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Using Cluster Correspondence Analysis to Explore Rainy Weather Crashes in Louisiana

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Abstract

Rainy weather significantly affects traffic safety, especially in the State of Louisiana. With the aim of identifying the patterns of collective association of attributes in rainfall-involved crashes statewide, crashes that occurred during rainy weather and resulted in two injury groups, fatal and severe injury (FSI) and moderate injury (MI), were extracted from databases acquired from the Louisiana Department of Transportation and Development. A total of 3,381 crashes were extracted, comprising 502 FSI crashes (14.85%) and 2,879 MI crashes (85.15%). This study applied the cluster correspondence analysis (CCA) method, a unique method in combination with cluster analysis and correspondence analysis, to generate clusters by partitioning of individual attributes based on the profiles over the categorical variables identified through dimensional reduction of the dataset. In addition to the biplots illustrating the association of all attributes in the clusters, the top 20 standardized residuals indicating the stronger association are presented in bar plots. Four optimum clusters from FSI and MI crashes reveal that the association of roadway, crash environment, and driver condition characteristics identified in the clusters are highly distinguishable across roadway functional classes. Specifically, varieties of attributes linked to speed limit, lighting condition, alignment, area type, manner of collision, restraint usage, and alcohol/drug can have associative impacts on these two injury severities. The identified associations of crash attributes across various functional class roadways could provide valuable understanding for the development of countermeasures which prioritize the prevention of fatalities and injuries.

Keywords

cluster correspondence analysis, unsupervised algorithm, rainy weather crashes, road weather, weather related crashes

There is growing interest in understanding the attributes that affect rainy-weather-related traffic safety as a part of the challenges to address the altered precipitation trends caused by climate change (*1*, *2*) and the incorporation of weather conditions in vehicle automation (*3*). Among the inclement weather conditions, rainy weather significantly affects traffic safety (*4*). Wet pavement surface and poor visibility caused by rain create substantially challenging conditions for drivers to control normal driving maneuvers. The Federal Highway Administration (FHWA) identifies crashes during rainfall to be the most prevalent among weather-related crashes (*5*). A total of 33,244 fatal crashes occurred on U.S. roadways in 2019, of which 2,569 (7.7%) involved rainy weather. In the same year, fatal crashes in rainy weather were as high as 74.5% among all fatal crashes with known inclement weather conditions (*6*). At the state level, Louisiana had 634 rainy-weather-related roadway crashes in 2019 that resulted in fatal, severe, or moderate injury.

A substantial body of literature has implied that rainfall plays a crucial role in crashes. An increase in rainfall intensity has often been found to be strongly connected to an increase in crash and injury risks (*4*, *7–12*). Studies also suggested that the simultaneous presence of multiple precipitation types could pose a higher risk (*13–15*). Factors associated with predominant precipitation types evidently vary by geographic and atmospheric

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conditions. However, considering the prevalence of rainfall among the precipitation types in Louisiana, the scope of this study is limited to rainfall crashes only. The average precipitation rate in Louisiana is above the national average and Louisiana has been among the states with the highest amount of precipitation, especially in recent years (*16*).

This study focuses on investigating the patterns in crashes related to rainy weather conditions, with the aim of presenting the collective associations of attributes that have not been previously explored. Instead of a single associative attribute, a combination of attributes would most likely trigger rainfall-related crashes. In addition to pavement surface condition and visibility during rainfall, the association of conditions of drivers and geometric properties of roadways could be influential to unsafe driving maneuvers creating a wide array of crash scenarios. This study only analyzes crashes that occurred during rainfall, although a continuation of impact after rainfall could exist to a lesser extent (*17*, *18*). To account for the categorical data in the crash dataset, this study used cluster correspondence analysis (CCA), a joint method to reduce the high dimensionality and to capture the simultaneous presence of factors.

Literature Review

A substantial amount of previous research has focused on adverse weather, including rainy weather, for investigating injury severity targeted at specific safety areas. Some examples are work zones (*19*), truck-involved crashes (*20*), pedestrian crashes (*21*), reduced visibility (*12*), and so forth. Several studies used the matched-pair method to estimate crash risk and revealed interesting findings on rainfall-involved crash risk. A Kansas study estimated that the risks of rainfall-involved crashes between daytime and nighttime are more distinguishable than other precipitation types (*13*). Applying the same method, a six-state (Arkansas, Georgia, Illinois, Maryland, Minnesota, and Ohio) study used 15-year crash data (1996–2010) and found that the most significant increases in estimated relative risk by rainfall intensity are predominantly in urban areas (*22*). In addition to finding a higher risk of crash and injury during rainfall by using radar rainfall data and the matched-pair method, a Louisiana study detected an increase in run-off-road crashes in freeways and Interstates, rear-end and left-turn crashes on urban multilane highways, and rear-end and sideswipe crashes on rural two-lane highways (*11*).

Several studies can be referred to that investigated the impacts of factors with rainfall-involved specific to one functional class (Interstate highways), or specific manner of collision (single-vehicle crashes). A Wisconsin study used microscopic rain and vertical grade data for 135 mi of Interstate highways with a median barrier and specifically focused mostly on geometric data. Using a multinomial logit model, several individual factors: slow grade, number of travel lanes, deep water-film, and the rear-end collision type, have been identified to have affected the severity of crashes (*23*). A crash severity prediction analysis with the mixed logit model and the latent class model revealed that curve, on grade, signal control, multiple lanes, pickup, straight road section, drug/alcohol-impaired, and seat belt not used can increase driver injury severity, using crash data from 2012 to 2014 in four South Central states (Texas, Arkansas, Oklahoma, and Louisiana) (*24*). Another Wisconsin study analyzing single-vehicle crash data from 2004 to 2006 on 75 mi of Interstate segments used a backward format of sequential logistic regression and identified rainfall intensity, wind speed, roadway terrain, driver's gender, and safety belt to be statistically significant factors for severity factors (*25*).

Two previous research works on statewide rainfall-involved crashes can be referred to that are not focused on a specific roadway or a crash type. An Arizona study with crash data from 2008 to 2012 of monsoon season (June to September) used four separate multinomial logit models for severity outcomes for specific weather (heavy rainfall or clear) and light conditions (daytime or nighttime) (*26*). "No safety device" was common in all heavy rainfall conditions. Other specific factors addressable with safety strategies and educational efforts include: age groups, speed limits, roadway types, slow driving in heavy rain, excessive speeding, and so forth. Using earlier rainfall-related crash data from 2004 to 2011 including all severity types, a Louisiana study applied an association rule-mining algorithm to generate 1,890 association rules using manually optimized minimum support and minimum confidence parameters (*27*). However, this study did not explore any association with the functional class of roadways.

In recent years, multiple correspondence analysis (MCA) has become a popular unsupervised algorithm tool to analyze categorical variables in exploring crash databases. For example, previous research studies investigated crash patterns through association knowledge of fatal run-off crashes (*28*), pedestrian crashes (*29*, *30*), wrong-way crashes (*31*, *32*), underage alcohol crashes (*33*), and so forth. It has been argued that the MCA is a better unsupervised machine-learning approach to tackle difficulties in other unsupervised approaches such as optimizing measurable thresholds in association rule mining (*28*). Although the MCA performs efficient dimensionality reductions and compiles results into presentable plots, one of the limitations of this approach is that researchers have to rely on a subjective approach to identify clusters based on the proximity of categorical variable attributes on the low-dimensional approximation (*33*). By combining the cluster analysis and correspondence analysis, the CCA provides specific clusters by partitioning individual attributes based on the profiles over the categorical variables through low-dimensional projection and reduction of multicollinearity of the crash dataset in the process (*34*).

Data

Data Preparation and Integration

The crash data used in this study were collected from the Louisiana Department of Transportation and Development (DOTD) data that were annually compiled in one Microsoft (MS) access file format and were extracted from police reports of crashes that occurred during 2015–2019. Using the knowledge from previous rainy weather studies and considering the availability in the crash databases, these variables were extracted from three major data tables: crash table (lighting condition, manner of collision, severity, intersection), vehicle table (driver age, driver gender, driver condition, restraint usage, vehicle type, violation, vision obscured), and highway section table (annual average daily traffic [AADT], road type, functional class, area, alignment, lane width, shoulder width, speed limit). It should also be mentioned that only information on the driver at fault and associated vehicle for each crash was included in the dataset for analytic simplicity. The weather condition attribute was filtered out to isolate only crashes with active rainfall at the time and location of the crash. Note that the data filtering was limited to the "weather" variable only; pavement condition (wet or dry) was not considered in the data filtering task.

This study applied a thorough data cleaning process for addressing the outliers and missing values present in each variable. Knowledge of a careful review of the existing coding of attributes in the crash dataset and associated explanations (*35*) was utilized in the quality control process aiming to ensure a well-distributed compilation of attributes under all variables. Following multiple reviews of the revised categorizations and analyzing the existing distributions of attributes, the "surface condition" attribute was excluded to avoid bias from an overwhelming presence of the "wet" pavement surface condition in the crash data.

Among the five injury severity classes in the KABCO injury scale, only the three confirmed injury classes (fatal [K], severe/incapacitating [A], and moderate/non-incapacitating [B]) were used, excluding complaint/possible (C) and non-injury/property-damage-only (O) crashes. To obtain a sufficient sample size, fatal and severe injury types were merged and collectively named as FSI. The resulting dataset is a multivariate categorical dataset with a total of 3,381 crashes, among which FSI crashes were 502 (14.85%) and MI (moderate injury) crashes were 2,879 (85.15%). The flowchart in Figure 1 presents the data integration process.

Data Description

Table 1 presents the distribution of crash attributes by total crashes and two injury severity groups. Crash occurring in dark conditions (both lighted and unlighted) was more prevalent in FSI crashes. The majority of crashes occurred on roadways with AADT higher than 20,000 vehicles per day (vpd), two-way roadways with no separation, and on principal arterials. FSI crashes occurred more on roadways with higher speed limits compared with MI crashes. With regard to driver

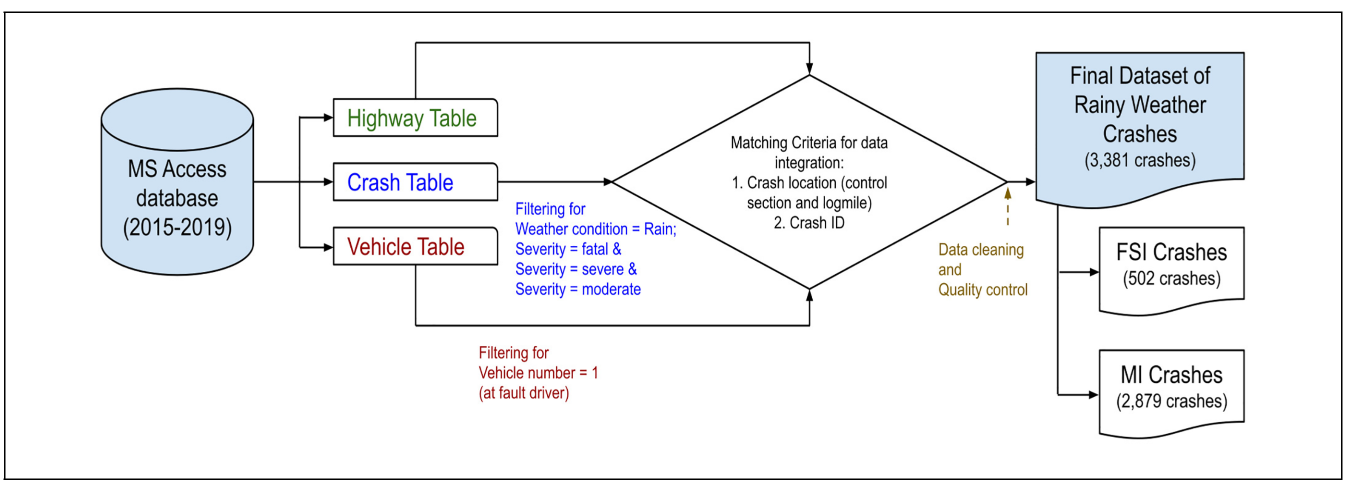

Figure 1. Data integration from crash databases.

Table 1. Comparison of Crash Attributes by Injury Severity

Variable attribute	Total (n = 3,381)	FSI (n = 502)	MI (n = 2,879)	Variable attribute	Total (n = 3,381)	FSI (n = 502)	MI (n = 2,879)
Lighting condition (LghtCnd)				Driver age (DrAge)			
Daylight	2,017 (59.66%)	246 (49%)	1,771 (61.51%)	19y_or_less	382 (11.3%)	47 (9.36%)	335 (11.64%)
Dark_lighted	715 (21.15%)	126 (25.1%)	589 (20.46%)	20–25y	650 (19.23%)	102 (20.32%)	548 (19.03%)
Dark_unlighted	492 (14.55%)	112 (22.31%)	380 (13.2%)	26–35y	806 (23.84%)	131 (26.1%)	675 (23.45%)
Dusk_dawn	125 (3.7%)	12 (2.39%)	113 (3.92%)	36–45y	483 (14.29%)	66 (13.15%)	417 (14.48%)
Other	32 (0.95%)	6 (1.2%)	26 (0.9%)	46–55y	369 (10.91%)	60 (11.95%)	309 (10.73%)
AADT (vehicles per day, vpd)				56–65y	289 (8.55%)	37 (7.37%)	252 (8.75%)
400_or_less	26 (0.77%)	4 (0.8%)	22 (0.76%)	>65y	254 (7.51%)	37 (7.37%)	217 (7.54%)
401–1,000 vpd	66 (1.95%)	12 (2.39%)	54 (1.88%)	Unknown	148 (4.38%)	22 (4.38%)	126 (4.38%)
1,001–5,000 vpd	509 (15.05%)	90 (17.93%)	419 (14.55%)	Driver gender (DrGndr)			
5,001–10,000 vpd	489 (14.46%)	92 (18.33%)	397 (13.79%)	Female	1,300 (38.45%)	153 (30.48%)	1,147 (39.84%)
10,001–20,000 vpd	647 (19.14%)	81 (16.14%)	566 (19.66%)	Male	1,946 (57.56%)	328 (65.34%)	1,618 (56.2%)
20,000 vpd	1,644 (48.62%)	223 (44.42%)	1,421 (49.36%)	Unknown	135 (3.99%)	21 (4.18%)	114 (3.96%)
Roadway type (RdTyp)				Driver condition (DrCnd)			
2-way_no_sep.	1,723 (50.96%)	263 (52.39%)	1,460 (50.71%)	Normal	977 (28.9%)	104 (20.72%)	873 (30.32%)
2-way_with_barr.	316 (9.35%)	51 (10.16%)	265 (9.2%)	Distracted	1,535 (45.4%)	111 (22.11%)	1,424 (49.46%)
2-way_with_sep.	991 (29.31%)	159 (31.67%)	832 (28.9%)	Drug/alcohol	325 (9.61%)	144 (28.69%)	181 (6.29%)
One-way	318 (9.41%)	28 (5.58%)	290 (10.07%)	Ill/fatigued/asleep	78 (2.31%)	12 (2.39%)	66 (2.29%)
Other	33 (0.98%)	1 (0.2%)	32 (1.11%)	Other	466 (13.78%)	131 (26.1%)	335 (11.64%)
Functional class (FncCls)				Restraint usage (RstraintUsg)			
Interstate/freeway	899 (26.59%)	133 (26.49%)	766 (26.61%)	Proper	2,444 (72.29%)	281 (55.98%)	2,163 (75.13%)
Principal_arterial	1,222 (36.14%)	162 (32.27%)	1,060 (36.82%)	Improper	58 (1.72%)	7 (1.39%)	51 (1.77%)
Minor_arterial	696 (20.59%)	117 (23.31%)	579 (20.11%)	None	337 (9.97%)	118 (23.51%)	219 (7.61%)
Collector	537 (15.88%)	87 (17.33%)	450 (15.63%)	Unknown	542 (16.03%)	96 (19.12%)	446 (15.49%)
Local	27 (0.8%)	3 (0.6%)	24 (0.83%)	Vehicle type (VehTyp)			
Area				Car	1,599 (47.29%)	225 (44.82%)	1,374 (47.72%)
Rural	854 (25.26%)	160 (31.87%)	694 (24.11%)	SUV	612 (18.1%)	80 (15.94%)	532 (18.48%)
Urban	2,527 (74.74%)	342 (68.13%)	2,185 (75.89%)	Van	94 (2.78%)	10 (1.99%)	84 (2.92%)
Intersection				Light_truck	831 (24.58%)	130 (25.9%)	701 (24.35%)
No	2,156 (63.77%)	351 (69.92%)	1,805 (62.7%)	Large_truck	100 (2.96%)	23 (4.58%)	77 (2.67%)
Yes	1,225 (36.23%)	151 (30.08%)	1,074 (37.3%)	Bus	8 (0.24%)	2 (0.4%)	6 (0.21%)
Roadway alignment (Algnmnt)				Other	137 (4.05%)	32 (6.37%)	105 (3.65%)
Straight-level	2,506 (74.12%)	364 (72.51%)	2,142 (74.4%)	Driver violation (Violation)			
Straight-level-elevated	177 (5.24%)	23 (4.58%)	154 (5.35%)	None	370 (10.94%)	80 (15.94%)	290 (10.07%)
Curve-level	365 (10.8%)	69 (13.75%)	296 (10.28%)	Failure_to_yield	496 (14.67%)	42 (8.37%)	454 (15.77%)
Curve-level-elevated	97 (2.87%)	11 (2.19%)	86 (2.99%)	Following_too_closely	305 (9.02%)	25 (4.98%)	280 (9.73%)
Hillcrest-straight	48 (1.42%)	4 (0.8%)	44 (1.53%)	Careless_operation	1,141 (33.75%)	154 (30.68%)	987 (34.28%)
Hillcrest-curve	14 (0.41%)	2 (0.4%)	12 (0.42%)	Exceeding_safe_speed_limit	89 (2.63%)	7 (1.39%)	82 (2.85%)
On_grade-straight	80 (2.37%)	12 (2.39%)	68 (2.36%)	Exceeding_stated_speed_limit	25 (0.74%)	11 (2.19%)	14 (0.49%)
On_grade-curve	73 (2.16%)	14 (2.79%)	59 (2.05%)	Improper_starting/parking/backing	11 (0.33%)	1 (0.2%)	10 (0.35%)
Other	21 (0.62%)	3 (0.6%)	18 (0.63%)	Turning	55 (1.63%)	5 (1%)	50 (1.74%)
Lane width (LnWdth)				Lane_change	103 (3.05%)	25 (4.98%)	78 (2.71%)
10ft_or_less	212 (6.27%)	20 (3.98%)	192 (6.67%)	Traffic_control	145 (4.29%)	11 (2.19%)	134 (4.65%)

(continued)

Table 1. (continued)

Variable attribute	Total (n = 3,381)	FSI (n = 502)	MI (n = 2,879)	Variable attribute	Total (n = 3,381)	FSI (n = 502)	MI (n = 2,879)
Greater_than_10ft_to_12ft	2,869 (84.86%)	434 (86.45%)	2,435 (84.58%)	Driver_condition	144 (4.26%)	30 (5.98%)	114 (3.96%)
Greater_than_12ft	300 (8.87%)	48 (9.56%)	252 (8.75%)	Vehicle_condition	43 (1.27%)	5 (1%)	38 (1.32%)
Shoulder width (ShWdth)				Other	454 (13.43%)	106 (21.12%)	348 (12.09%)
2ft_or_less	993 (29.37%)	130 (25.9%)	863 (29.98%)	Visual obstruction (VisObscr)			
Greater_than_2ft_to_4ft	486 (14.37%)	75 (14.94%)	411 (14.28%)	None	2,098 (62.05%)	276 (54.98%)	1,822 (63.29%)
Greater_than_4ft_to_6ft	198 (5.86%)	27 (5.38%)	171 (5.94%)	Rain_on_windshield	759 (22.45%)	98 (19.52%)	661 (22.96%)
Greater_than_6ft	1,704 (50.4%)	270 (53.78%)	1,434 (49.81%)	Moving_vehicle	40 (1.18%)	0 (0%)	40 (1.39%)
Posted speed limit (SpLmt)				Other	66 (1.95%)	8 (1.59%)	58 (2.01%)
25 mph_or_less	307 (9.08%)	34 (6.77%)	273 (9.48%)	Unknown	418 (12.36%)	120 (23.9%)	298 (10.35%)
30_to_35 mph	534 (15.79%)	63 (12.55%)	471 (16.36%)	Manner of collision (MannColl)			
40_to_45 mph	842 (24.9%)	111 (22.11%)	731 (25.39%)	Single_vehicle	1,200 (35.49%)	230 (45.82%)	970 (33.69%)
50_to_55 mph	936 (27.68%)	170 (33.86%)	766 (26.61%)	Head-on	202 (5.97%)	54 (10.76%)	148 (5.14%)
60 mph_or_more	762 (22.54%)	124 (24.7%)	638 (22.16%)	Rear-end	857 (25.35%)	88 (17.53%)	769 (26.71%)

Note: AADT = annual average daily traffic; FSI = fatal or severe injury crash; MI = moderate injury crash; SUV = sports utility vehicle; vpd = vehicles per day.

condition, drug or alcohol intoxication was more involved with FSI crashes. Single-vehicle crashes were proportionately higher for FSI crashes than MI crashes. The proportions of FSI crashes are higher than MI crashes on high posted speed limit (50 mph or above) roadways.

Methodology

The CCA method conjointly performs dimension reduction and cluster analysis for categorical data. This novel method was proposed by van de Velden et al. (*34*). With regard to cluster convergence, this method has outperformed other previous methods that aim either sequentially or jointly to apply dimension reduction and clustering (*36*). This section provides a brief overview of this method. Readers can consult van de Velder et al. (*34*) for details on this method.

Let us assume that, n number of rainfall-involved crashes are distributed in q number of categorical variables. For cluster membership, K is the number of clusters, and d is the dimension of the reduced subspace. Each variable can also have p_j modalities, with $j = 1, 2, \ldots\ldots, q$ and $Q = \sum_{j=1}^{q} p_j$. The objective function for the CCA can be formulated as:

$$min\phi'_{clusca}(Z_k, G) = \| \sqrt{\frac{n}{q}} MZD_z^{-\frac{1}{2}} B^* - Z_K G\|^2 \quad (1)$$

where
$B^* = I_d$ and $D_z = diag(Z'Z)$ with
$M =$ centering operator of Z
$Z : n \times Q =$ binary matrix, where Z_j is an $n \times p_j$ indicator matrix for the j th categorical variable; $j = 1, 2, \ldots\ldots, q$
$B = \left[B'_1, B'_2, \ldots, B'_q\right]$ as the $Q \times d$ matrix of orthogonal loadings also interpreted as category quantifications
$Z_k : n \times K =$ binary matrix indicating cluster memberships
$G : K \times d =$ cluster centroid matrix.

Additionally, the CCA method provides an approach to extract the Calinski-Harabasz (CH) index (*37*) of each element in the clusters and present them in residual bar plots. The CH index is the ratio of between-cluster variance to within-cluster variance, corrected according to the number of clusters, and takes values between zero and ∞.

Results

The CCA method was applied to FSI and MI crashes separately. The analysis was run using the 'clustrd' package (*38*) in R software (*39*). The selection of the optimal number of clusters is crucial in performing the CCA. After conducting the k -means runs randomly multiple

Table 2. Measures Associated With Clusters

Cluster	Centroid of the cluster		Size	Coverage (%)	Sum of squares
	Dimension 1	Dimension 2			
Fatal or severe injury (FSI) crashes					
C1-FSI	0.0294	0.0342	146	29.1	0.0530
C2-FSI	0.0309	−0.0465	122	24.3	0.0505
C3-FSI	−0.0593	−0.0057	119	23.7	0.0402
C4-FSI	−0.0088	0.0117	115	22.9	0.0446
Moderate injury (MI) crashes					
C1-MI	0.0085	−0.0113	1152	40	0.0750
C2-MI	0.0092	0.0177	801	27.8	0.0554
C3-MI	−0.0091	−0.0051	515	17.9	0.0340
C4-MI	−0.0303	0.0035	411	14.3	0.0231

times, four optimal clusters were established in the crash data of both severity groups. The optimal values of the objective criterion for FSI and MI crashes were 6.7653 and 6.5315, respectively. Along with the dimensions of the identified clusters, Table 2 presents the other key estimates of clusters: sample size, coverage, and the sum of squares. The FSI crash clusters are relatively evenly distributed, with the first three clusters containing about 70% of the FSI crash data. In the case of MI crashes, most of the information is possessed by the first three clusters (about 85%), with the smallest cluster (C4-MI) holding 14.3% of the data.

FSI Crash Clusters

Figure 2 illustrates the corresponding biplot presenting the first two dimensions of FSI crashes. Four clusters (C1-FSI, C2-FSI, C3-FSI, and C4-FSI) identified in this biplot are displayed in orange, green, cyan, and purple colors, respectively. This biplot maps the projection of individual variable categories and helps to understand the visualization of their associations. The C4-FSI cluster is the closest centroid among all other clusters. The point patterns of C4-FSI and C1-FSI are located on the upper side of the plot. While the points of C2-FSI are located in the bottom right of the biplot, C3-FSI points are located on the left side of the biplot. Note that biplots are an excellent visualization tool to represent many variables in a two-dimensional space. However, observation of cluster-based individual attributes is not possible because of the presence of many attributes in the same space. To address this issue, cluster-based attributes and their residual scores are plotted in bar chart format in the section below.

To simplify the association of the attributes in clusters, the top 20 variable categories with the highest standardized residuals are presented. Figure 3 displays the top 20 residuals (in absolute values) of the variable categories of each of the four FSI crash clusters. In general, higher values of residuals imply stronger associations, based on cluster compactness and cluster separation.

In this series of residual bar plots, the bars with higher standardized residuals from the independence of the attribute distributions contribute to the greater similarity of the low-dimensional configurations and the cluster partitions. A variable category with an above-average frequency within the cluster is represented by a positive residual, and, similarly, a negative residual implies a variable category with a below-average frequency. Although negative residuals imply negative association, the categories with positive residual means are typically explained for reasonable and meaningful interpretation of crash patterns. The attributes with the top positive residuals are better representative of the clusters. The positive residuals in the top 20 attributes with the highest absolute residuals in Figure 3 are discussed for FSI crash patterns.

C1-FSI: Intersection Crashes on Principal Arterials. Cluster 1 has several attributes with positive residuals: principal arterial highways, 2 ft or narrower shoulders, intersections, failure to yield violations, speed limits ranging from 30 to 45 mph, dark conditions with lighting, and right-angle collisions (Figure 3*a*). Cluster 1 indicates an association of right-angle collisions caused by failure to yield violations at intersections on principal arterial highways in dark-lighted conditions in the presence of streetlights. The results also show that gender and restraint usage of the drivers in this cluster are mostly unknown.

C2-FSI: Interstate or Freeway Crashes. Cluster 2 possesses eight attributes with positive residuals: Interstate or freeway, 60 mph or higher posted speed limits, roadways with barriers, AADT of 20,000 vpd or more, straight-level-elevated roadways, 6 ft or wider shoulders, rear-end collisions, and one-way roads (Figure 3*b*). The FSI rear-end crashes in rainy weather have been identified

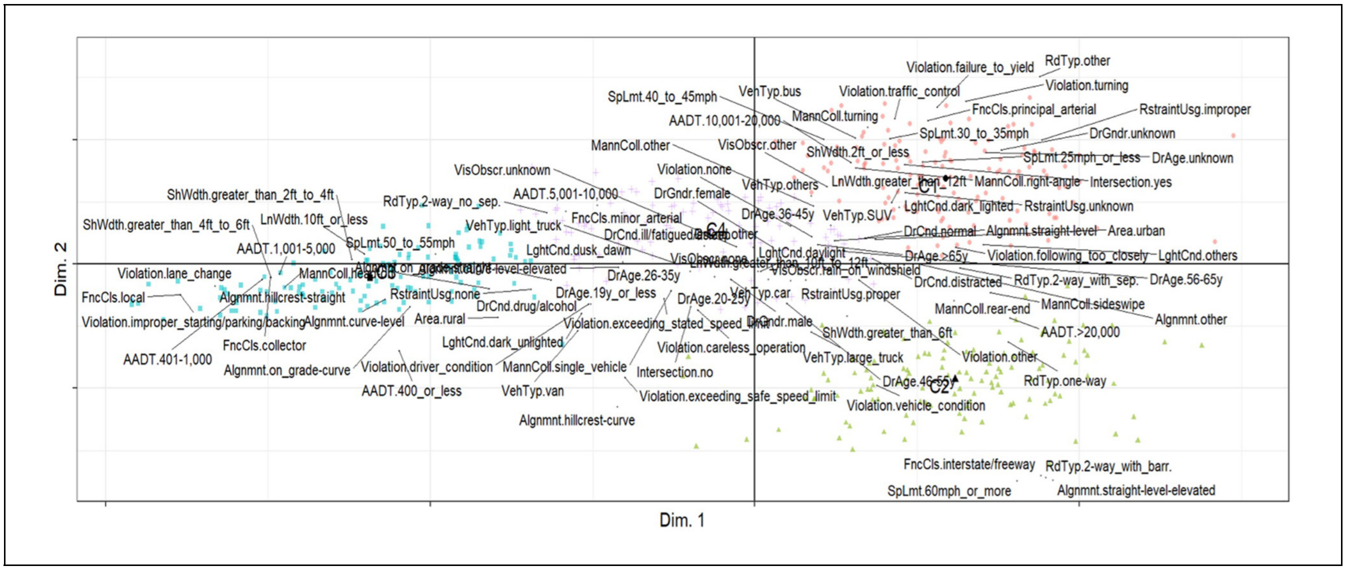

Figure 2. A biplot presenting two-dimensional projection for fatal and severe injury (FSI) crashes.

to be associated with Interstates and freeways. These crashes are also associated with roadways with one-way traffic.

C3-FSI: Low Volume Rural Collector Road Crashes. Attributes with positive residuals in cluster 3 are AADT of 1,001 to 5,000 vpd, collector roads, rural areas, undivided two-way roadways, lane width of 10 ft or less, narrow to moderate shoulder (2 ft to 6 ft), moderate speed limits (50–55 mph), curve-level roads, head-on collisions, lane change violations, no restraint usage, and drug/alcohol (Figure 3*c*). Head-on FSI crashes in rainy weather exhibit association with lane change violation on curve segments of low volume rural collector roads with narrow lane width and narrow or moderate shoulders. These crashes are also related to drivers' alcohol or drug intoxication and no restraint usage.

C4-FSI: Minor Arterial Road Crashes. The fourth cluster has several variable categories with positive residuals: AADT of 5,001 to 20,000 vpd, minor arterial roads, two-way roadways with no separation, low speed limits (30–35 mph), moderate speed limits (50–55 mph), dark with no lighting, and straight-level roads (Figure 3*d*). It indicates that FSI crashes on minor arterials are associated with dark-unlighted conditions.

MI Crash Clusters

Similar to the FSI biplot presented in Figure 2, all four clusters of MI crash clusters are in four different quadrants (Figure 4). The C3-MI cluster, located on the bottom left side, is the closest centroid among all MI clusters. The point patterns of clusters show that C4-MI and C2-MI are located on the upper side of the plot, on the left and right sides, respectively. C3-FSI cluster points are mainly located in the bottom right part of the biplot.

The positive residuals in the top 20 attributes with the highest absolute residuals are discussed for the MI crash patterns.

C1-MI: Intersection Crashes on Principal Arterials. Cluster 1 has nine attributes with positive residuals: principal arterial highways, 2 ft or narrower shoulders, intersections, failure to yield violations, right-angle collisions, speed limits of 30 to 35 mph, AADT of 10,001 to 20,000 vpd, speed limits of 40 to 45 mph, and turning collisions (Figure 5*a*). This cluster associates right-angle and turning collisions at intersections on principal arterials resulting in moderate injuries caused by failure to yield in rainy weather.

C2-MI: Interstate or Freeway Crashes. Cluster 2 has seven attributes with positive residuals: Interstate or freeway, speed limits of 60 mph or more, two-way roadways with barriers, AADT of 20,000 vpd or more, 6 ft or wider shoulders, one-way roads, and straight-level-elevated roadways (Figure 5*b*). This cluster represents MI crashes on Interstates and freeways and also on roadways with one-way traffic.

C3-MI: Minor Arterial and Collector Road Crashes. Cluster 3 has several attributes with positive residuals: AADT of 1,001 to 10,000 vpd, minor arterial roads, two-way

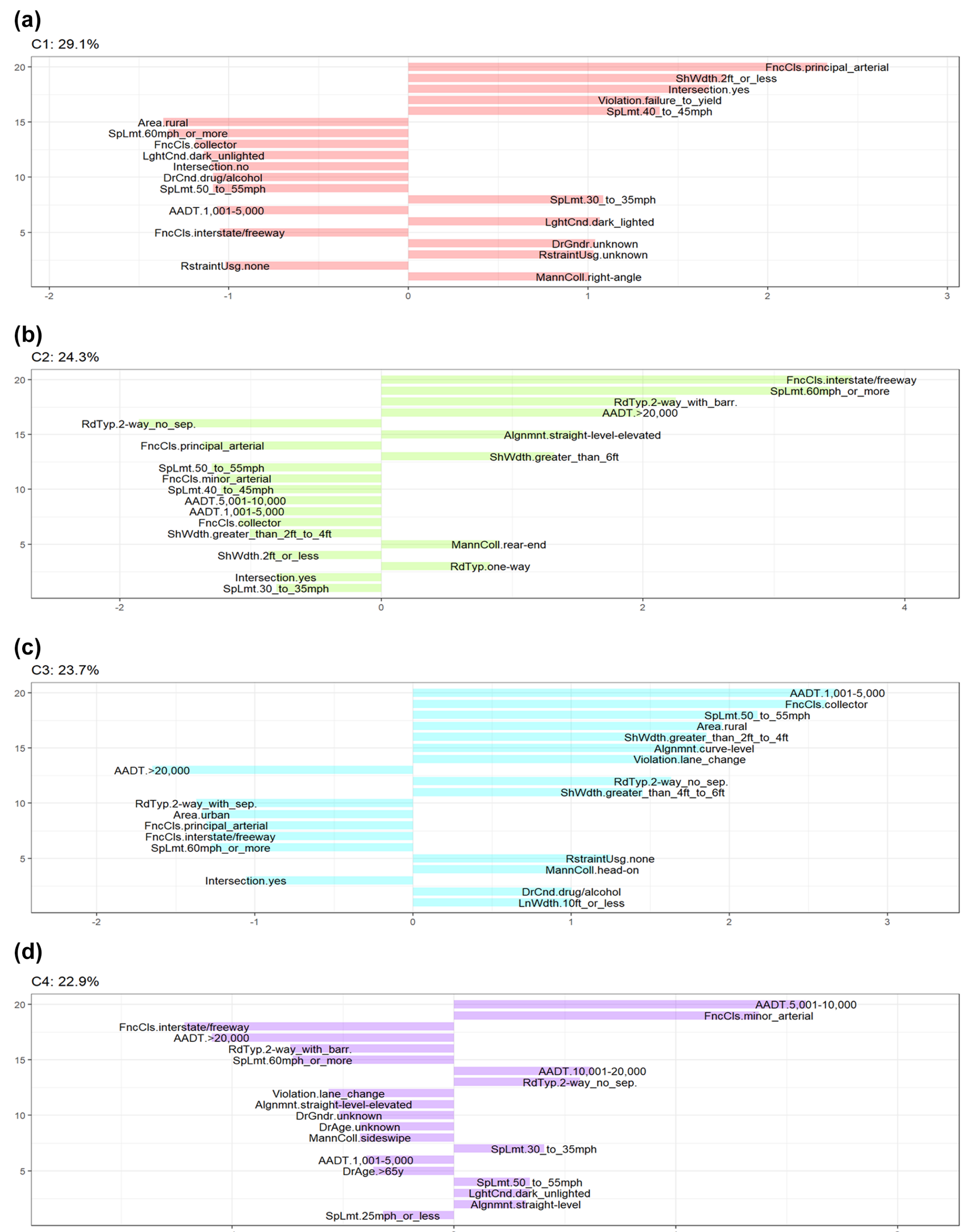

Figure 3. Top 20 largest standardized residuals for four fatal and severe injury (FSI) crash clusters: (*a*) Cluster C1-FSI, (*b*) Cluster C2-FSI, (*c*) Cluster C3-FSI, and (*d*) Cluster C4-FSI.

roadways with no separation, shoulder width of greater than 2 ft to 6 ft, speed limits of 50 to 55 mph, collector roads, head-on collisions, and rural areas (Figure 5*c*). It implies that head-on crashes resulting in moderate injuries are associated with rural minor arterial and collector roads.

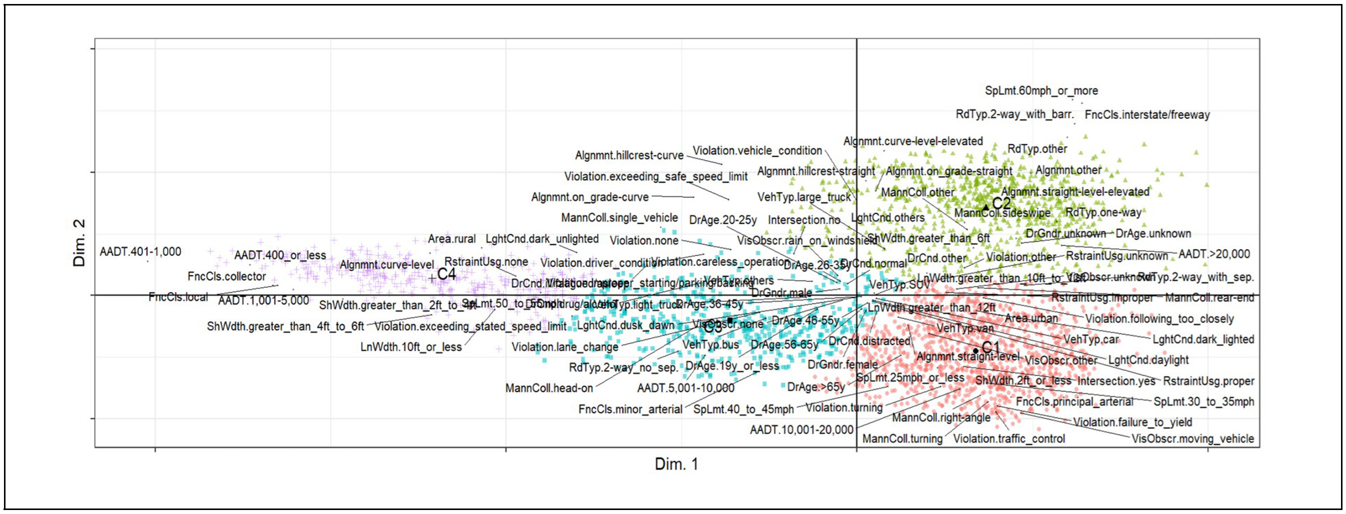

Figure 4. A biplot presenting two-dimensional projection for moderate injury (MI) crashes.

C4-MI: Low Volume Collector Road Crashes. The fourth cluster contains several attributes with positive residuals: collector roads, AADT of 401 to 5,000 vpd, rural areas, shoulder width of greater than 2 ft to 6 ft, speed limits of 50 to 55 mph, curve-level roads, single-vehicle crashes, lane width of 10 ft or less, dark-unlighted conditions, two-way roadways with no separation, and no restraint usage (Figure 5*d*). Single-vehicle MI crashes are associated with low volume rural collector road curves with narrow lanes in dark-unlighted conditions. These crashes are also associated with drivers' non-usage of restraints.

Discussion

Investigation of rainy weather crashes based on severity is complex because of homeostasis or behavioral adaption. Drivers usually become more attentive in response to the nature of visibility during rainfall. The results show that the clusters are highly distinguishable based on roadway functional classes and their associated geometric and exposure characteristics rather than driver-based characteristics, although these variables are considered in the analysis. Comparison of attributes identified in clusters facilitates the understanding of similarities and differences of the distinct interpretable patterns for rainy weather crashes with FSI and MI severities. In addition to the varying comparable patterns associated with the functional class of highways, the collective presence of attributes illustrates specific rainfall-related crash scenarios that uncover unique findings that enhance the knowledge of rainy weather crashes from previous literature.

- Under rainy weather conditions, intersection crashes—specifically right-angle and turning related crashes—are prominently associated with principal arterials; whereas non-intersection crashes—specifically single-vehicle and rear-end crashes—are associated with relatively lower functional class roads and Interstates, respectively.
- Poor visibility in conditions of darkness combined with rainfall is among the most important factors contributing to rainfall-involved crashes (*26*, *40*). The dark-unlighted condition is associated with a lower functional class: straight-level minor arterial (C4-FSI) and curve-level collector (C4-MI) roads. The dark but lighted condition (i.e., presence of streetlights) in adverse weather is associated with angle and turning crashes at intersections (*41*). This study specifies an additional association of principal arterial intersections and FSI crashes (C1-FSI).
- Cluster C3-MI involves both minor arterial and collector roads with a combined AADT of 1,001 to 10,000 vpd, whereas the equivalent cluster C4-FSI involves only minor arterial road crashes with a relatively higher combined AADT ranging from 5,000 to 20,000 vpd. Additionally, the C4-MI cluster presents crashes on the collector road which had an AADT from 401 to 5,000 vpd. Considering that lower than the average traffic volume depending on the rainfall intensity at the time of the crash (*22*) on a rainy day could underestimate the safety impact of rainfall (*42*), the crash patterns suggest that the MI clusters have a relatively lower AADT for lower functional classes compared with FSI crash clusters.
- Findings from this study suggest that several of both FSI (cluster C4-FSI) and MI (C1-MI) crash scenarios involve a relatively wide range of speed limits. Alongside other relevant attributes, this

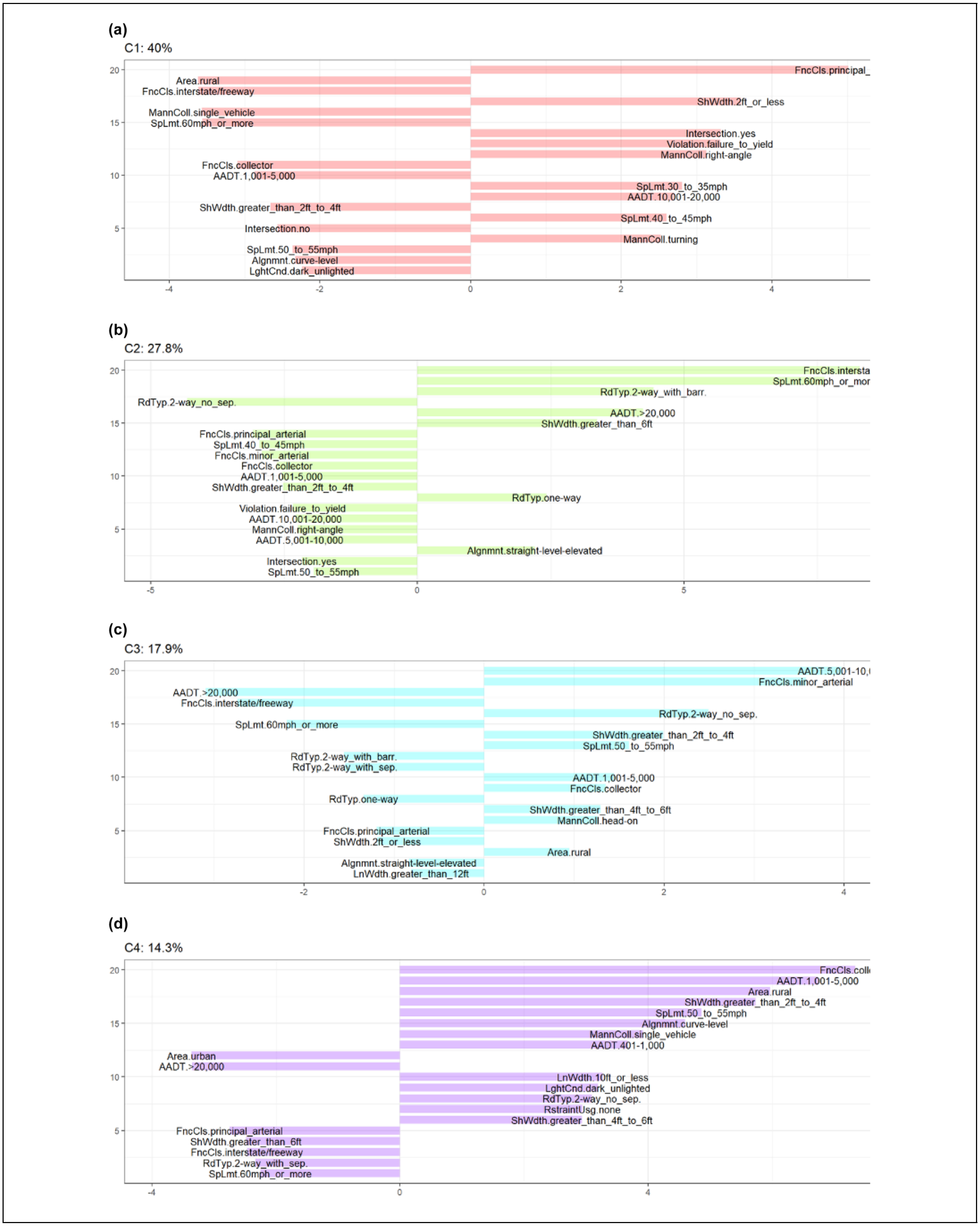

Figure 5. Top 20 largest standardized residuals for four moderate injury (MI) crash clusters: (*a*) Cluster C1-MI, (*b*) Cluster C2-MI, (*c*) Cluster C3-MI, and (*d*) Cluster C4-MI.

could be associated with the finding that drivers tend to adjust vehicle speed with adverse weather more on roadways with a high speed limit than on roadways with a low speed limit (*40*).

- "Failure to yield" is most likely to be attributed to the loss of control of the vehicle while slowing/braking, as inadequate skid resistance at an intersection on a wet pavement surface requires a longer stopping sight distance. This study presents a strong association of intersection crashes with principal arterials (C1-FSI and C1-MI) where drivers' perception of safe speed compounded by poor visibility could be among crucial determinants for safe stopping and accelerating maneuvers at intersections, as speed limits on these roads could vary relatively frequently with the presence of short speed zone lengths based on corresponding characteristics of surrounding land environment (*43*).
- Cluster C1-FSI contains two attributes with incomplete information. Driver's gender and restraint usage are unknown in this cluster. The presence of unknown driver gender and unknown propriety of restraint usage in the top standardized residuals of FSI crashes from right-angle collisions uncovers heavy implications for a potential association with hit-and-run scenarios. The overall finding was partially corroborated by studies that individually associated a higher likelihood of fatal hit-and-run crashes with intersections, dark conditions, and angle crashes (*44*, *45*). Contradictory interpretations can be found with regard to the association of rainfall and hit-and-run crashes since wet pavement condition would be either a mitigating factor that negates a driver's fault (*46*) or an aggravating factor for fleeing the crash scene, because the presence of rain may cause a longer wait for the arrival of law enforcement (*17*).
- Rear-end FSI crashes have been identified on high-speed Interstates with a speed limit of 60 mph or more. The results of the association of rear-end crashes with Interstates during rainfall can be corroborated by the study by Jung et al. (*23*). One plausible explanation for these crashes on high-speed Interstates and freeways (C2-FSI) is the failure to maintain a safe speed and a longer headway to adjust speed. Despite the general tendency to drive vehicles at a safer operating level in rainy conditions (*12*, *47*, *48*), higher variability of operating speed (*49*) and longer clearance time for slowdown events such as events of crashes (*50*) could challenge many drivers to adjust and maintain safe operating speeds, enhancing the possibility of rear-end crashes.
- Reduced friction between the tires and the wet road surface caused by rain poses more challenges to drivers to maintain lanes and avoid lane departure on lower functional roads with narrow lane width. This could be further intensified by the presence of curves (C3-FSI and C4-MI) or dark-unlighted conditions (C4-MI). This particular finding—that single-vehicle crashes resulting in MI injury are associated with dark-unlighted conditions (i.e., absence of streetlights) on curve-level roadways—conforms with the results identified by Das et al. (*27*).
- Intoxication by drug or alcohol has been proven to be a critical factor that adds to the challenges of unfavorable driving conditions during rain for maintaining lateral stability of the vehicle to avoid veering off to opposite lane(s) at curves. In this case, driver intoxication has been strongly associated with head-on collisions resulting in FSI crashes in this scenario, specifically on low volume rural collector roads with narrow lanes (C3-FSI). The influence of alcohol or drugs has already been found to increase the probability of FSI crashes from head-on collisions on curved road segments (*51*), which will further be enhanced by rainfall conditions.
- Expanding on the proven results of poor lane-keeping on curves under rainy weather conditions (*52*), this study identified the association of FSI crashes on rural collector curves with lane change violation as identified in the C3-FSI cluster. This implies that any aggressive driving behavior, such as overtaking in a geometrically restrictive roadway condition (i.e., curve in a narrow roadway), instead of expected compensatory safe driving behavior in rainy weather, may possess a substantially high injury severity risk.
- The presence of non-usage of restraints in one FSI crash cluster (C3-FSI) and one MI crash cluster (C4-MI) indicates that proper use of restraints could very well make the difference between no injury crashes and these visible injury crashes. Multiple studies have also revealed a stronger association between restraint usage and injury severity under rainfall conditions (*24*, *26*). In this study, it was interesting to find that this driving behavior was associated with crashes on low volume rural collector roads where a lack of enforcement of restraint use is expected.

Conclusion

This study investigated the associations of attributes of FSI and MI crashes in rainy weather by exploring a recent five-year crash dataset from Louisiana. Various combinations of crash attributes are affected by the factors attributed to the presence of wet and slippery pavement surface conditions and poor visibility during rainfall. By employing a novel approach known as CCA, this study identified associative attributes following dimension reduction in a large crash dataset of categorical variables. In addition to the two-dimensional factorial maps, through the estimation of top positive residuals, this approach enables researchers to find relationships of various observable attributes illustrating predominant crash scenarios during rainfall. The findings show that roadway characteristics play critical roles in severity types in rainfall-related crashes. Driver traits are less recognizable in rainfall-related crash severity types because of the controlling nature of driving with lower visibility.

This study provides unique contributions to the study of rainfall-related roadway crashes in several aspects. By using the latest (2015–2019) statewide crash data from Louisiana DOTD, this study accounts for the impact of attributes associated with the latest trend. To prioritize the countermeasure implications, the study places emphasis on two injury groups: FSI and MI. To investigate efficiently the collective and coherent associations of attributes, an advanced unsupervised algorithm, CCA analysis, was applied, which uses an automated clustering approach following dimensional reduction of categorical data instead of a subjective approach.

The four clusters for FSI crashes and four clusters for MI crashes provide interesting insights. This study reveals that rainy weather crash patterns are highly distinguishable in relation to roadway functional class regardless of FSI or MI crash severity, mostly explained by posted speed limit and other geometric variables. In addition to functional class and geometric properties of lane width and shoulder width, specific manner of collision, intersections, roadway alignment, and lighting conditions were found to be interrelated. Both FSI and MI crashes can be characterized by a wider range of speed limits and non-usage of restraints.

The associations of attributes identified in this study provide implications for potential preventive measures to prevent FSI and MI crashes. In highways of higher functional class, on Interstates, and at principal arterial intersections, perception of reaction/braking distance in a driving condition, possibly compounded by wet surface pavement during rainfall, is most likely a crucial factor. The real-time advisory speed limit on Interstates during rainfall and advance warning of intersection (retroreflective sign or flashing lights) on principal arterials can mitigate corresponding rear-end crashes and right-angle/turning related crashes, respectively. Considering the findings of crashes occurring at a wide range of speed limits, strategic installation of a weather-responsive variable speed limit system should be highly beneficial following traffic engineering judgments, based on analysis from rainfall crash records and speed studies (*53*). Considering that expensive countermeasures on lower function, low volume roadway curves, such as widening pavement to extend lane width, would require economically unfeasible resources, relatively inexpensive countermeasures such as centerline rumble strips, shoulder rumble strips, and retroreflective marking should be a better alternative to provide navigational aids to prevent single-vehicle run-off-road crashes and head-on crashes (*54*). Transfer of the knowledge of the strong association of rainy weather crashes with the non-usage of restraints and drug/alcohol intoxication could benefit active safety campaigns against these risky behaviors. Factoring the association of curves, non-usage of restraints, and intoxication into the strategic employment of enforcement on low volume roadways should be highly beneficial in preventing crashes during rainfall. It is generally hypothesized that drivers, regardless of their conventional driving nature, become more mindful and drive slowly in response to visibility issues during rain. This study considered several driver-related traits and it showed that road and environmental characteristics are more crucial in rainfall-related crash severity types rather than driver-related traits. Additionally, visually challenged drivers may refrain from driving during rainy weather. The CCA method is robust enough to address these biases. Findings from the CCA analysis suggest more proactive interventions in geometrical design to address concerns associated with rainy weather crashes.

It needs to be acknowledged that the findings of this study may be constrained by several limitations, specifically from data availability. Integration of pavement friction data and accurate spatiotemporal precipitation data could shed more light on rainfall-related crashes. For brevity and simplicity, the researchers limited the scope of the research, aiming at a specific focus on FSI and MI crashes and excluding the possible and no injury crashes. The findings of the results are limited to Louisiana or regions with similar geographic and weather conditions. Applicability of the research findings in other regions requires careful interpretation. Despite these limitations, the crash patterns extracted from the findings related to the combinations of factors encompassing roadway, crash environment, vehicle, and driver can provide useful knowledge in understanding the mechanism of crashes that occur during rainfall. The identified associations of crash attributes across various functional class roadways could provide valuable understanding for incorporation into the development of countermeasures that prioritize the prevention of fatalities and injuries. By integrating a potentially available extended number of attributes in the identification of associations with crash severity, future studies could link precipitation intensity and geospatial information in the combined framework of both preventive and reactive measures against crashes under rainy weather conditions.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M. Ashifur Rahman, S. Das; data collection: M. Ashifur Rahman; analysis and interpretation of results: M. Ashifur Rahman, S. Das, X. Sun; draft manuscript preparation: M. Ashifur Rahman, S. Das, X. Sun. All authors reviewed the results and approved the final version of the manuscript.

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