Analysis of Motorcycle Crashes in Chile Using Spatial Statistics

Carola Blazquez[1(✉)] and María José Fuentes[2]

[1] Department of Engineering Sciences, Universidad Andres Bello, Viña del Mar, Chile
cblazquez@unab.cl
[2] Universidad Andres Bello, Viña del Mar, Chile

Abstract. In this study, spatial statistical methods were used to perform a global and local spatial autocorrelation of motorcycle crashes at the commune level, and to determine whether crash clusters with high crash-related variable values tend to persist during the 2011–2015 period. High global spatial patterns of motorcycle crashes are perceived during the spring at signalised intersections and resulting in fatality outcomes throughout the five-year study period. Recurrent high local spatial clustering of motorcycle collisions arose in the morning on weekdays and on sunny days due to the loss of control of the vehicle, or the imprudence of the driver or pedestrian, and involving male young adults. Communes located in the city of Santiago and the surrounding areas present high spatial clustering for most crash attributes. The results of this study should guide authorities to target efforts towards policy measures, in order to improve motorcycle safety in Chile.

Keywords: Motorcycle crashes · Spatial autocorrelation · Spatial clusters

1 Introduction

According to the World Health Organization, traffic crashes cause 1.2 million fatalities every year and are the main cause of death of young adults between 15 and 29 years of age worldwide. Approximately 23% of these deaths are motorcyclists, 22% are pedestrians, and 4% are cyclists [1]. In Chile, 2,178 people were killed as a result of traffic crashes in 2016, presenting an increase of 4.9% with respect to 2010. This high mortality rate is partly due to the exponential increase of vehicles in the last few years. Additionally, Chile is the OECD member country with the worst fatality rate with 11.9 deaths per 100,000 inhabitants and with 4.5 deaths per 10,000 motorised vehicles [2].

In Chile, almost 19,000 crashes occurred between 2011 and 2015 that involved motorcycles. The national statistics indicate that deaths caused by such crashes are ranked third and that the total number of injuries are placed fourth with respect to other types of crashes [3]. Being vulnerable road users, motorcyclists are 27 times more frequently killed in crashes per travelled vehicle mile than motor vehicle passengers [4].

The motorcycle market increases every year in many countries worldwide, and it is expected to continue increasing in Chile as well [5, 6]. On average, the total number of motorcycles increased in 16.7% between 2017 and 2018 [7]. In 2018, motorcycles

M. Helfert et al. (Eds.): SMARTGREENS 2019/VEHITS 2019, CCIS 1217, pp. 220–244, 2021.
https://doi.org/10.1007/978-3-030-68028-2_11

constituted 3.5% (189, 588) of all registered vehicles in the country with approximately 10.1 motorcycles per 1,000 inhabitants [8]. Motorcycles are deemed as an economical and convenient transport mode with respect to congestion, fuel consumption, ease of parking, etc. Therefore, it may be anticipated that the number of motorcycle crashes will grow in time. Thus, there is a need for a spatial and temporal analysis of these crashes in Chile.

Recent studies have analysed motorcycle crashes employing different approaches. A multiple correspondence analysis was performed by Jalayer and Zhou [9] to conclude that light conditions, time of day, driver condition, and weather conditions are the key factors contributing to the frequency and severity of at-fault motorcycle-involved crashes in the state of Alabama. Flask et al. [10] employed Bayesian multi-level mixed effects models to analyse motorcycle crashes at the road segment level. The authors concluded that among different characteristics of the road segments, smaller lanes and shoulder widths, larger horizontal degree of curvature and larger maximum vertical grades will increase the prediction of crashes. In another study, a deep learning framework was developed to predict motorcycle crash severities, which were related to rider ejection, two-way roads, curved roads, and weekends [11]. Lee et al. [12] employed a flexible mixed multinomial logit fractional split model to analyse the proportions of crashes by vehicle type (including motorcycles). This study concluded that the total employment density has the most significant and negative influence on the motorcycle crash proportion, and that the proportions of households with no vehicle negatively impact the proportion of motorcycle crashes. Chung and Song [13] employed multivariable statistical methods to identify the critical factors associated to age, motorcycle speed, curved sections, among others that impact motorcycle crash severity in Korea. Ding et al. [14] developed multivariate injury risk models for motorcyclists in Germany. The authors concluded that a strong relation exists between relative speed and injury risk for motorcyclists. The potential temporal instability in the factors (e.g., motorcyclists' attributes, rider behaviour, and roadway conditions) affecting motorcycle crash-injury severities in the state of Florida was assessed by Alnawmasi and Mannering [15] using random parameters multinomial logit models. Finally, by employing ordered probit models, Zhou and Chin [16] studied the high injury severity of motorised vehicles and motorised two-wheelers (motorcycles) involved in loss-of-control of single vehicle crashes in Singapore. The findings of this study reveal that race, at-fault status, road traffic type, lighting and colliding with stationary object are factors that impact particularly the high severity of motorcyclists.

Other researchers have studied the spatial problem using statistical methods such as spatial autocorrelation to identify spatial clusters of road crashes. For example, Dezman et al. [17] analysed hotspots of traffic crashes at the census tract level in Baltimore using spatial autocorrelation techniques. Spatial autocorrelation was used to examine hotspots of time of occurrence, severity, and location of traffic crashes aggregated to the traffic analysis zonal level in Shiraz, Iran [18]. In another study, Pour et al. [19] applied spatial autocorrelation to detect any dependency between time and location of vehicle-pedestrian crashes in Melbourne. Blazquez et al. [20] performed a spatial autocorrelation analysis of cargo trucks on Chilean highways at the global and local level. Yet another study was performed by Aghajani et al. [21] to identify spatial and temporal patterns of traffic crashes, and to determine hotspots of fatal and injury outcomes in Iran. Saadat et al.

[22] employed spatial autocorrelation to identify spatial patterns of fatality outcomes in motorcycle crashes at the district level in Tehran. Ghandour et al. [23] used spatial autocorrelation with the Lebanese crash dataset to study the spatial clustering behaviour and hazard vulnerability of vehicle crashes. Recently, Blazquez and Fuentes [24] studied motorcycle crash attributes in Chile using spatial autocorrelation analysis. This study advances the work of [24] by determining global and local significant patterns of different motorcycle crash-related variables (e.g., type of crash, relative location, contributing factors, and road safety measures) at the commune level in Chile, and assessing whether a spatial dependence of such patterns persisted during the 2011–2015 period. The results of this macroscopic crash study provides a decision-making tool for helping authorities and safety professionals allocate resources and apply policy based countermeasures.

2 Methodology

The spatial statistical methods were applied to determine the spatial association of the value of a certain variable at a given location with values of that variable at neighbouring locations at the global and local level [25]. First, the global Moran's I index was employed to test the general spatial autocorrelation of the main crash attributes and road safety indicators for each year of the studied period. Second, a local Moran's I statistic was employed to detect statistically significant clusters with respect to each of the crash-related variables.

The global Moran's I indicator is used to identify statistically significant spatial patterns of crashes by quantifying the magnitude of clustering or dispersion of these crashes with Eq. 1.

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})\left(x_j - \overline{x}\right)}{S_o \sum_{i=1}^{n}(x_i - \overline{x})^2} \forall i, j \tag{1}$$

where x_i is the variable value at a particular location i, $\overline{x}$ is the mean of the variable, w_{ij} are the elements of a spatial matrix with weights representing proximity relationships between location i and neighbouring location j, S_0 is the summation of all elements w_{ij}, and n is the total number of locations.

The values of Moran's I may range between −1 (representing perfect dispersion with a strong negative autocorrelation) and 1 (indicating perfect clusterisation with a strong positive autocorrelation). A random spatial pattern exists when the value of Moran's I is near zero. The results of the spatial autocorrelation are interpreted within the context of its null hypothesis, which denotes that an attribute is randomly distributed among features in the study area. The Z score method is employed to compute the statistical significance of the Moran's I index. A positive Z score for a feature indicates that the neighbouring features have similar values, whereas a negative Z score denotes that the feature is surrounded by dissimilar values.

While the global Moran's I provides a single value to measure the overall spatial pattern of a certain attribute throughout a complete study area, Anselin´s local Moran's I examines the existence of local spatial clusters of similar high, low, or atypical values (e.g., high value surrounded by low attribute value location, and low values with high attribute value neighbouring features) at certain locations, as described in Anselin [26]. Thus, the results of this statistic shows the value similarity of a location to its neighbours, and in addition, tests the significance of this similarity [27]. The local Moran's I index is expressed by Eq. 2.

$$I_i = \frac{x_i - \overline{X}}{S_i^2} \sum_{j=1, j \neq 1}^{n} w_{ij}\left(x_i - \overline{X}\right) \tag{2}$$

where x_i is the variable value at location i, $\overline{x}$ is the mean of the variable, w_{ij} is the spatial weight between locations i and j, S_i is the sum of the weights, and n is the total number of locations.

Similarly to the global indicator, the spatial patterns are associated to Z score values to determine the statistical significance of the results. Positive Z score values imply that neighbouring values are similar and negative values indicate that near values are dissimilar [28]. This study will focus on identifying locations of clusters of high motorcycle crash attribute values.

3 Data Description

The National Commission of Traffic Safety (CONASET, acronym in Spanish) provided the 2011–2015 crash database employed in this study. A total of 18,826 motorcycle crashes were successfully aggregated into 343 communes, as shown in Fig. 1. This figure shows that five communes (Arica, Antofagasta, Copiapó, La Serena, and Coquimbo) present a high number of such crashes in the north zone of Chile, many crashes prevailed in several communes of the centre zone of the country, and the communes of Coyhaique and Punta Arenas in the south zone have the largest number of motorcycle crashes.

The main variables of the motorcycle crashes were classified into eight groups (road safety measures, temporal attributes, personal characteristics, type of crash, relative location, contributing factors, type of zone, and weather conditions), as shown in Table 1. This table shows an increase in the total number of motorcycle crashes over time and that this number almost doubled in 2015 with respect to previous years. Similarly, an evident increase is perceived in 2015 in the road safety measures related to crasher per 100,000 population and 10,000 registered vehicles. On average, approximately 74% of the crashes occurred on a weekday and 26% during the weekend. For every year of the study period, motorcycle crashes occurred during night between 6 pm and 6 am with an average of 40.9%, followed by the afternoon between 12 pm and 6 pm with an average of 32.8%, and the morning between 6 am and 12 pm with an average of 24%. Regarding the season of the year, most motorcycle crashes arose during the summer (30.7%), followed by crashes during the fall (29%), spring (20.3%), and winter (20%). Additionally, most crashes occurred in urban areas (85%) and on sunny days (86%).

The imprudence of the driver was the main contributing cause of these crashes, representing 40% of the total number of crashes. On average, collision between two or more moving vehicles (56.8%) was the most frequent type of crash, followed by impacts with static vehicles or objects (19.9%), pedestrian crashes (10.3%), and rollovers (8.9%). With respect to the relative location of motorcycle crashes, 38.0% of these crashes

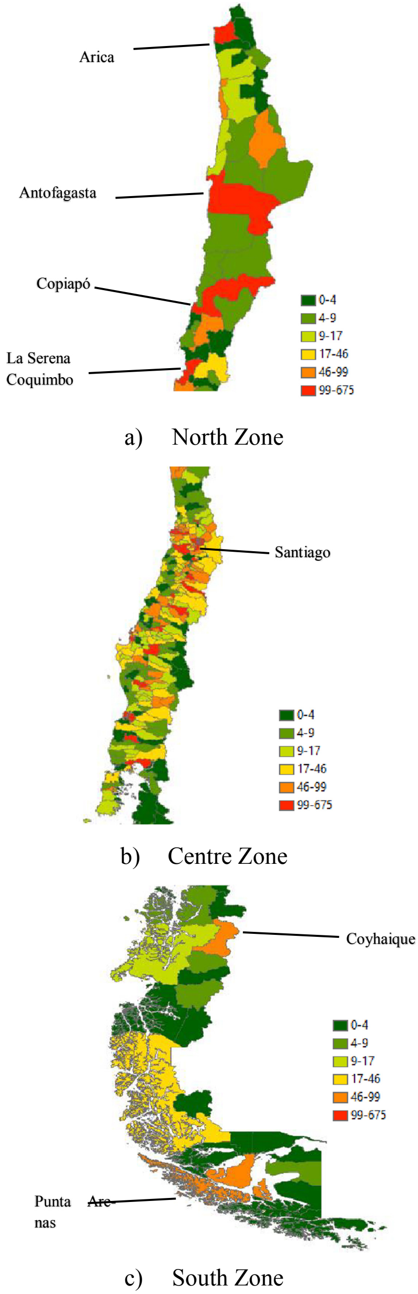


Fig. 1. Motorcycle crashes for the 2011–2015 period aggregated at the commune level for the a) North Zone, b) Centre Zone, and c) South Zone [24].

Table 1. Descriptive statistics for each analysed variable per year (adapted from [24]).

Variable	2011	2012	2013	2014	2015	Total
Road safety measures						
Number of crashes	2315	2786	3463	3445	6819	18828
Crashes per 100,000 population	13.5	14.0	23.9	16.1	32.8	20.1
Crashes per 10,000 registered vehicles	10.8	6.7	8.3	6.3	11.9	8.8
Type of injury						
Fatalities	29	78	72	75	151	405
Seriously injured	146	285	349	334	1336	2450
Slightly injured	2127	2647	2588	6569	5339	19270
Temporal attributes						
Day of week						
Weekday	1651	2063	2543	2580	5017	13854
Weekend	664	723	920	865	1802	4974
Time of day						
Morning	618	724	878	820	1585	4625
Afternoon	808	970	1211	1148	2183	6320
Night	889	1092	1374	1477	3051	7883
Season						
Spring	466	745	765	947	1842	3818
Summer	581	699	922	1699	1874	5775
Fall	710	712	969	1386	1690	5467
Winter	558	630	807	360	1413	3768
Personal characteristics						
Age group						
<18 years old	195	234	272	255	365	1321
19–33 years old	756	913	1141	1130	4075	8015
34–64 years old	1117	1365	1603	1565	1848	7498
>65 years old	113	166	200	212	114	805
Gender						
Female	571	786	878	907	901	4043
Male	1744	2000	2585	2538	5918	14785
Type of crash						
Collision	1150	1393	1811	1826	4508	10684

(*continued*)

Table 1. (*continued*)

Variable	2011	2012	2013	2014	2015	Total
Impact	579	649	854	899	779	3763
Pedestrian crash	318	410	431	407	370	603
Rollover	156	170	217	175	950	1668
Relative location						
Straight section	1250	1513	1850	1783	3660	10056
Curved section	138	162	242	265	461	1268
Intersection with signage	654	822	967	1019	1877	4282
Intersection without signage	111	123	147	148	324	837
Contributing factors						
Imprudence of driver	866	1079	1756	1433	2428	7562
Imprudence of pedestrian	242	296	312	357	467	1674
Loss of control	225	282	272	309	1900	2988
Driving under influence alcohol	197	213	237	244	748	1639
Other causes	420	533	639	732	944	3268
Type of zone						
Urban	1962	2341	2903	2928	5868	16002
Rural	353	445	560	517	949	2824
Weather conditions						
Sunny	2154	2323	2907	2799	5939	16122
Drizzly	8	41	28	38	34	149
Foggy	5	15	23	19	16	1619
Rainy	55	133	150	180	332	850
Cloudy	93	272	351	408	495	1619

occurred on straight road segments and 6.7% on curved road sections, whereas 22.7% and 4.4% of motorcycle crashes arose at intersections with traffic signals and without signage, respectively.

Regarding the type of injury, 405 victims were killed and 2,450 people suffered serious injuries as a result of motorcycle crashes during the studied period. Male victims were more involved in motorcycle crashes than females with 78.5%. In addition, young adults between 19 and 33 years old and adults between 34 and 64 years old represent the largest age groups of victims involved in motorcycle crashes with 45.4% and 42.5%, respectively, during the study period.

4 Results

An incremental spatial autocorrelation analysis was first performed to obtain a distance threshold or bandwidth value for each analysed crash variable and year. This parameter value maximizes the spatial autocorrelation (Z score), meaning that a cluster exists up to this calculated distance with a statistical significance of 0.01. These distance thresholds were employed in both global and local spatial autocorrelation analyses. Z score values greater than 1.96 with a 95% confidence were utilised to determine the statistical significance for each value of the motorcycle crash variables in such analyses.

Table 2 shows the global spatial autocorrelation results. The average and standard deviation values of the global Moran's I index were computed only for those crash variables that presented a recurrent clustering of at least three years during the studied period. Different strength measures of persistent global spatial patterns are observed among the different crash variables. For example, motorcycle crashes that occurred at signalised intersections present a stronger positive spatial pattern with an average global Moran's I value of 0.088 during the five years of the study period than any other analysed variable in the table.

Among all road safety measures, crashes per 100,000 population presents the highest positive clustering of 0.51. With respect with the type of injury, crash-caused fatalities clustered during all five years of the 2011–2015 period with a high average clustering intensity of 0.073, followed by slight injury outcomes with an average global positive autocorrelation of 0.050, and victims that were seriously injured with a value of 0.021. Although a large percentage of crashes occurred during weekdays, similar global spatial clustering of motorcycle crashes is observed during weekdays and weekends with 0.048 and 0.042, respectively. Similarly, approximately 1.4 and 1.7 times more crashes occurred in the afternoon and night, respectively, than during the morning. However, the highest overall clustering of crashes occurred during the morning with 0.048. While most motorcycle crashes occurred in the summer, a large average global clustering is observed in the spring (0.087). The largest percentage of motorcycle crashes involve young adults and adults, nevertheless, the largest global spatial clustering is perceived in the age group of victims over 65 years old during the five years of the study period. Female and male victims are positively clustered with values of 0.055 and 0.059, respectively.

Regarding the type of crash, collisions between moving vehicles present a global positive autocorrelation of 0.053 and are clustered during the whole study period, followed by impacts with static vehicles (0.036) and pedestrian crashes (0.034). Whereas, rollovers of motorcycle crashes were insignificant during the study period. The relative locations of motorcycle crashes show positive global spatial dependences of arising along straight (0.053) and curved (0.066) road sections, and at intersections with and without traffic signals for all studied years. Insignificant results were obtained for crashes that occurred on rural zones, and thus, these are not listed in Table 2. Whilst motorcycle crashes that arose in urban zones tend to cluster during four years of the study period with an average clustering intensity of 0.051.

The contributing cause related to driving under the influence of alcohol shows the largest clustering intensity (0.064) among all contributing factors, as in the results of [29]. However, the loss of control of the vehicle, the imprudence of pedestrians, and the imprudence of drivers are other causes with high average Moran's I values of 0.059,

Table 2. Results of recurrent global spatial autocorrelation of motorcycle crashes (adapted from [24]).

Variable	Average Moran's I	Standard deviation Moran's I	Number of clustering years
Road safety measures			
Number of crashes	0.049	0.009	5
Crashes per 100,000 population	0.051	0.026	5
Crashes per 10,000 registered vehicles	0.024	0.022	5
Type of injury			
Fatalities	0.073	0.029	5
Seriously injured	0.021	0.019	3
Slightly injured	0.050	0.041	5
Temporal attributes			
Day of week			
Weekday	0.048	0.009	5
Weekend	0.042	0.017	5
Time of day			
Morning	0.048	0.025	5
Afternoon	0.037	0.016	5
Night	0.030	0.012	5
Season			
Spring	0.087	0.102	5
Summer	0.035	0.018	5
Fall	0.043	0.018	5
Winter	0.042	0.018	5
Personal characteristics			
Age group			
<18 years old	0.043	0.031	4
19–33 years old	0.041	0.027	4
34–64 years old	0.046	0.018	5
>65 years old	0.065	0.040	5
Gender			
Female	0.055	0.036	4

(*continued*)

Table 2. (*continued*)

Variable	Average Moran's I	Standard deviation Moran's I	Number of clustering years
Male	0.059	0.033	5
Type of crash			
Collision	0.053	0.027	5
Impact	0.036	0.015	5
Pedestrian crash	0.034	0.036	3
Relative location			
Straight section	0.053	0.027	5
Curved section	0.066	0.031	5
Intersection with signage	0.088	0.017	5
Intersection without signage	0.053	0.028	5
Contributing factors			
Imprudence of driver	0.051	0.041	4
Imprudence of pedestrian	0.055	0.041	3
Loss of control	0.059	0.036	5
Driving under influence alcohol	0.064	0.039	4
Other causes	0.037	0.023	5
Type of zone			
Urban	0.051	0.035	4
Weather conditions			
Sunny	0.064	0.023	5
Drizzly	0.085	0.023	4
Foggy	0.044	0.023	4

0.055, and 0.051, respectively, which persisted for three or more years. Finally, the weather conditions of motorcycle crashes tend to cluster during all five years of the study period for sunny days with an average statistic value of 0.064, and during four years for drizzly and foggy days with an average global Moran's I value of 0.085 and 0.044, respectively. No significant results were observed for motorcycle crashes that occurred on rainy or cloudy days.

This study focuses on the location of motorcycle crash clusters with high crash-related variable values surrounded by high crash-related variable values (High-High local spatial pattern, HH). The number of HH spatial clusters for each analysed motorcycle crash variable per year are shown in Table 3. This table indicates that the largest total number of HH crashes (287) during the studied period are related to motorcycle crashes that occurred on road with straight sections, followed by roads with curved sections (253) and fatality outcomes (253). In addition, morning crashes present the largest average clustering intensity of 72.6, followed by those crashes that occurred at signalised intersections with a value of 71.7.

Note that although approximately 7% of all reported crashes occurred on curved road segments, these tend to locally cluster with high values over time. Similarly, very few motorcycle crashes occurred on drizzly days compared to the other weather conditions. However, 226 HH clusters of such crashes arise on drizzly days during the 2011–2015 period. Although approximately 5% of the crashes involve the elderly, this age group presents 181 HH clusters. Additionally, 42.5% of the victims are adults (34–64 years old) and 182 HH clusters are observed for this age group.

Over the study period, most crashes clustered locally during the morning with 163 HH and presented the highest clustering intensity, but the largest number of crashes occurred at night, as indicated in Table 1. Interestingly, among all seasons, the winter season has the highest number of HH with 168, but the strongest clustering intensity is observed in crashes that occurred in the spring (68.2). Similar number of HH clusters is identified in crashes that arose in the weekdays and weekends, concurring with the global spatial autocorrelation analysis results.

Note that motorcycle crashes that resulted in rollovers on rainy or cloudy days along rural areas present a low existence or lack of clustering over time. Additionally, notice that the total number of HH clusters for all contributing causes of motorcycle crashes is greater than 200, which highlights the importance of these factors among the generation of these crashes. On average, there are several large numbers of HH clusters of motorcycle collisions that occurred on sunny days along straight or curved road segments caused by the loss of control of the vehicle or the imprudence of the driver or the pedestrian generating fatality outcomes.

Figure 2–11 present spatial clusters at the commune level for each analysed motorcycle crash variable that persisted for three, four, or five years of the studied period using the local Moran's I statistic. These figures depict that the communes belonging to four out of 16 regions of the country (Metropolitan Region, and regions of Valparaiso, O´Higgins, and Maule) represent statistically significant HH spatial patterns. This result may be explained by the high population and the substantial increase in the usage of motorcycles as a transport mode in these four regions between 2011 and 2015.

The HH clustering of road safety indicators are presented in Fig. 2. The communes of Viña del Mar, Valparaiso, and Quilpue in the Region of Valparaiso, several communes in the Metropolitan Region, Rancagua in the Region of O´Higgins, and Curico in the Region of Maule presented recurrent HH crash clusters for all years of the study period. Whereas, crashes per 100,000 population clustered for 3 years in the communes of San José de Maipo, Providencia, and Vitacura in the Metropolitan Region, and Curico in the Region of Maule. Crashes per 10,000 vehicles clustered spatially for less than three years, and thus, a figure is not presented for this variable. Figure 3 depicts the recurrent HH clusters of fatality outcomes that persisted for the whole studied period in

Table 3. Number of HH spatial clusters of motorcycle crash attributes that arose during the 2011–2015 period (adapted from [24]).

Variable	Year					$\sum$ HH
	2011	2012	2013	2014	2015	
Road safety measures						
Number of crashes	28 (62.6)	36 (56.4)	37 (60.2)	39 (58.9)	31 (92.5)	171 (66.1)
Crashes per 100,000 population	7 (38.5)	30 (25.7)	1 (3.9)	64 (57.1)	18 (27.9)	120 (30.6)
Crashes per 10,000 registered vehicles	2 (42.9)	16 (27.6)	3 (69.4)	48 (29.7)	32 (24.2)	101 (38.7)
Type of injury						
Fatalities	54 (46.4)	46 (44.9)	52 (48.4)	51 (58.4)	50 (61.5)	253 (51.9)
Seriously injured	46 (31.5)	0	23 (33.0)	31 (38.4)	49 (44.7)	149 (36.9)
Slightly injured	55 (44.7)	39 (20.8)	20 (12.8)	48 (45.7)	61 (56.4)	223 (36.1)
Temporal attributes						
Day of week						
Weekday	31 (62.1)	34 (57.9)	40 (59.2)	35 (80.2)	33 (86.5)	173 (69.2)
Weekend	27 (48.8)	37 (53.5)	32 (59.4)	40 (60.7)	35 (75.2)	171 (59.5)
Time of day						
Morning	25 (62.6)	32 (59.5)	33 (50.5)	36 (95.4)	37 (94.8)	163 (72.6)
Afternoon	28 (57.9)	27 (53.9)	23 (50.6)	33 (77.4)	31 (82.9)	142 (64.5)
Night	28 (47.5)	29 (49.7)	23 (44.9)	35 (66.9)	37 (77.0)	152 (57.2)
Season						
Spring	23 (59.8)	31 (52.9)	38 (72.5)	33 (72.0)	31 (83.6)	156 (68.2)
Summer	25 (41.6)	25 (56.0)	33 (48.6)	40 (80.0)	34 (72.8)	157 (59.8)
Fall	31 (75.6)	26 (53.1)	32 (61.1)	37 (68.0)	34 (82.5)	160 (68.1)
Winter	35 (49.9)	34 (59.6)	35 (57.5)	26 (67.4)	38 (85.9)	168 (64.1)
Personal characteristics						
Age group						
<18 years old	24 (44.3)	18 (37.1)	34 (46.6)	35 (75.9)	35 (45.9)	146 (50.0)
19–33 years old	21 (50.9)	38 (66.7)	34 (58.9)	39 (87.8)	28 (77.7)	160 (68.4)
34–64 years old	35 (63.8)	30 (52.8)	40 (57.8)	37 (63.5)	40 (87.5)	182 (65.1)
>65 years old	35 (41.9)	45 (53.1)	30 (50.4)	32 (68.1)	39 (56.9)	181 (54.1)
Gender						
Female	23 (42.8)	31 (71.3)	36 (52.9)	38 (76.4)	29 (65.6)	157 (61.8)

(*continued*)

Table 3. (*continued*)

Variable	Year					∑ HH
	2011	2012	2013	2014	2015	
Male	31 (59.5)	36 (53.0)	38 (60.3)	38 (72.6)	34 (85.3)	177 (66.1)
Type of crash						
Collision	57 (41.6)	45 (31.3)	53 (33.6)	24 (59.8)	45 (42.5)	224 (41.8)
Impact	61 (32.6)	30 (70.3)	31 (80.7)	38 (52.2)	4 (72.3)	164 (61.6)
Pedestrian crash	62 (28.4)	12 (4.4)	7 (11.6)	54 (45.4)	49 (45.3)	184 (27.0)
Rollover	10 (23.4)	0	7 (16.3)	14 (5.9)	25 (39.6)	56 (16.8)
Relative location						
Straight section	61 (34.7)	50 (38.2)	58 (37.1)	68 (35.9)	50 (53.7)	287 (39.9)
Curved section	35 (41.2)	50 (39.4)	60 (37.4)	51 (53.2)	57 (55.0)	253 (45.3)
Intersection with signage	30 (83.3)	34 (63.8)	39 (52.2)	39 (75.1)	34 (84.1)	176 (71.7)
Intersection without signage	34 (42.5)	35 (37.5)	39 (54.8)	40 (52.1)	35 (77.6)	183 (52.9)
Contributing factors						
Imprudence of driver	51 (44.5)	44 (17.1)	43 (37.5)	55 (58.9)	47 (20.2)	240 (35.6)
Imprudence of pedestrian	30 (24.3)	48 (39.7)	53 (43.1)	56 (53.5)	53 (58.3)	240 (43.8)
Loss of control	27 (13.3)	50 (61.2)	56 (36.9)	53 (49.1)	59 (53.7)	245 (42.8)
Driving under influence alcohol	25 (12.1)	55 (31.3)	45 (15.1)	54 (56.2)	53 (54.6)	232 (33.9)
Other causes	48 (62.9)	38 (38.4)	42 (21.3)	49 (63.9)	29 (44.3)	206 (46.2)
Type of zone						
Urban	56 (46.9)	4 (13.3)	24 (11.3)	51 (5.9)	60 (20.8)	195 (18.5)
Rural	0	8 (9.8)	5 (5.1)	49 (39.1)	61 (20.4)	123 (14.9)
Weather conditions						
Sunny	50 (49.6)	41 (42.5)	47 (36.2)	48 (52.4)	54 (53.1)	240 (46.8)
Drizzly	0	57 (48.1)	62 (50.7)	52 (59.5)	55 (57.2)	226 (53.9)
Foggy	0	30 (26.4)	17 (41.9)	48 (44.2)	55 (35.2)	150 (29.5)
Rainy	19 (43.2)	0	0	21 (52.5)	16 (61.4)	56 (52.4)
Cloudy	40 (72.8)	0	0	0	36 (59.9)	76 (26.5)

Note: Average local Moran´s I values of HH crashes are shown in parenthesis.

the communes situated in the Metropolitan Region, and the regions of Valparaiso and O´Higgins. Whereas HH clusters of seriously or slightly injured victims are recurrent

a) Number of crashes b) Crashes per 100,000 population

Fig. 2. HH spatial clusters for each road safety measure.

for a smaller number of years and only in some communes of these regions. Although Fig. 4a) and 4b) present communes with similar HH clusters, slightly more communes are perceived as recurrent HH clusters during the weekday. Regarding the time of day, 32 communes are perceived as HH clusters of morning and night crashes, whereas 25 communes are observed as HH clusters of afternoon crashes over three or more years (See Fig. 5). The communes of Ñuñoa, Puente Alto, and Santiago in the Metropolitan Region, Quilpue and Valparaiso in the Region of Valparaiso, and Rancagua in the Region of O´Higgins persisted as HH crash clusters during the complete study period for all seasons of the year, as shown in Fig. 6.

a) Fatalities b) Seriously injured c) Slightly injured

Fig. 3. HH spatial clusters for each type of injury [24].

As the results presented in Table 3, Fig. 7 shows that collisions represent the largest number of HH spatial clusters among all types of crashes. These clusters are mostly located in communes of the Region of Valparaiso and Metropolitan Region. Notice that

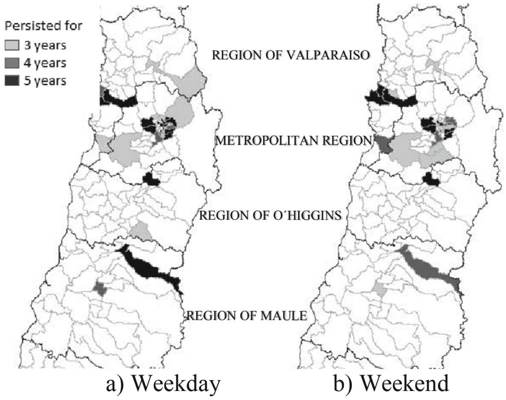


Fig. 4. HH spatial clusters for days of the week.

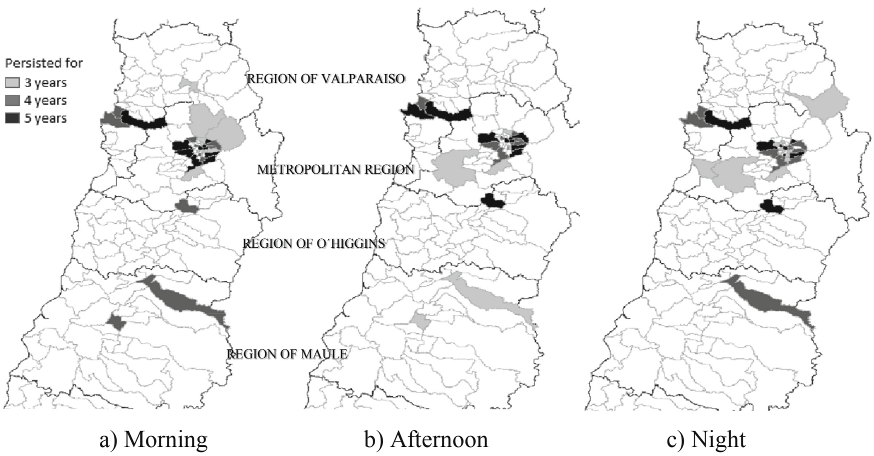


Fig. 5. HH spatial clusters for each time of the day.

rollover-related crash HH clusters are not shown since such clusters in all communes were positive and significant for less than three years.

Figure 8 presents the recurrent HH clusters of motorcycle crashes with respect to their relative location at the commune level. For all types of relative locations, this figure shows that HH clusters in some communes in the Region of Valparaiso and in the Metropolitan Region, and in the commune of Rancagua in the Region of O´Higgins persisted for the five years of the studied period. Conversely, recurrent HH clusters appeared along straight and curved road sections in many communes in the centre of the Metropolitan Region (particularly in the city of Santiago).

Communes in the four regions shown in Fig. 9 present persistent HH clusters due to the imprudence of the pedestrian, whereas clustering of crashes due to imprudence of the driver that persisted for all five years of the 2011–2015 are concentrated in the city of Santiago, a couple of communes in the Region of Valparaiso, and Rancagua in

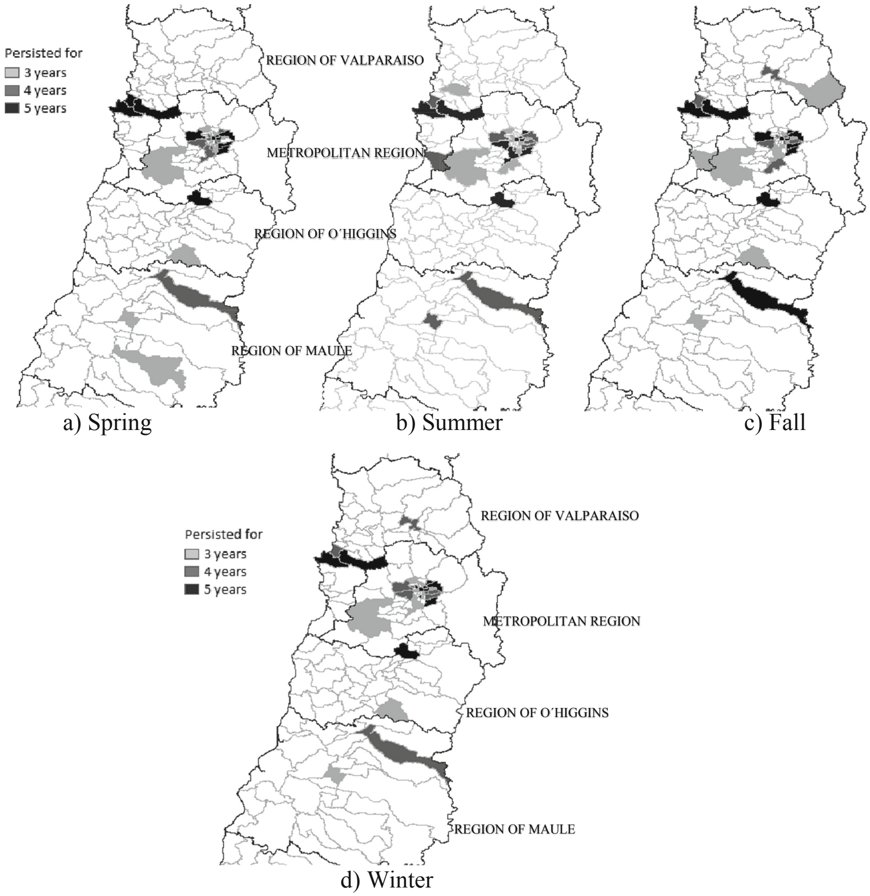
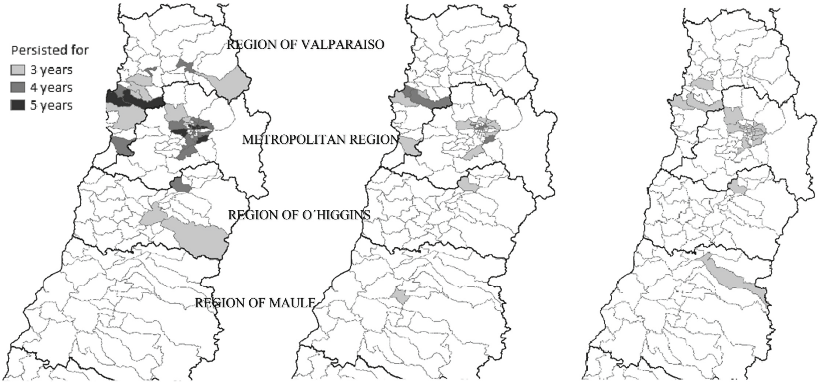


Fig. 6. HH spatial clusters for each season.

the Region of O´Higgins. This figure also suggests that motorcycle crashes due to the loss of control and driving under the influence of alcohol are highly clustered during the five years of the studied period in few communes in the city of Santiago and Region of Valparaiso. HH clusters appear in a lesser degree as a result of other causes.

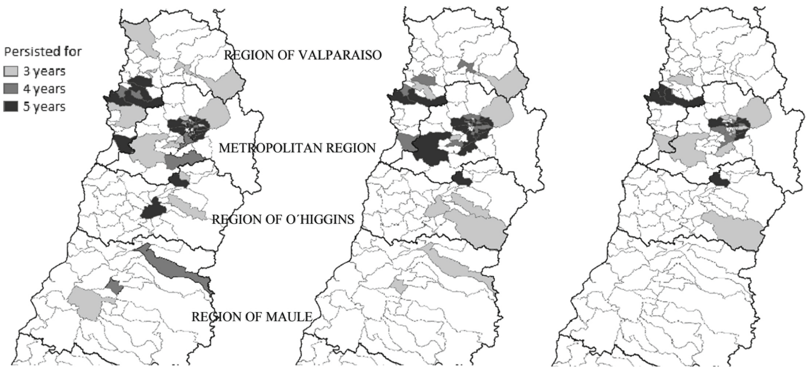
Recurrent spatial clustering of crashes that occurred in urban areas are recurrent for 3 or 4 years during the studied period in communes of the regions of O´Higgins and Maule, as shown in Fig. 10. No HH clustering of crashes in rural zones was perceived in any commune for three or more years.

Regarding the weather conditions, Fig. 11 depicts HH spatial clusters of crashes that arose on sunny and drizzly days that persisted for three or more years. Concurring with the results in Table 3, this figure shows that communes with clustering of crashes on sunny days persisted for three to five years, whilst more communes are displayed with crash clusters during drizzly days for three and four years of the studied period.

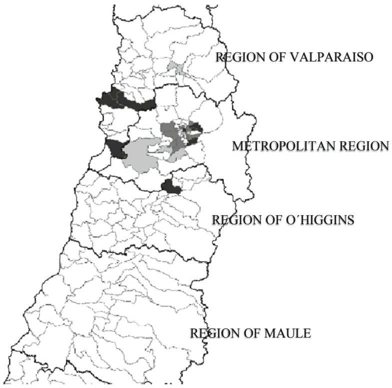


a) Collision b) Impact c) Pedestrian crash

Fig. 7. HH spatial clusters for each type of crash [24].

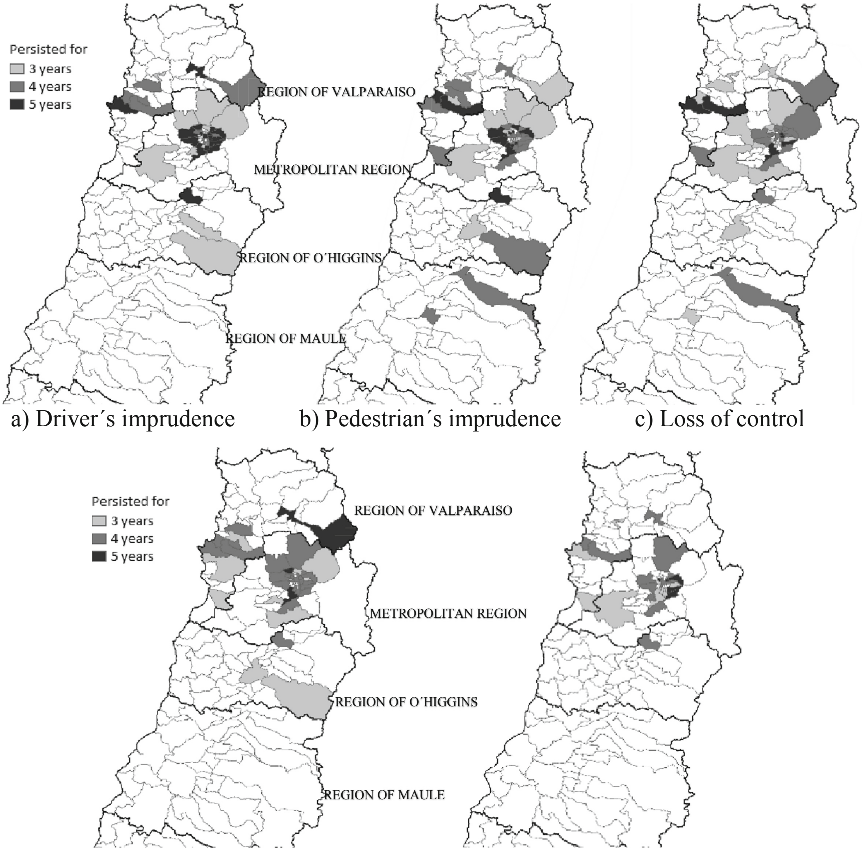


a) Straight section b) Curved section c) With signage



d) Without signage

Fig. 8. HH spatial clusters for the relative location of motorcycle crashes [24].



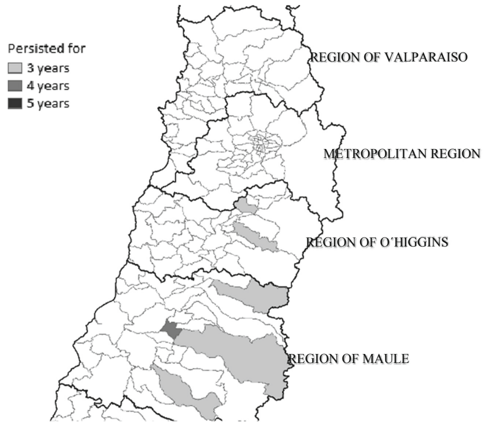
a) Driver´s imprudence b) Pedestrian´s imprudence c) Loss of control

d) Alcohol of driver e) Other causes

Fig. 9. HH spatial clusters for each contributing factor [24].

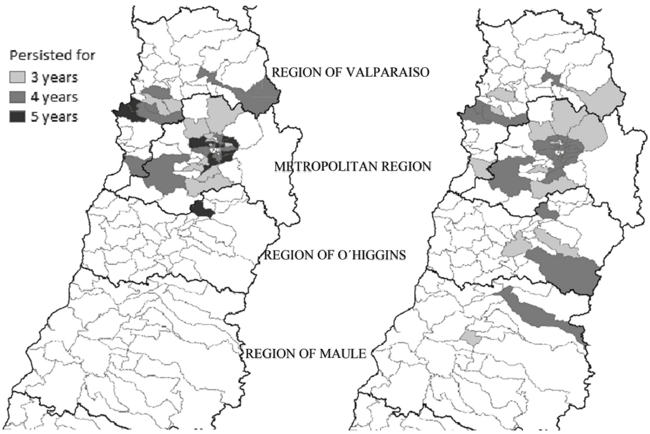
The top five Chilean communes with the largest number of HH for the 41 analysed crash-related variables in the five-year period are shown in Fig. 12. This figure shows that four out of these five communes with the most number of HH crash attributes are located in the Metropolitan Region.

Table 4 presents the average values of the local Moran's I index and the Z score in parenthesis for recurrent crash attributes for the five communes depicted in Fig. 12. Those communes with no values indicate that that particular variable was significant for less than three years. Overall, Santiago has the highest intensity of HH clusters in 27 of the crash-related variables when compared to the rest of the communes, similarly to the findings in Blazquez and Celis [30] and Blazquez et al. [31]. In particular, significantly higher clustering of morning crashes at intersections with traffic signs on weekdays generating fatality outcomes are perceived in this commune.



a) Urban zone

Fig. 10. HH spatial clusters of crashes in urban zones [24].



a) Sunny days b) Drizzly days

Fig. 11. HH spatial clusters for each weather condition [24].

Fig. 12. Communes with the largest number of HH attribute clusters during the 2011–2015 period (adapted from [24]).

Table 4. Local autocorrelation results of motorcycle crash attributes for the top five communes with most HH crash clusters (adapted from [24]).

Variable	Commune				
	Las Condes	Ñuñoa	Puente Alto	Rancagua	Santiago
Road safety measures					
Crashes	106.5 (11.8)	113.9 (12.6)	154.2 (17.0)	121.3 (13.3)	199.1 (22.1)
Crashes per 100,000 population	45.5 (5.0)	38.8 (4.4)	–	40.5 (4.5)	33.9 (3.8)
Crashes per 10,000 registered vehicles	–	28.9 (3.4)	–	18.4 (2.2)	28.0 (3.3)
Type of injury					
Fatalities	107.2 (4.2)	118.1 (4.2)	162.5 (4.2)	120.0 (4.0)	207.1 (4.2)
Seriously injured	42.3 (2.7)	41.3 (2.8)	80.4 (2.5)	50.2 (2.7)	48.7 (2.7)
Slightly injured	71.5 (3.4)	138.3 (3.8)	147.5 (3.8)	85.8 (3.7)	113.7 (3.3)
Temporal attributes					
Day of week					
Weekday	111.4 (12.3)	129.9 (14.3)	144.3 (15.9)	116.7 (12.8)	201.4 (22.2)
Weekend	87.1 (9.6)	53.3 (5.9)	156.2 (17.2)	86.5 (9.6)	151.8 (16.8)
Time of day					
Morning	158.3 (17.4)	147.3 (16.3)	150.7 (16.6)	88.2 (9.7)	207.5 (22.9)

(*continued*)

Table 4. (*continued*)

Variable	Commune				
	Las Condes	Ñuñoa	Puente Alto	Rancagua	Santiago
Afternoon	92.7 (10.3)	95.2 (10.6)	137.0 (15.2)	113.6 (12.5)	169.6 (18.8)
Night	92.8 (10.3)	86.4 (9.6)	134.6 (14.8)	102.0 (11.2)	135.9 (15.0)
Season					
Spring	104.2 (11.5)	104.9 (11.6)	116.8 (12.8)	66.7 (7.3)	176.8 (19.5)
Summer	89.5 (9.9)	80.6 (8.1)	141.9 (15.6)	106.2 (11.7)	141.9 (15.1)
Fall	106.5 (11.8)	106.5 (11.8)	150.7 (16.6)	110.2 (12.1)	181.8 (20.0)
Winter	91.6 (10.2)	112.7 (12.5)	112. (12.5)	112.7 (12.4)	162.8 (18.1)
Personal characteristics					
Age group					
<18 years old	56.8 (6.6)	54.4 (6.3)	106.5 (12.2)	88.1 (10.1)	118.6 (13.5)
19–33 years old	107.2 (12.3)	124.5 (14.2)	146.7 (16.8)	112.3 (12.8)	179.8 (20.5)
34–64 years old	118.8 (13.1)	109.3 (12.0)	147.4 (16.2)	108.7 (11.9)	191.3 (21.0)
>65 years old	63.0 (7.1)	79.4 (8.9)	92.7 (10.3)	118.9 (13.3)	110.8 (12.5)
Gender					
Female	78.5 (8.8)	61.1 (6.9)	131.1 (14.7)	109.8 (12.3)	175.4 (19.7)
Male	108.4 (11.9)	121.6 (13.4)	147.9 (16.2)	106.8 (11.7)	188.5 (20.7)
Type of crash					
Collision	58.6 (3.6)	96.2 (3.7)	124.7 (3.6)	84.7 (3.0)	141.1 (3.5)
Impact	82.1 (3.4)	72.9 (2.7)	71.1 (3.7)	73.0 (3.2)	180.4 (3.6)
Pedestrian crash	105.8 (3.5)	40.3 (3.6)	117.4 (3.5)	62.8 (3.5)	149.6 (3.5)
Relative location					
Straight section	74.4 (3.7)	108.6 (3.8)	163.2 (3.7)	95.5 (3.6)	134.4 (3.6)
Curved section	86.1 (4.0)	87.9 (3.9)	129.1 (3.8)	84.1 (3.5)	176.0 (3.8)
Intersection with signage	132.5 (15.6)	122.3 (14.3)	169.9 (19.8)	136.7 (16.0)	216.5 (25.2)
Intersection without signage	53.3 (6.3)	151.2 (17.6)	88.8 (10.4)	84.6 (9.9)	117.3 (13.6)
Contributing factors					
Imprudence of driver	64.2 (3.6)	58.2 (3.3)	68.5 (3.4)	97.5 (3.2)	153.7 (3.1)
Imprudence of pedestrian	98.0 (3.8)	104.1 (4.0)	142.1 (4.1)	86.3 (3.5)	187.1 (4.1)

(*continued*)

Table 4. (*continued*)

Variable	Commune				
	Las Condes	Ñuñoa	Puente Alto	Rancagua	Santiago
Loss of control	124.0 (4.2)	111.7 (3.8)	174.8(4.2)	70.8 (4.0)	194.6 (4.2)
Driving under influence alcohol	105.3 (3.7)	103.9 (3.6)	111.3 (3.7)	95.7 (3.5)	149.3 (3.5)
Other causes	59.9 (3.4)	122.3 (3.3)	93.4 (3.2)	67.2 (3.3)	62.8 (2.9)
Type of zone					
Urban	–	–	–	57.0 (2.6)	–
Weather conditions					
Sunny	98.1 (4.1)	71.9 (4.0)	161.8 (3.9)	94.7 (3.9)	133.5 (3.9)
Drizzly	122.5 (4.5)	136.0 (4.7)	171.5 (4.5)	129.0 (4.2)	235.8 (4.5)
Rainy	–	–	–	–	62.3 (2.3)

5 Discussion

The vast majority of the crash-related variables have their highest value in the year 2015 (See Table 1). For example, the age group of young adults (particularly, male drivers) presented a dramatic increase of 360.6% in crash involvement as the number of crashes increased. The share of collisions almost tripled between 2014 and 2015, resulting in double the number of deaths and four times the number of seriously injured victims. These results suggest the urgency of further research using the Chilean crash dataset of recent years, in order to provide prioritise interventions of safety measures in those communes with high motorcycle crash risk.

The global spatial autocorrelation results reveal that certain crash-related variables tend to cluster although these present low values. Approximately 2% of the victims are killed as a results of motorcycle crashes, but this variable presents the highest global Moran's I value of 0.073 when compared to the other types of injuries. Analogously, 61.2% of the crashes occur along straight road segments. However, crashes at signalised intersections resulted in the largest positive global spatial clustering among all relative locations. Additionally, crashes that occur during drizzly days in the spring are more incline to globally cluster than other weather conditions and seasons, respectively.

Both global and local spatial autocorrelation analyses obtained similar results for some variables. For example, over 250 out of 343 communes were identified as HH clusters of fatalities with the strongest clustering intensity among other injury types. In addition, motorcycle crashes have a tendency to cluster locally particularly in the morning and weekdays during drizzly days.

Overall, a large number of HH clusters of collisions due to the loss of control are present on sunny days in the Metropolitan Region and regions of Valparaiso, O´Higgins, and Maule. Regarding the personal characteristics of the victims, more HH crash clusters are obtained that involve adults between 34 and 64 years of age, but crashes that involve young adults present a higher clustering intensity. More male drivers participate in motorcycle crashes than female drivers (78.5% vs 21.5%) perhaps because approximately 94% of motorcycle riders are males [5].

A large number of motorcycle crashes tend to cluster spatially along straight and curved road segments. Drivers have a tendency to increase their travel speeds as straight road sections are encountered, which may increase the likelihood of causing crashes with serious outcomes. Motorcyclists are more prone to crashes at curves, which may generate a significant impact on crash severity or fatality, as shown in [13]. The highest intensity of local crash clusters appear at signalised intersections, possibly due to the imprudence of the driver and pedestrians. Motorcyclists are particularly vulnerable at signalised intersections since they are over exposed as they gather near the stop line [32].

With respect to the zone type, crashes that occurred in urban zones are globally and locally clustered. According to the ANIM database [5], 90% of the motorcycles are employed in urban areas for commuting trips to work. Thus, a low number of crashes (15%) occur in rural areas. However, although no positive spatial pattern of rural crashes are observed from a global perspective, a considerable increase in the number of HH spatial crash clusters that arose in rural areas are detected in the last couple of years. This increase should be further investigated using crash data from more recent years to identify any additional trend.

The analysis results indicate that over 40% of the motorcycle crashes occurred in the Metropolitan Region during the studied period. The large number of HH clusters of crashes in this area is due to the fact that over 50% of Chile´s population resides in the Metropolitan Region and the surrounding areas, and approximately 55.5% of the total number of motorcycles nationwide are registered in these regions, which are more prone to be exposed to traffic crashes.

Amid the top five communes with most number of HH clusters, the commune of Santiago presents the strongest intensity of such clusters for most of the analysed variables. This result may be attributed to that this commune has the largest number of registered motorcycles in Chile with a total of 5.571 motorcycles in 2015, and an increase of 23.6% in the number of registered motorcycles between 2011 and 2015. Additionally, Santiago is a commune that has a daily floating population of approximately 2 million people due to its strong political, economic, and commercial activities in an area of only 23.2 km^2, and a residential population of 404,495 inhabitants [33]. Authorities and CONASET should prioritize the promotion and education of the community about road safety in this commune.

6 Conclusions

This study employed spatial statistics to identify global and local spatial autocorrelation of motorcycle crashes in Chile at the commune level. Recurrent statistically significant crash clusters were also obtained during the 2011–2015 period. Eight groups of motorcycle crash variables were analysed in the autocorrelation analysis. Global autocorrelation results indicate that variables associated with collisions occurring at signalised intersections on drizzly days during the spring, and resulting in fatality outcomes are spatially autocorrelated for the whole study period.

The local spatial autocorrelation results suggest the presence and persistence of HH spatial clusters of crash-related variables in the communes located in the Region of Valparaiso, Metropolitan Region, Region of O´Higgins, and Region of Maule. The commune of Santiago located in the Metropolitan Region presents the highest clustering intensity of motorcycle crashes. Local authorities should prioritize this commune to implement specific interventions that may help improve traffic safety.

References

1. World Health Organization, WHO. Global status report on road safety (2015). https://www.who.int/violence_injury_prevention/road_safety_status/2015/GSRRS2015_Summary_EN_final2.pdf. Accessed 30 Sep 2018
2. International Traffic Safety Data and Analysis Group, IRTAD, Road Safety Annual Report (2017). https://www.oecd-ilibrary.org/transport/road-safety-annual-report-2017_irtad-2017-en. Accessed 31 Jul 2018
3. Comisión Nacional de la Seguridad del Tránsito, CONASET, Siniestros de Tránsito de ocupantes de motocicletas y consecuencias (2016). https://www.conaset.cl/programa/observatorio-datos-estadistica/biblioteca-observatorio/informes-tematicos/#motocicletas. Accessed 13 Apr 2018
4. National Highway Traffic Safety Administration, NHTSA, Traffic Safety Facts (2012). https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812016. Accessed 10 Nov 2018
5. Asociación Nacional de Importadores de Motocicletas, ANIM. Actualidad del mercado en Mundo Motos 2016 (2015). http://www.anim.cl/anim-clp1820/. Accessed 22 Sep 2018
6. MT Motores, Espacial Mercado de motos en Chile. Diario La Tercera (2016). https://www.pressreader.com/chile/la-tercera-mt-motores/20160930/281505045711190. Accessed 02 Oct 2018
7. Smotos, Mercado chileno: Venta de motos 2018 sube un 16.7 y ¡vamos por la calle! (2018). https://smotos.cl/mercado-chileno-venta-de-motos-2018-sube-un-16-7-y-vamos-por-la-calle/. Accessed 08 Aug 2019
8. Instituto Nacional de Estadística, INE, Anuario Estadísticas Vitales (2018). http://www.ine.cl/estadisticas/demograficas-y-vitales. Accessed 31 Jul 2019
9. Jalayer, M., Zhou, H.: A multiple correspondence analysis of at-fault motorcycle-involved crashes in Alabama. J. Adv. Transp. **50**, 2089–2099 (2016)
10. Flask, T., Schneider, W., Lord, D.: A segment level analysis of multi-vehicle motorcycle crashes in Ohio using Bayesian multi-level mixed effects models. Saf. Sci. **66**, 47–53 (2014)
11. Das, S., Dutta, A., Dixon, K., Minjares-Kyle, L., Gillette, G.: Using deep learning in severity analysis of at-fault motorcycle rider crashes. J. Transp. Res. Board **2672**(34), 122–134 (2018)
12. Lee, J., Yasmin, S., Eluru, N., Abdel-Aty, M., Cai, Q.: Analysis of crash proportion by vehicle type at traffic analysis zone level: A mixed fractional split multinomial logit modeling approach with spatial effect. Accid. Anal. Prev. **111**, 12–22 (2018)
13. Chung, Y., Song, T.-J.: Safety analysis of motorcycle crashes in Seoul metropolitan area, South Korea: an application of nonlinear optimal scaling methods. Int. J. Environ. Res. Public Health **15**(12), 2702 (2018)
14. Ding, C., Rizzi, M., Strandroth, J., Sander, U., Lubbe, N.: Motorcyclist injury risk as a function of real-life crash speed and other contributing factors. Accid. Anal. Prev. **123**, 374–386 (2019)
15. Alnawmasi, N., Mannering, F.: A statistical assessment of temporal instability in the factors determining motorcyclist injury severities. Anal. Methods Accid. Res. **22**, 100090 (2019)
16. Zhou, M., Chin, H.C.: Factors affecting the injury severity of out-of-control single-vehicle crashes in Singapore. Accid. Anal. Prev. **124**, 104–112 (2019)

17. Dezman, Z., et al.: Hotspots and causes of motor vehicle crashes in Baltimore, Maryland: a geospatial analysis of five years of police crash and census data. Injury **47**(11), 2450–2458 (2016)
18. Soltani, A., Askari, S.: Exploring spatial autocorrelation of traffic crashes based on severity. Injury **48**(3), 637–647 (2017)
19. Pour, A., Moridpour, S., Tay, R., Rajabifard, A.: Influence of pedestrian age and gender on spatial and temporal distribution of pedestrian crashes. Traffic Inj. Prev. **19**(1), 81–87 (2018)
20. Blazquez, C., Picarte, B., Calderon, J.F., Losada, F.: Spatial autocorrelation analysis of cargo trucks on highway crashes in Chile. Accid. Anal. Prev. **120**, 195–210 (2018)
21. Aghajani, M., Dezfoulian, R., Arjroody, A., Rezaei, M.: Applying GIS to identify the spatial and temporal patterns of road accidents using spatial statistics (case study: Ilam Province, Iran). Transp. Res. Procedia **25**, 2126–2138 (2017)
22. Saadat, S., Rahmani, K., Moradi, A., Zaini, S., Darabi, F.: Spatial analysis of driving accidents leading to deaths related to motorcyclists in Tehran. Chin. J. Traumatol. **22**, 148–154 (2019)
23. Ghandour, A., Hammoud, H., Telesca, L.: Transportation hazard spatial analysis using crowd-sourced social network data. Phys. A: Stat. Mech. Appl. **520**, 309–316 (2019)
24. Blazquez, C., Fuentes, M.J.: Global and local spatial autocorrelation of motorcycle crashes in Chile. In: Proceedings of the 5th International Conference on Vehicle Technology and Intelligent Transport Systems, pp. 159–170. SciTePress, Heraklion, Crete (2019)
25. Mitra, S.: Spatial autocorrelation and bayesian spatial statistical method for analysing intersections prone to injury crashes. J. Transp. Res. Board **2136**, 92–100 (2009)
26. Anselin, L.: Local indicators of spatial association-LISA. Geog. Anal. **27**, 93–115 (1995)
27. Meng, Q.: The spatiotemporal characteristics of environmental hazards caused by offshore oil and gas operations in the Gulf of Mexico. Sci. Total Environ. **565**, 663–671 (2016)
28. Manepalli, U., Bham, G., Kandada, S.: Evaluation of hot spots identification using Kernel Density Estimation (K) and Getis-Ord (Gi*) on I-630. In: Proceedings 3rd International Conference on Road Safety and Simulation 17, Transportation Research Board, Indianapolis, Indiana (2011)
29. Blazquez, C., Puelma, I., Khan, G.: Spatial analysis of bicycle crashes in Chile. In: Proceedings 18th IEEE International Conference on Intelligent Transportation Systems. IEEE Intelligent Transportation Systems Society, Las Palmas de Gran Canaria, Spain, pp. 2745–2750 (2015)
30. Blazquez, C., Celis, M.: A spatial and temporal analysis of child pedestrian crashes in Santiago, Chile. Accid. Anal. Prev. **50**, 304–311 (2013)
31. Blazquez, C., Lee, J.S., Zegras, C.: Children at risk: an initial comparison of child pedestrian traffic collisions in Santiago, Chile and Seoul, South Korea. Traffic Inj. Prev. **17**(3), 304–312 (2016)
32. Haque, M., Chin, H., Huang, H.: Applying Bayesian hierarchical models to examine motorcycle crashes at signalized intersections. Accid. Anal. Prev. **42**(1), 203–212 (2010)
33. Instituto Nacional de Estadística, INE. Censo (2017). https://www.censo2017.cl/. Accessed 18 Apr 2018