Rd between Northline Dr and Domino Ln, on the North-West Freeway between Hahl Dr and Windfern Rd, and near the junction of Highway 73 and Highway 82.

Large truck crash concentrations were high in the south and west parts of downtown Dallas along Interstate 35 and Interstate 30, on Interstate 20 between Highway 67 and Highway 310 on the south side of the city, on Stemmons Fwy between Highway 366 and Oak Lawn Ave, and on Interstate 35 between E Belt Line Rd and Walnut Hill Ln. The intersections on Highway 310 with Linfield Rd, E Illinois St, and Highway 12; the intersection at Interstate 30 and President George Bush Hwy; the intersection at Interstate 35 and FM308; and N Interstate Highway 45 between Malloy Bridge Rd and Patrick Pike Rd were involved in a high proportion of severe large truck crashes.

Large truck crash concentrations were highest at the intersections on Interstate 35 W with Highway 287 and Highway 183 in Fort Worth. Interstate 35 W between Highway 180 and Highway 183 had the highest large truck crash concentration. Interstate 20 between Shorewood Dr and Woodfield Dr; Interstate 35 between Ripy St and E Bewick St; NE Loop

820 in front of Walmart Supercenter/Sam's Club; and Interstate 35 W just north of Basswood Blvd had clusters of severe large truck crashes.

Between 2017 and 2021, large truck crashes accounted for 8.9% (272,788) of Texas's total crashes, including 15.2% (2701) of fatal, 9.2% (6321) of incapacitating-injury, and 7.5% (21,131) of non-incapacitating-injury incidents. Large truck drivers were deemed to be at fault for 52.2% (141,908) of these crashes, resulting in a comparatively lower incidence of fatalities and incapacitating injuries compared to crashes where the other drivers were at fault (Figure 6). Large truck drivers are relatively more protected in traffic crashes, and the lower proportion of severe crashes involving faulty large truck drivers might imply that mistakes on the truck drivers' end created relatively fewer fatal situations. The annual analysis in Figure 7 illustrates the proportions of large truck crashes, severe crashes (KA), and confirmed injury crashes (KAB) throughout the study period. Notably, the proportion of severe crashes involving large trucks exceeds their overall contribution to total crashes.

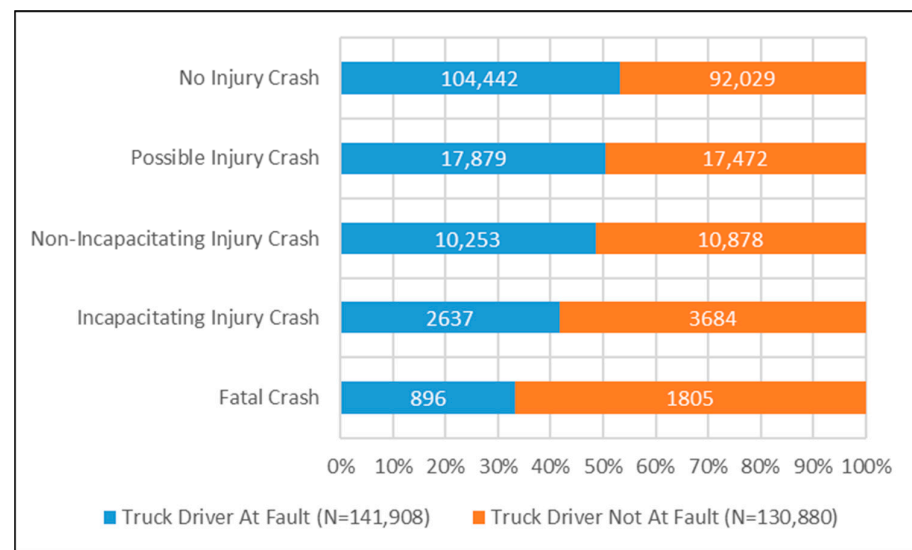


Figure 6. Proportions of different types of injury in large truck crashes by the party at fault.

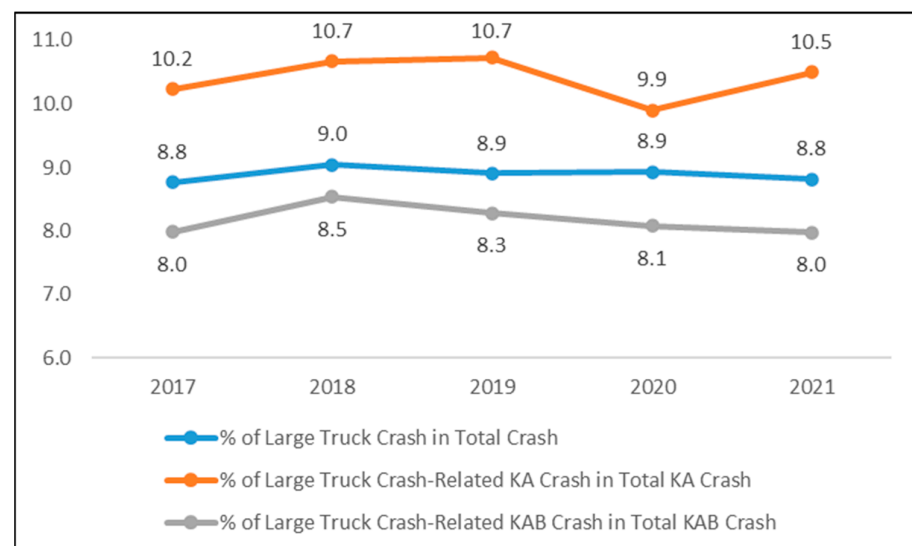


Figure 7. The proportion of large truck crashes and injuries compared to all traffic crashes and injuries.

3.2. Bivariate Analysis

The frequencies and proportions of large truck crashes, as delineated in Tables 2–4 for various crash severity levels and associated variables, offer preliminary insights into

potential relationships between these variables and the severity levels and frequency of large truck crashes. Variables exhibiting the strongest association with large truck crashes resulting in any form of confirmed injury encompassed conditions such as “dark, not lighted” lighting, crash occurrences on Sundays, curved road alignments, night-time incidents (8:00 p.m.–6:00 a.m.), higher posted speed limits, farm-to-market roads, traffic control indicating a “no passing zone” or “marked lane”, incidents involving male and older primary persons, and cases where the license class of the involved driver was “C/CM” or “Unknown”. Across almost all crash-associated variables, the risk of severe injury in large truck crashes significantly escalated when the large truck drivers were not identified as the at-fault party.

Table 2. Proportions of severe-injury (KA) and any-injury (KAB) crashes involving large trucks by environmental, temporal, and vehicle-related variables in Texas, 2017–2021.

Variable	All Large Truck Crashes			Large Truck Driver at Fault			Large Truck Driver Not at Fault		
	N = 272,788	KA%	KAB%	N = 141,908	KA%	KAB%	N = 130,880	KA%	KAB%
Lighting Condition: Daylight	200,346	2.7	10.0	105,672	2.1	8.8	94,674	3.4	11.3
Dark, not lighted	24,542	7.8	18.4	12,495	5.9	16.7	12,047	9.9	20.2
Dark, lighted	39,421	3.6	11.9	19,474	2.6	9.8	19,945	4.5	13.9
Weather Condition: Clear	200,942	3.3	11.0	103,217	2.5	9.5	97,725	4.2	12.5
Rain	24,544	3.1	11.0	13,576	2.4	9.7	10,968	3.9	12.5
Cloudy	41,941	3.3	11.2	22,030	2.3	10.0	19,911	4.3	12.6
Day of Week: Saturday	26,850	3.5	11.8	13,814	2.6	10.5	13,036	4.5	13.2
Sunday	19,169	4.1	12.5	9822	3.1	10.9	9347	5.1	14.1
Monday	43,029	3.3	11.0	22,617	2.6	9.6	20,412	4.1	12.4
Tuesday	45,436	3.1	10.8	23,669	2.3	9.7	21,767	3.9	12.1
Wednesday	45,366	3.3	11.0	23,684	2.6	9.8	21,682	4.1	12.3
Thursday	45,147	3.2	10.7	23,532	2.4	9.3	21,615	4.2	12.3
Friday	47,791	3.2	10.7	24,770	2.3	9.3	23,021	4.1	12.2
Time: 8:00 p.m. to 6:00 a.m.	50,022	5.5	14.8	24,712	4.0	12.8	25,310	6.9	16.8
6:00 a.m.–8:00 p.m.	222,766	2.8	10.2	117,196	2.2	9.1	105,570	3.5	11.5
Season: Winter	65,070	3.2	10.7	34,062	2.5	9.5	31,008	4.0	11.9
Spring	67,292	3.3	11.1	34,792	2.4	9.6	32,500	4.2	12.7
Summer	68,987	3.4	11.3	35,789	2.6	9.9	33,198	4.3	12.8
Fall	71,439	3.4	11.1	37,265	2.5	9.8	34,174	4.3	12.5

Note: The cumulative percentage for a variable may not total 100% due to missing information for certain crashes.

Table 3. Proportions of severe-injury (KA) and any-injury (KAB) crashes involving large trucks by road-related variables in Texas, 2017–2021.

Variable	All Large Truck Crashes			Large Truck Driver at Fault			Large Truck Driver Not at Fault		
	N = 272,788	KA%	KAB%	N = 141,908	KA%	KAB%	N = 130,880	KA%	KAB%
Road Class: Interstate	75,274	3.4	11.6	36,118	2.8	10.5	39,156	4.0	12.6
US/State Highway	76,710	5.1	14.8	38,797	3.7	12.9	37,913	6.6	16.6
FM Roads	18,954	5.2	15.7	10,363	4.1	14.6	8591	6.6	17.0
City streets	66,660	1.6	8.0	35,391	1.2	7.1	31,269	2.0	9.0
Non-trafficway	19,421	0.6	2.4	12,233	0.5	2.2	7188	0.9	2.8
Surface Condition: Dry	233,156	3.4	11.1	119,988	2.5	9.7	113,168	4.2	12.6
Wet	33,588	3.2	11.2	18,446	2.6	10.3	15,142	4.0	12.4
Road Alignment: Level: Straight	220,719	3.0	10.4	112,769	2.2	8.9	107,950	3.9	11.9
Grade/Hillcrest: Straight	28,131	4.5	14.2	14,725	3.3	12.2	13,406	5.7	16.3
Level: Curve	12,322	5.2	15.4	7540	4.4	15.0	4782	6.5	16.0
Grade/Hillcrest: Curve	7878	5.2	16.2	4723	4.5	16.3	3155	6.3	16.1
Traffic Control: None	55,817	1.7	6.9	30,824	1.3	5.8	24,993	2.2	8.2
Signal Light	35,851	2.1	9.6	18,856	1.6	8.4	16,995	2.6	10.9
Stop Sign	20,468	4.0	12.0	10,798	2.7	10.3	9670	5.4	13.9
Yield Sign or Warning Sign	4782	3.5	11.7	2691	3.4	12.6	2091	3.5	10.6
Divider or Centre Stripe	21,761	6.2	16.2	11,489	4.6	14.5	10,272	8.0	18.1
No Passing Zone	3462	11.2	25.5	1977	7.7	22.3	1485	15.9	29.7
Marked Lanes	119,046	3.6	12.1	58,887	2.8	10.8	60,159	4.4	13.4

Table 3. Cont.

Variable	All Large Truck Crashes			Large Truck Driver at Fault			Large Truck Driver Not at Fault		
	N = 272,788	KA%	KAB%	N = 141,908	KA%	KAB%	N = 130,880	KA%	KAB%
Speed Limit: 25 mph or less over 25 mph	12,953 244,482	0.7 3.6	3.2 11.8	8004 125,650	0.6 2.7	2.8 10.4	4949 118,832	1.0 4.5	3.9 13.2
Intersection Status: Yes No	64,850 207,938	3.2 3.3	11.7 10.9	108,607 33,301	2.5 2.5	10.5 9.5	31,549 99,331	4.0 4.3	12.9 12.4

Note: The cumulative percentage for a variable may not total 100% due to missing information for certain crashes.

Table 4. Proportions of severe-injury (KA) and any-injury (KAB) crashes involving large trucks by human-related variables in Texas, 2017–2021.

	All Large Truck Crashes			Large Truck Driver at Fault			Large Truck Driver Not at Fault		
	N = 272,788	KA%	KAB%	N = 141,908	KA%	KAB%	N = 130,880	KA%	KAB%
Gender: Male Female	373,473 112,568	1.9 1.7	8.3 5.7	185,725 54,103	1.4 1.3	7.1 5.3	187,748 58,465	2.4 2.1	9.4 6.0
Age: 18 or less 19 to 64 65 or older	12,815 430,773 36,185	2.1 1.7 2.6	8.1 6.2 7.8	5215 212,448 17,429	1.1 1.3 2.0	5.8 5.7 6.7	7382 215,197 18,417	2.6 2.0 3.0	9.1 6.6 8.6
Ethnicity: White Hispanic Black Asian Other	193,102 173,397 90,178 11,762 12,415	2.1 1.6 1.5 1.3 1.1	6.8 5.9 6.4 5.6 4.4	94,141 86,822 43,764 5929 6641	1.6 1.3 1.2 1.1 1.1	5.9 5.5 6.2 5.4 4.6	98,961 86,575 46,414 5833 5774	2.6 2.0 1.8 1.6 1.1	7.6 6.4 6.7 5.8 4.2
License Class: A/AM B/BM C/CM Unknown	118,869 10,117 244,274 34,281	1.1 1.2 2.0 2.8	4.0 4.7 7.4 9.6	60,677 5243 126,958 14,381	1.4 1.2 1.4 1.8	5.1 5.1 6.2 8.0	58,192 4874 126,817 19,900	0.8 1.2 2.7 3.6	2.9 4.3 8.6 10.7

Note: The cumulative percentage for a variable may not total 100% due to missing information for certain crashes.

Tables 5–7 present the outcomes of chi-square tests, accompanied by corresponding odds ratio values, for all large truck crashes, large truck driver-at-fault crashes, and large truck driver-not-at-fault crashes, respectively. Some adjustments to variable classes were made compared to Tables 2–4 to enhance clarity regarding their impact. Notably, the “dark, lighted” and “dark, not lighted” classes were consolidated into a single category labeled “dark”. Inclement weather conditions with minimal observations (snow, fog, and hail) were omitted from the chi-square test. Interstate roads, field-to-market (FM) roads, and U.S./state highways were amalgamated into a unified group denoted as “Highway/FM Road”, while the remaining roads were categorized as “Other Roads”. The road alignment variable was regrouped into two classes: “Straight/Curve (Level)” and “Straight/Curve (Grade/Hillcrest)”. Additionally, the primary person’s ethnicity was reclassified into two categories: “Hispanic” and “non-Hispanic”.

Table 5. Results of chi-square tests and odds ratios for different types of injuries involving all large truck crashes.

Factor	df	KA			KAB		
		Chi-Square Statistic	p-Value	OR	Chi-Square Statistic	p-Value	OR
Lighting condition: Daylight Dark	1	1097.7	2.2×10^{-16}	0.48 1.00	1205.5	2.2×10^{-16}	0.63 1.00
Weather Condition: Rain Clear/Cloudy	1	4.1	4.3×10^{-02}	0.93 1.00	0.89	3.5×10^{-01}	0.98 1.00
Road Class: Highway/FM Roads City/County/Other Roads	1	804.0	2.2×10^{-16}	1.00 0.51	1102.5	2.2×10^{-16}	1.00 0.65
Speed limit: ≤25 mph >25 mph	1	206.1	2.2×10^{-16}	1.00 3.95	596.0	2.2×10^{-16}	1.00 3.23
Day of Week: Weekend Weekday	1	52.2	5.1×10^{-13}	1.20 1.00	112.5	2.2×10^{-16}	1.18 1.00

Table 5. Cont.

Factor	df	KA			KAB		
		Chi-Square Statistic	p-Value	OR	Chi-Square Statistic	p-Value	OR
Intersection Status: Yes	1	5.2	2.2×10^{-02}	0.94	10.8	1.0×10^{-03}	1.05
No				1.00			1.00
Season: Winter	3	6.4	9.3×10^{-02}	0.95	14.8	2.0×10^{-03}	0.96
Spring				0.98			1.00
Summer				1.02			1.02
Fall				1.00			1.00
Time of Day: 8:00 p.m.–6:00 a.m.	1	1075.9	2.2×10^{-16}	1.00	1171.6	2.2×10^{-16}	1.00
6:00 a.m.–8:00 p.m.				0.47			0.61
Alignment: Level: Straight/Curve	1	186.1	2.2×10^{-16}	0.69	438.9	2.2×10^{-16}	0.71
Grade/Hillcrest: Straight/Curve				1.00			1.00
Surface Condition: Wet	1	2.7	1.0×10^{-01}	0.95	0.03	8.6×10^{-01}	1.00
Dry				1.00			1.00
Traffic Control: Marked Lane or No Passing Zone	1	522.2	2.2×10^{-16}	1.00	782.1	2.2×10^{-16}	1.00
Stop Sign/Signal/Crosswalk/Other				0.58			0.69
Gender: Male	1	243.3	2.2×10^{-16}	1.34	27.1	1.9×10^{-07}	1.06
Female				1.00			1.00
Age: ≤18	2	26.6	1.7×10^{-06}	1.00	18.3	1.1×10^{-04}	1.00
19–64				1.10			1.01
≥65				1.24			1.08
Ethnicity: Non-Hispanic	1	6.1	1.3×10^{-02}	1.04	2.5	1.1×10^{-01}	1.01
Hispanic				1.00			1.00
License Class: A/AM	3	310.4	2.2×10^{-16}	1.00	204.1	2.2×10^{-16}	1.00
B/BM				0.70			0.84
C/CM				0.74			0.93
Unknown				0.94			1.15

Table 6. Results of chi-square tests and odds ratios for different types of injuries involving large truck driver-at-fault crashes.

Factor	df	KA			KAB		
		Chi-Square Statistic	p-Value	OR	Chi-Square Statistic	p-Value	OR
Lighting condition: Daylight	1	387.1	2.2×10^{-16}	0.50	508.0	2.2×10^{-16}	0.64
Dark				1.00			1.00
Weather Condition: Rain	1	2.3	1.3×10^{-01}	0.92	0.0	8.6×10^{-01}	0.99
Clear/Cloudy				1.00			1.00
Road Class: Highway/FM Roads	1	312.1	2.2×10^{-16}	1.00	530.9	2.2×10^{-16}	1.00
City/County/Other Roads				0.52			0.65
Speed limit: ≤25 mph	1	98.6	2.2×10^{-16}	1.00	359.8	2.2×10^{-16}	1.00
>25 mph				3.86			3.43
Day of Week: Weekend	1	18.9	1.4×10^{-05}	1.21	56.3	6.2×10^{-14}	1.19
Weekday				1.00			1.00
Intersection Status: Yes	1	0.2	6.4×10^{-01}	0.98	17.9	2.3×10^{-05}	1.09
No				1.00			1.00
Season: Winter	3	4.2	2.4×10^{-01}	0.99	4.4	2.2×10^{-01}	0.97
Spring				0.97			0.97
Summer				1.06			1.01
Fall				1.00			1.00
Time of Day: 8:00 p.m.–6:00 a.m.	1	358.4	2.2×10^{-16}	1.00	464.7	2.2×10^{-16}	1.00
6:00 a.m.–8:00 p.m.				0.49			0.63
Alignment: Level: Straight/Curve	1	98.4	2.2×10^{-16}	0.65	264.1	2.2×10^{-16}	0.68
Grade/Hillcrest: Straight/Curve				1.00			1.00
Surface Condition: Wet	1	0.03	8.6×10^{-01}	1.01	4.2	4.1×10^{-02}	1.06
Dry				1.00			1.00
Traffic Control: Marked Lane or No Passing Zone	1	242.2	2.2×10^{-16}	1.00	460.4	2.2×10^{-16}	1.00
Stop Sign/Signal/Crosswalk/Other				0.55			0.66
Gender: Male	1	71.1	2.2×10^{-16}	1.30	13.0	3.1×10^{-04}	1.06
Female				1.00			1.00
Age: ≤18	2	19.4	6.1×10^{-05}	1.00	17.1	2.0×10^{-04}	1.00
19–64				1.09			1.00
≥65				1.31			1.11

Table 6. Cont.

Factor	df	KA			KAB		
		Chi-Square Statistic	<i>p</i> -Value	OR	Chi-Square Statistic	<i>p</i> -Value	OR
Ethnicity: Non-Hispanic	1	0.2	6.5×10^{-01}	1.01	0.5	4.7×10^{-01}	1.01
Hispanic				1.00			1.00
License Class: A/AM	3	142.3	2.2×10^{-16}	1.00	99.7	2.2×10^{-16}	1.00
B/BM				0.77			0.88
C/CM				0.72			0.91
Unknown				0.94			1.16

Table 7. Results of chi-square tests and odds ratios for different types of injuries involving large truck driver-not-at-fault crashes.

Variable	df	KA			KAB		
		Chi-Square Statistic	<i>p</i> -Value	OR	Chi-Square Statistic	<i>p</i> -Value	OR
Lighting condition: Daylight	1	659.7	2.2×10^{-16}	0.48	652.3	2.2×10^{-16}	0.63
Dark				1.00			1.00
Weather Condition: Rain	1	0.24	6.3×10^{-01}	0.97	0.17	6.8×10^{-01}	0.99
Clear/Cloudy				1.00			1.00
Road Class: Highway/FM Roads	1	411.6	2.2×10^{-16}	1.00	485.2	2.2×10^{-16}	1.00
City/County/Other Roads				0.53			0.67
Speed limit: ≤ 25 mph	1	83.4	2.2×10^{-16}	1.00	197.8	2.2×10^{-16}	1.00
> 25 mph				3.51			2.75
Day of Week: Weekend	1	30.5	3.4×10^{-08}	1.21	53.0	3.4×10^{-13}	1.17
Weekday				1.00			1.00
Intersection Status: Yes	1	7.8	5.3×10^{-03}	0.91	0.1	7.7×10^{-01}	1.01
No				1.00			1.00
Season: Winter	3	5.1	1.6×10^{-01}	0.92	13.3	4.0×10^{-03}	0.95
Spring				0.98			1.02
Summer				0.99			1.03
Fall				1.00			1.00
Time of Day: 8:00 p.m.–6:00 a.m.	1	662.1	2.2×10^{-16}	1.00	659.9	2.2×10^{-16}	1.00
6:00 a.m.–8:00 p.m.				0.47			0.61
Alignment: Level: Straight/Curve	1	101.3	2.2×10^{-16}	0.69	196.1	2.2×10^{-16}	0.73
Grade/Hillcrest: Straight/Curve				1.00			1.00
Surface Condition: Wet	1	2.6	1.1×10^{-01}	0.93	1.0	3.1×10^{-01}	0.97
Dry				1.00			1.00
Traffic Control: Marked Lane or No	1	243.9	2.2×10^{-16}	1.00	289.7	2.2×10^{-16}	1.00
Passing Zone				0.62			0.73
Stop Sign/Signal/Crosswalk/Other	1	189.4	2.2×10^{-16}	1.34	19.4	1.1×10^{-05}	1.06
Gender: Male				1.00			1.00
Female				1.00			1.00
Age: ≤ 18	2	13.9	9.8×10^{-04}	1.00	5.6	6.1×10^{-02}	1.00
19–64				1.17			1.05
≥ 65				1.27			1.09
Ethnicity: Non-Hispanic	1	5.3	2.2×10^{-02}	1.05	0.9	3.3×10^{-01}	1.01
Hispanic				1.00			1.00
License Class: A/AM	3	191.3	2.2×10^{-16}	1.00	91.7	2.2×10^{-16}	1.00
B/BM				0.66			0.81
C/CM				0.74			0.93
Unknown				0.88			1.11

3.2.1. Environmental and Temporal Characteristics

Vehicle speed significantly influences crash severity, particularly for large trucks, as the crashes involving large trucks result in higher momentum upon impact. In instances where large truck drivers were at fault on roads with relatively higher posted speed limits, the likelihood of a severe crash substantially increased (OR 3.9). This study categorized all crashes into two groups based on the posted speed limit on the road. Further exploration across various posted speed limit groups could provide additional insights. While higher posted road speed limits generally heightened the risk of severe crashes, incidents on US/state highways and FM roads were more likely to result in severe crashes across all road classes. The likelihood of a severe crash nearly doubled on interstate, highway, and

FM roads compared to other roads (city streets, county roads, and non-trafficways), with severity risk remaining consistent regardless of fault attribution for both high-speed and low-speed roads.

Intersections frequently serve as crash hotspots, elevating crash risk by acting as converging points for vehicles from different directions. Navigating large vehicles, such as trucks, through intersections presents more challenges, demanding greater driver skill, attention, and focus. Approximately 23.8% of all large truck crashes occurred at intersections, a slightly lower proportion than that observed for other motor vehicles in Texas (around 30% of all crashes). Large truck drivers typically exhibit enhanced skills and experience compared to regular drivers, likely contributing to the relatively low proportion of large truck crashes at intersections. While the presence of intersections marginally decreased the likelihood of severe crashes, especially when large truck drivers were not at fault, it slightly elevated the likelihood of non-severe crashes, particularly when large truck drivers were at fault.

Navigating on a curved road, especially with a steep road gradient, presents a more formidable challenge compared to straight and level roads, a challenge exacerbated for large trucks due to their considerable length and weight in comparison to other vehicles, often contributing to involuntary speeding. Despite only 10.4% of all large truck crashes occurring on curved roads, these incidents were substantially more likely to result in severe crashes. The likelihood of severe large truck crashes notably increased on roads with steeper gradients when the large truck drivers were not at fault. In line with previous research, the highest risk of severe large truck crashes occurred when “no passing zones” were the primary road traffic control. Furthermore, the proportions of both severe and non-severe crashes were notably higher when “marked lanes”, “center stripes”, or “stop signs” served as the primary traffic control. This can be attributed to the potential for errors on the part of the truck driver catching other vehicle drivers off-guard under such traffic control conditions, with a limited available reaction time increasing the risk of severe crashes for other drivers.

3.2.2. Primary Person Characteristics

Among the key factors related to individuals involved in large truck crashes, the license class of drivers and the age and gender of the involved primary persons showed a significant association with the severity of large truck crashes. While male drivers were found to have a higher likelihood of being engaged in severe large truck crashes overall, female drivers exhibited a greater susceptibility to both severe and non-severe crashes when large truck drivers were not at fault. This suggests that female drivers may face challenges in effectively navigating hazardous situations involving larger vehicles on the road. When the fault was attributed to the truck driver, 141,908 large truck crashes involved a total of 239,828 primary persons. Conversely, when large truck drivers were not at fault, there were 130,880 large truck crashes involving 246,213 primary persons. Despite the nearly equal proportion of male and female drivers on the road, males accounted for over 75% of all primary persons involved in large truck crashes. This notable imbalance is likely attributed to the predominantly male composition of truck drivers. Previous research suggests male drivers are more likely to sustain severe injuries from traffic crashes [63].

The license class of drivers was a strong predictor of severe crashes. Tractor-trailer drivers (license class A/AM) had lower probabilities of being in severe crashes compared to those with C/CM or unknown license classes. This aligns with expectations, considering the greater protection and experience of drivers operating large commercial vehicles. However, when A/AM-class drivers were involved in crashes, the odds of severe injuries, predominantly affecting occupants of other vehicles, were higher. Hispanic and white drivers constituted most of the primary persons involved, consistent with Texas’s ethnic distribution. Both groups had a slightly elevated likelihood of severe crashes. Older and younger drivers had relatively higher probabilities of sustaining injuries, with older drivers

facing the highest odds of severe injuries. The impact of age on non-severe injuries was less pronounced.

Major contributors to traffic crashes include speeding, lane departure, driving under the influence (DUI), and distracted driving. Throughout the study period, there were 56,499 large truck crashes related to speeding, involving 117,603 primary persons, resulting in 765 fatal and 1953 incapacitating-injury crashes. Lane departure-related large truck crashes totaled 49,262 incidents (involving 98,505 primary persons), with 366 fatal and 780 incapacitating-injury crashes. Distracted driving-related large truck crashes numbered 32,628 occurrences, involving 59,440 primary persons, causing 155 fatal and 679 incapacitating-injury crashes. The frequencies of speeding-, lane departure-, and distracted driving-related large truck crashes were nearly halved on weekend days compared to weekdays. These crashes exhibited reduced frequencies in the evening and night hours, followed by an increase during the daytime. Conversely, DUI crashes had higher frequencies during the night-time, with weekend days experiencing significantly more DUI crashes than a weekday. A total of 3477 DUI-related large truck crashes occurred during the study period, involving 6303 primary persons, resulting in 140 fatal and 208 incapacitating-injury crashes. Overall, speeding, lane-departure, DUI, and distracted-driving crashes demonstrated an increasing trend over the study period. However, except for DUI-related crashes, other crash types experienced a decline in frequency in 2020, likely influenced by the COVID-19 outbreak.

3.3. Logistic Regression Results

In this study, separate logit models were developed for each dataset and injury severity combination. One model incorporated the variables related to human characteristics, while the other included the remaining variables. Tables 8 and 9 present the coefficient estimates, standard errors, significance levels, odds ratios, and reference categories for each variable. In the context of large truck crash severity, the negative coefficient estimates denote a decrease in the likelihood of a severe crash, while positive estimates indicate an increase. For instance, when all large truck crashes are considered, a negative coefficient estimate (−0.49) for the daylight lighting condition signifies a decrease in the likelihood (by 0.49 in log-odds) of a severe crash when transitioning from dark to daylight conditions. Asterisks, along with coefficient estimates, denote statistical significance. The positive coefficient (0.24 ***) associated with the presence of an intersection signifies increased odds of a severe large truck crash at intersections, with asterisks indicating a statistically significant association ($p < 0.001$). Furthermore, the estimate of the regression coefficient allows for the calculation of the strength of association (odds ratio) between the crash severity and the predictor variable. For example, a large truck crash (with the truck driver at fault) on a road with a higher speed limit has higher odds of resulting in a severe crash (OR 2.37) compared to a severe crash where the driver is not at fault (OR 1.90).

Table 8. Results from logistic regression models involving severe large truck crashes.

Variable	Reference	All Large Truck Crashes			Large Truck Driver at Fault			Large Truck Driver Not at Fault		
		Estimates	Std Error	OR	Estimates	Std Error	OR	Estimates	Std Error	OR
intercept 1		−3.05 ***	0.13		−3.35 ***	0.18		−2.71 ***	0.17	
Stop Sign/Signal/ Crosswalk/Other	Marked Lane or No Passing Zone	−0.41 ***	0.03	0.66	−0.46 ***	0.05	0.63	−0.36 ***	0.04	0.70
Daylight	Dark	−0.49 ***	0.04	0.61	−0.51 ***	0.07	0.60	−0.46 ***	0.06	0.63
Rain	No Rain	−0.15.	0.08	0.87	−0.15	0.12	0.86	−0.11	0.10	0.90
Other Roads	Highway	−0.47 ***	0.03	0.62	−0.41 ***	0.05	0.66	−0.47 ***	0.04	0.62
Weekend	Weekday	0.09 **	0.03	1.09	0.11 *	0.05	1.12	0.07.	0.04	1.07
Speed Limit > 25	Speed Limit ≤ 25	0.81 ***	0.12	2.25	0.86 ***	0.17	2.37	0.64 ***	0.17	1.90
Level	Grade/Hillcrest	−0.26 ***	0.03	0.77	−0.33 ***	0.05	0.72	−0.23 ***	0.02	0.80
Wet	Dry	−0.13 *	0.07	0.88	−0.12	0.10	0.89	−0.12	0.09	0.89
6:00 a.m.—8:00 p.m.	8:00 p.m.—6:00 a.m.	−0.36 ***	0.05	0.70	−0.32 ***	0.07	0.73	−0.36 ***	0.06	0.70
Spring	Fall	0.01	0.03	1.01	0.03	0.05	1.03	−0.01	0.04	0.99
Summer	Fall	0.07 *	0.03	1.07	0.12	0.05	1.12	0.04	0.04	1.04

Table 8. Cont.

Variable	Reference	All Large Truck Crashes			Large Truck Driver at Fault			Large Truck Driver Not at Fault		
		Estimates	Std Error	OR	Estimates	Std Error	OR	Estimates	Std Error	OR
Winter	Fall	−0.09 *	0.04	0.92	−0.03	0.06	0.97	−0.12 **	0.05	0.89
At Intersection: Yes	At Intersection: No	0.24 ***	0.03	1.28	0.24	0.05	1.27	0.25 ***	0.04	1.28
intercept 2		−3.40 ***	0.06		−3.60 ***	0.10		−3.60 ***	0.10	
Male	Female	0.24 ***	0.02	1.27	0.20 ***	0.04	1.22	0.20 ***	0.04	1.22
Age 19–64	Age ≤ 18	0.09.	0.05	1.09	0.07	0.09	1.07	0.07	0.09	1.07
Age ≥ 65	Age ≤ 18	0.22 ***	0.06	1.25	0.24 *	0.10	1.27	0.24 *	0.10	1.27
Non–Hispanic	Hispanic	0.07 **	0.02	1.08	0.04	0.03	1.04	0.04	0.03	1.04
Lic. Class: B/BM	Lic. Class: A/AM	−0.34 ***	0.06	0.71	−0.26 **	0.09	0.77	−0.26 **	0.09	0.77
Lic. Class: C/CM	Lic. Class: A/AM	−0.23 ***	0.02	0.80	−0.28 ***	0.03	0.76	−0.28 ***	0.03	0.76
Lic. Class: Unknown	Lic. Class: A/AM	0.04	0.03	1.04	0.01	0.05	1.01	0.01	0.05	1.01

Note: *** indicates $p < 0.001$; ** indicates $p < 0.01$; * indicates $p < 0.05$; "." indicates $p < 0.1$.

Table 9. Results from logistic regression models involving large truck crashes resulting in any type of injury.

Variable	Reference	All Large Truck Crashes			Large Truck Driver at Fault			Large Truck Driver Not at Fault		
		Estimates	Std Error	OR	Estimates	Std Error	OR	Estimates	Std Error	OR
intercept 1		−2.10 ***	0.06		−2.29 ***	0.09		−1.84 ***	0.09	
Stop Sign/Signal/Crosswalk/Other	Marked Lane or No Passing Zone	−0.28 ***	0.02	0.76	−0.34 ***	0.03	0.71	−0.22 ***	0.02	0.81
Daylight	Dark	−0.29 ***	0.03	0.75	−0.29 ***	0.04	0.75	−0.28 ***	0.04	0.75
Rain	No Rain	−0.15 ***	0.04	0.86	−0.23 ***	0.06	0.80	−0.05	0.06	0.95
Other Roads	Highway	−0.26 ***	0.02	0.78	−0.23 ***	0.02	0.80	−0.25 ***	0.02	0.78
Weekend	Weekday	0.12 ***	0.03	1.12	0.12 ***	0.03	1.13	0.11 ***	0.02	1.11
Speed Limit > 25	Speed Limit ≤ 25	0.85 ***	0.06	2.34	0.94 ***	0.08	2.55	0.67 ***	0.09	1.95
Level	Grade/Hillcrest	−0.25 ***	0.02	0.78	−0.29 ***	0.03	0.75	−0.24 ***	0.03	0.79
Wet	Dry	0.00	0.04	1.00	0.08	0.05	1.09	−0.06	0.05	0.94
6:00 a.m.–8:00 p.m.	8:00 p.m.–6:00 a.m.	−0.26 ***	0.03	0.77	−0.25 ***	0.04	0.78	−0.26 ***	0.04	0.77
Spring	Fall	0.02	0.02	1.02	−0.00	0.03	1.00	0.03	0.03	1.03
Summer	Fall	0.06 **	0.02	1.06	0.05.	0.03	1.06	0.06 *	0.03	1.06
Winter	Fall	−0.06 **	0.02	0.94	−0.05.	0.03	0.95	−0.07 **	0.03	0.93
Intersection_Yes	Intersection_No	0.23 ***	0.02	1.26	0.26 ***	0.03	1.29	0.20 ***	0.02	1.22
intercept 2		−2.03 ***	0.03		−2.17 ***	0.05		−2.18 ***	0.05	
Male	Female	0.07 ***	0.01	1.07	0.07 ***	0.02	1.07	0.07 ***	0.02	1.07
Age 19–64	Age ≤ 18	0.07 *	0.02	1.07	0.06	0.05	1.07	0.06	0.05	1.07
Age ≥ 65	Age ≤ 18	0.14 ***	0.03	1.15	0.17 **	0.05	1.19	0.17 **	0.05	1.19
Non–Hispanic	Hispanic	0.05 ***	0.01	1.05	0.04 *	0.02	1.04	0.04 *	0.02	1.04
Lic. Class: B/BM	Lic. Class: A/AM	−0.16 ***	0.03	0.85	−0.12 *	0.05	0.89	−0.12 *	0.05	0.89
Lic. Class: C/CM	Lic. Class: A/AM	−0.05 ***	0.01	0.95	−0.07 ***	0.02	0.93	−0.07 ***	0.02	0.93
Lic. Class: Unknown	Lic. Class: A/AM	0.19 ***	0.02	1.20	0.19 ***	0.03	1.21	0.19 ***	0.03	1.21

Note: *** indicates $p < 0.001$; ** indicates $p < 0.01$; * indicates $p < 0.05$; "." indicates $p < 0.1$.

The observed statistical significance of the variables and their respective strengths of association were different between the logistic regression model and the bivariate analysis results. Nonetheless, irrespective of severity level and fault attribution in large truck crashes, both models consistently indicated the same directional relationships (positive or negative). Certain variables, including the time of the day, primary road traffic control, road type, speed limit, road alignment, lighting conditions, driver gender, and license class, emerged as strong predictors of severe large truck crashes regardless of fault attribution. While the weekend period considerably increased severe crash risk for various vehicle types in Texas [64,65], the increase in large truck crash severity was only marginal during weekends. Although a substantial portion of weekend crashes involved DUI and distracted driving, the proportion of large truck drivers in such incidents did not vary significantly on weekends. However, the association of the weekend with severe large truck crashes strengthened when the fault lay with the large truck driver. Unlike in bivariate analysis, the presence of intersections had a more pronounced effect on increasing severe large truck crash risk in logistic regression analysis. The increased risk of severe crashes at

intersections in Texas is consistent with prior research [66]. The association of intersection presence with severe large truck crashes was statistically significant only when the large truck drivers were not at fault. This is intuitive, as errors from other drivers would leave the truck drivers with less visibility and reaction time to maneuver such large vehicles at convergence locations such as intersections. Large truck crashes at intersections tend to be more severe when trucks traverse unsignalized intersections without stopping and errors come from other drivers unaware of the approaching large trucks.

In contrast to severe crashes, nearly all selected variables exhibited statistically significant associations with crashes resulting in any form of confirmed injury, albeit with a relatively weaker strength of association. Adverse weather conditions markedly reduced the likelihood of injuries in crashes where large truck drivers were at fault, highlighting their swift response and adaptability in challenging situations after committing errors. However, on wet roads, the probability of crashes resulting in any form of injury slightly increased, suggesting that the proficiency of large truck drivers may be insufficient to control larger vehicles on slippery surfaces and entirely evade any form of injury. Errors from the drivers of other vehicles involved in large truck crashes slightly increased during the summer season and slightly decreased during the winter season. During the winter season, the likelihood of both severe and non-severe large truck crashes significantly decreased when drivers of other vehicles were at fault. The winter season, characterized by off-peak demands for freight transportation, may contribute to fewer freight vehicles on roadways, potentially aiding drivers of other vehicles in recovering from errors.

4. Conclusions

Freight transportation plays a crucial role in the economic sectors of production, trade, and agriculture in the United States. The principal aim of this research was to evaluate the intricate relationships among various elements of large truck crashes and their respective impacts on crash severity. The analysis of large truck-related crashes identified several high-risk factors, including night-time driving, navigating curved roads, the involvement of older male drivers, high-speed scenarios, and intersections characterized by limited visibility, all of which are linked to an increased likelihood of severe crashes, irrespective of the party at fault. Large truck crashes in Texas were mostly concentrated within and around the major cities, especially around downtown areas and near intersections along major highways. Additionally, this study reveals a consistent pattern in crashes related to lane departure, speeding, and distractions, which, though less frequent during weekends, exhibit a substantially higher severity. DUI-related incidents, while comparatively infrequent, exhibit a pronounced tendency towards severe outcomes, underscoring the heightened risk associated with driving under the influence. Furthermore, the findings underscore the heightened vulnerability of pedestrians, cyclists, and motorcyclists to incidents involving large trucks, indicating a critical need for targeted safety interventions to mitigate the risks faced by these road users [67].

To mitigate the incidence of large truck crashes, it is imperative for policymakers and transportation planners to adopt a multi-faceted approach focusing on intersection safety, infrastructure improvements, the embrace of safety technologies, and the protection of vulnerable road users. The enhancement of intersection safety could be achieved by the strategic placement of traffic signals at intersections with limited visibility, lowering speed limits in adjacent areas, and deploying warning signs where large truck traffic is prevalent. Infrastructure enhancements should include the implementation of dual left-turn lanes, right-turn slip lanes, and elongated entrance and exit ramps, along with extending stop lines at intersections frequented by trucks to aid in safer turning maneuvers. Furthermore, the adoption of advanced safety technologies such as side view assist, lane departure warnings, forward collision warnings, and sophisticated braking systems could substantially reduce large truck crashes [68,69]. Supporting the research and development of autonomous vehicles and promoting the use of ride-sharing services after drinking alcohol could serve as additional measures to curtail drunk driving incidents. To safeguard

vulnerable road users, the construction of designated bicycle lanes and raised sidewalks, the enactment of mandatory helmet laws for motorcyclists and cyclists, and the installation of voice-assisted pedestrian crossings are recommended. These comprehensive strategies, when implemented effectively, could significantly reduce the risks and severity of large truck crashes.

This study recognizes several constraints. Firstly, the assessment of injury severity in crashes depended on the judgment of responding police officers, introducing potential inaccuracies without external verification. Additionally, the subjective assignment of fault could bias the results. Moreover, crashes that result in minor injuries or no injuries to involved persons are often underreported in the crash data and might introduce bias to the research outcomes. As crashes involving primary persons may not fully represent the broader road-user population, there could be inherent sample selection bias. Furthermore, the lack of reliable statewide AADT data hindered its incorporation into the analysis. Approximately one-fifth of the large truck crashes lacked coordinate information, resulting in the heat map analysis and hotspot analysis being conducted solely on crashes with location data. Comparison of the results from this study with classification tree models and other regression models might provide further insights. Despite these limitations, the research offers valuable insights for Texas's efforts to mitigate traffic-related injuries and fatalities through spatial and statistical analyses. Future investigations should assess the impact of integrated technological interventions, driver training and awareness programs, and autonomous truck platooning on reducing large truck crash severity and enhancing road safety.

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References

1. Crainic, T.G.; Laporte, G. Planning models for freight transportation. In *Design and Operation of Civil and Environmental Engineering Systems*; Wiley: New York, NY, USA, 1997; Volume 343.
2. Chambers, M.; Goworowska, J.; Rick, C.; Sedor, J. Freight Facts and Figures 2015. 2015. Available online: <https://rosap.ntl.bts.gov/view/dot/32797> (accessed on 24 May 2022).
3. Freight Activity in the U.S Expected to Grow Fifty Percent by 2050 | Bureau of Transportation Statistics. Available online: <https://www.bts.gov/newsroom/freight-activity-us-expected-grow-fifty-percent-2050> (accessed on 26 January 2024).
4. Maurer, M.; Gerdes, J.C.; Lenz, B.; Winner, H. *Autonomous Driving*; Springer: Berlin, Germany, 2016.
5. Resolution Adopted by the United Nations General Assembly: 64/255. Improving Global Road Safety. A/RES/64/255. United Nations, New York, 2 March 2010. Available online: http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/64/255 (accessed on 24 May 2022).
6. *Report to Congress on the Large Truck Crash Causation Study*; Federal Motor Carrier Safety Administration, U.S. Department of Transportation: Washington, DC, USA, 2005.
7. Geedipally, S.R.; Lord, D. Investigating the Effect of Modeling Single-Vehicle and Multi-Vehicle Accidents Separately on Confidence Intervals of Poisson–Gamma Models. *Accid. Anal. Prev.* **2010**, *42*, 1273–1282. [CrossRef] [PubMed]
8. California Department of Transportation (Caltrans). Longer Combination Vehicles Operational Tests. 2009. Available online: <http://www.dot.ca.gov/hq/traffops/trucks/exemptions/lcvs.htm> (accessed on 15 May 2022).

9. Abdel-Rahim, A.; Berrio-Gonzales, S.G.; Candia, G.; Taylor, W. *Longer Combination Vehicle Safety: A Comparative Crash Rate Analysis*; Final Report; Report Number N06-21; National Institute for Advanced Transportation Technology (NIATT): Moscow, ID, USA, 2006.
10. The Average Cost of Commercial Vehicle Accidents. Arnold & Itkin LLP. Available online: <https://www.arnolditkin.com/blog/truck-accidents/the-average-cost-of-commercial-vehicle-accidents/> (accessed on 26 May 2022).
11. Zaloshnja, E.; Miller, T. Costs of large truck-involved crashes in the United States. *Accid. Anal. Prev.* **2004**, *36*, 801–808. [CrossRef]
12. How Much is the Average Cost of a Truck Accident? Available online: <https://www.cashort.com/blog/transportation-how-much-does-a-truck-accident-cost> (accessed on 26 May 2022).
13. Traffic Safety Fact Sheets. Crash Stats. NHTSA—DOT. 2019. Available online: <https://crashstats.nhtsa.dot.gov/#!/DocumentTypeList/11> (accessed on 26 May 2022).
14. Behnood, A.; Mannering, F. Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes. *Anal. Methods Accid. Res.* **2019**, *23*, 100102. [CrossRef]
15. Dong, C.; Dong, Q.; Huang, B.; Hu, W.; Nambisan, S.S. Estimating Factors Contributing to Frequency and Severity of Large Truck-Involved Crashes. *J. Transp. Eng. Part A Syst.* **2017**, *143*, 04017032. Available online: <https://trid.trb.org/view/1463331> (accessed on 19 May 2022). [CrossRef]
16. Das, S.; Islam, M.; Dutta, A.; Shimu, T.H. Uncovering Deep Structure of Determinants in Large Truck Fatal Crashes. *Transp. Res. Rec.* **2020**, *2674*, 742–754. [CrossRef]
17. Dong, C.; Nambisan, S.S.; Richards, S.H.; Ma, Z. Assessment of the effects of highway geometric design features on the frequency of truck-involved crashes using bivariate regression. *Transp. Res. Part A Policy Pract.* **2015**, *75*, 30–41. [CrossRef]
18. Azimi, G.; Asgari, H.; Rahimi, A.; Jin, X. Investigation of Heterogeneity in Severity Analysis for Large Truck Crashes (No. 19–02748). In Proceedings of the Transportation Research Board 98th Annual Meeting Transportation Research Board, Washington, DC, USA, 13–17 January 2019; Article 19-02748. Available online: <https://trid.trb.org/view/1658006> (accessed on 19 May 2022).
19. Behnood, A.; Al-Bdairi, N.S.S. Determinant of injury severities in large truck crashes: A weekly instability analysis. *Saf. Sci.* **2020**, *131*, 104911. [CrossRef]
20. Osman, M.; Paleti, R.; Mishra, S.; Golias, M.M. Analysis of injury severity of large truck crashes in work zones. *Accid. Anal. Prev.* **2016**, *97*, 261–273. [CrossRef] [PubMed]
21. Zhao, Q.; Goodman, T.; Azimi, M.; Qi, Y. Roadway-Related Truck Crash Risk Analysis: Case Studies in Texas: Transportation Research Record. *Transp. Res. Rec.* **2018**, *2672*, 20–28. [CrossRef]
22. Li, J.; Liu, J.; Liu, P.; Qi, Y. Analysis of Factors Contributing to the Severity of Large Truck Crashes. *Entropy* **2020**, *22*, 1191. [CrossRef]
23. Zhu, X.; Srinivasan, S. A comprehensive analysis of factors influencing the injury severity of large-truck crashes. *Accid. Anal. Prev.* **2011**, *43*, 49–57. [CrossRef] [PubMed]
24. Azimi, G.; Rahimi, A.; Asgari, H.; Jin, X. Severity analysis for large truck rollover crashes using a random parameter ordered logit model. *Accid. Anal. Prev.* **2020**, *135*, 105355. [CrossRef] [PubMed]
25. Zhu, X.; Srinivasan, S. Modeling occupant-level injury severity: An application to large-truck crashes. *Accid. Anal. Prev.* **2011**, *43*, 1427–1437. [CrossRef]
26. Bezwada, N.N.K. Characteristics and Contributory Causes Associated with Fatal Large Truck Crashes. Ph.D. Thesis, Kansas State University, Manhattan, KS, USA, 2010. Available online: <https://krex.k-state.edu/dspace/handle/2097/6820> (accessed on 22 May 2022).
27. Newnam, S.; Blower, D.; Molnar, L.; Eby, D.; Koppel, S. Exploring crash characteristics and injury outcomes among older truck drivers: An analysis of truck-involved crash data in the United States. *Saf. Sci.* **2018**, *106*, 140–145. [CrossRef]
28. Lee, J.; Abdel-Aty, M.; Choi, K.; Siddiqui, C. Analysis of residence characteristics of drivers, pedestrians, and bicyclists involved in traffic crashes. In Proceedings of the Transportation Research Board 92nd Annual Meeting (No. 13-2228), Washington, DC, USA, 13–17 January 2013.
29. Tay, R.; Rifaat, S.M. Factors contributing to the severity of intersection crashes. *J. Adv. Transp.* **2007**, *41*, 245–265. [CrossRef]
30. Lemp, J.D.; Kockelman, K.M.; Unnikrishnan, A. Analysis of large truck crash severity using heteroskedastic ordered probit models. *Accid. Anal. Prev.* **2011**, *43*, 370–380. [CrossRef] [PubMed]
31. Kabli, A.; Bhowmik, T.; Eluru, N. A Multivariate Approach For Modeling Driver Injury Severity By Body Region. *Anal. Methods Accid. Res.* **2020**, *28*, 100129. [CrossRef]
32. Fountas, G.; Anastasopoulos, P.C. Analysis of accident injury-severity outcomes: The zero-inflated hierarchical ordered probit model with correlated disturbances. *Anal. Methods Accid. Res.* **2018**, *20*, 30–45. [CrossRef]
33. Qin, X.; Wang, K.; Cutler, C.E. Logistic Regression Models of the Safety of Large Trucks. *Transp. Res. Rec.* **2013**, *2392*, 1–10. [CrossRef]
34. Moomen, M.; Rezapour, M.; Ksaibati, K. An investigation of influential factors of downgrade truck crashes: A logistic regression approach. *J. Traffic Transp. Eng. (Engl. Ed.)* **2019**, *6*, 185–195. [CrossRef]
35. Rezapour, M.; Ksaibati, K. Application of multinomial and ordinal logistic regression to model injury severity of truck crashes, using violation and crash data. *J. Mod. Transport.* **2018**, *26*, 268–277. [CrossRef]
36. Stoltzfus, J.C. Logistic Regression: A Brief Primer. *Acad. Emerg. Med.* **2011**, *18*, 1099–1104. [CrossRef]

37. Rahimi, A.; Azimi, G.; Asgari, H.; Jin, X. Clustering Approach toward Large Truck Crash Analysis. *Transp. Res. Rec.* **2019**, 2673, 73–85. [\[CrossRef\]](#)
38. Pahukula, J.; Hernandez, S.; Unnikrishnan, A. A time of day analysis of crashes involving large trucks in urban areas. *Accid. Anal. Prev.* **2015**, 75, 155–163. [\[CrossRef\]](#)
39. Al-Bdairi, N.S.S.; Hernandez, S. An empirical analysis of run-off-road injury severity crashes involving large trucks. *Accid. Anal. Prev.* **2017**, 102, 93–100. [\[CrossRef\]](#)
40. Alrejfal, A.; Farid, A.; Ksaibati, K. A correlated random parameters approach to investigate large truck rollover crashes on mountainous interstates. *Accid. Anal. Prev.* **2021**, 159, 106233. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Al-Bdairi, N.S.S.; Hernandez, S. Comparison of contributing factors for injury severity of large truck drivers in run-off-road crashes on rural and urban roadways: Accounting for unobserved heterogeneity. *Int. J. Transp. Sci. Technol.* **2020**, 9, 116–127. [\[CrossRef\]](#)
42. Hallmark, S.L.; Hsu, Y.-Y.; Maze, T.H.; McDonald, T.J.; Fitzsimmons, E.J. Investigating Factors Contributing to Large Truck Lane Departure Crashes Using the Federal Motor Carrier Safety Administration's Large Truck Crash Causation Study (LTCCS) Database. 2009. Available online: <https://trid.trb.org/view/885603> (accessed on 27 May 2022).
43. Hosseinzadeh, A.; Moeinaddini, A.; Ghasemzadeh, A. Investigating factors affecting severity of large truck-involved crashes: Comparison of the SVM and random parameter logit model. *J. Saf. Res.* **2021**, 77, 151–160. [\[CrossRef\]](#) [\[PubMed\]](#)
44. Islam, S.; Jones, S.L.; Dye, D. Comprehensive analysis of single- and multi-vehicle large truck at-fault crashes on rural and urban roadways in Alabama. *Accid. Anal. Prev.* **2014**, 67, 148–158. [\[CrossRef\]](#)
45. Islam, M.B.; Hernandez, S. Modeling Injury Outcomes of Crashes Involving Heavy Vehicles on Texas Highways. *Transp. Res. Rec.* **2013**, 2388, 28–36. [\[CrossRef\]](#)
46. Large Truck and Bus Crash Facts 2019 | FMCSA. (n.d.). Available online: <https://www.fmcsa.dot.gov/safety/data-and-statistics/large-truck-and-bus-crash-facts-2019#A1> (accessed on 27 May 2022).
47. Al-Bdairi, N.S.S.; Hernandez, S.; Anderson, J. Contributing Factors to Run-Off-Road Crashes Involving Large Trucks under Lighted and Dark Conditions. *J. Transp. Eng. Part A Syst.* **2018**, 144, 04017066. [\[CrossRef\]](#)
48. Peng, Y.; Boyle, L.N. Commercial Driver Factors in Run-off-Road Crashes. *Transp. Res. Rec.* **2012**, 2281, 128–132. [\[CrossRef\]](#)
49. Khorashadi, A.; Niemeier, D.; Shankar, V.; Mannering, F. Differences in rural and urban driver-injury severities in accidents involving large-trucks: An exploratory analysis. *Accid. Anal. Prev.* **2005**, 37, 910–921. [\[CrossRef\]](#) [\[PubMed\]](#)
50. RStudio Team. *RStudio: Integrated Development for R*; RStudio, PBC: Boston, MA, USA, 2020. Available online: <http://www.rstudio.com/> (accessed on 10 June 2022).
51. ArcGIS [GIS Software], Version 10.6; Environmental Systems Research Institute, Inc.: Redlands, CA, USA, 2018.
52. Environmental Systems Research Institute (ESRI). ArcGIS Pro Tool Reference. Density Toolset Concept. 2014. Available online: <https://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/how-kernel-density-works> (accessed on 12 June 2022).
53. Chainey, S.; Ratcliffe, J. *GIS and Crime Mapping*; John Wiley & Sons: Hoboken, NJ, USA, 2013.
54. Silverman, B.W. *Density Estimation for Statistics and Data Analysis*; CRC Press: Boca Raton, FL, USA, 1986.
55. Vemulapalli, S.S. GIS-Based Spatial and Temporal Analysis of Aging-Involved Crashes in Florida. Ph.D. Thesis, The Florida State University, Florida, FL, USA, 2015.
56. Harirforoush, H.; Bellalite, L. A new integrated GIS-based analysis to detect hotspots: A case study of the city of Sherbrooke. *Accid. Anal. Prev.* **2019**, 130, 62–74. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Young, J.; Park, P.Y. Hotzone identification with GIS-based post-network screening analysis. *J. Transp. Geogr.* **2014**, 34, 106–120. [\[CrossRef\]](#)
58. Plug, C.; Xia, J.C.; Caulfield, C. Spatial and temporal visualisation techniques for crash analysis. *Accid. Anal. Prev.* **2011**, 43, 1937–1946. [\[CrossRef\]](#) [\[PubMed\]](#)
59. Truong, L.; Somenahalli, S. Using GIS to Identify Pedestrian-Vehicle Crash Hot Spots and Unsafe Bus Stops. *J. Public Transp.* **2011**, 14, 99–114. [\[CrossRef\]](#)
60. RTA. *Road Traffic Accidents in NSW—1993*; Roads and Traffic Authority of NSW: Sydney, Australia, 1994.
61. Geurts, K.; Wets, G.; Brijs, T.; Vanhoof, K. Identification and ranking of black spots: Sensitivity analysis. *Transp. Res. Rec. J. Transp. Res. Board* **2004**, 1897, 34–42. [\[CrossRef\]](#)
62. Islam, M.; Hernandez, S. Large Truck-Involved Crashes: Exploratory Injury Severity Analysis. *J. Transp. Eng.* **2013**, 139, 596–604. [\[CrossRef\]](#)
63. Billah, K.; Sharif, H.O.; Dessouky, S. How Gender Affects Motor Vehicle Crashes: A Case Study from San Antonio, Texas. *Sustainability* **2022**, 14, 7023. [\[CrossRef\]](#)
64. Billah, K.; Sharif, H.O.; Dessouky, S. Analysis of Pedestrian–Motor Vehicle Crashes in San Antonio, Texas. *Sustainability* **2021**, 13, 6610. [\[CrossRef\]](#)
65. Billah, K.; Adegbite, Q.; Sharif, H.O.; Dessouky, S.; Simcic, L. Analysis of Intersection Traffic Safety in the City of San Antonio, 2013–2017. *Sustainability* **2021**, 13, 5296. [\[CrossRef\]](#)
66. Billah, K.; Sharif, H.O.; Dessouky, S. Bivariate-Logit-Based Severity Analysis for Motorcycle Crashes in Texas, 2017–2021. *Sustainability* **2023**, 15, 10377. [\[CrossRef\]](#)
67. Billah, K.; Sharif, H.O.; Dessouky, S. Analysis of Bicycle-Motor Vehicle Crashes in San Antonio, Texas. *Int. J. Environ. Res. Public Health* **2021**, 18, 9220. [\[CrossRef\]](#) [\[PubMed\]](#)

-
68. Jermakian, J.S. Crash avoidance potential of four large truck technologies. *Accid. Anal. Prev.* **2012**, *49*, 338–346. [[CrossRef](#)] [[PubMed](#)]
 69. Battelle. *Evaluation of the Volvo Intelligent Vehicle Initiative Field Operational Test Version 1.3*; Cooperative Agreement No. DTFH61-96-C-00077, Task Order 7721; Federal Highway Administration: Washington, DC, USA, 2007.

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