Global and Local Spatial Autocorrelation of Motorcycle Crashes in Chile

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Abstract: In Chile, the usage of motorcycles as a mode of transport is growing in unison with the number of crashes that have arisen in recent years. Spatial statistical methods were used in this study to determine whether motorcycle crashes showed spatial clustering over time from a global and local perspective. The global spatial autocorrelation results indicate that high intensity clusters of collisions at intersections with traffic signals and curved road sections resulting in fatalities persisted during the five-year study period. Locally, recurrent high spatial patterns of motorcycle collisions arose along straight road sections and on sunny days due to the loss of control of the vehicle, or the imprudence of the driver or pedestrian. Communes located in the centre zone of Chile, particularly in the city of Santiago and the surrounding areas, presented a large number of highly clustered crash attributes. The findings of this study may help authorities to target efforts towards policy measures to improve motorcycle safety in Chile.

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 (WHO, 2015). 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 per 100,000 inhabitants (IRTAD, 2017).

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 (CONASET, 2016). Being vulnerable road users, motorcyclists are 27 times more frequently killed in crashes per travelled vehicle mile than motor vehicle passengers (NHTSA, 2012).

The motorcycle market increases every year in many countries worldwide, and it is expected to continue increasing in Chile as well (ANIM, 2015; MT Motores, 2016). On average, the total number of motorcycles has increased in 65% between 2011 and 2015. In 2016, 175,019 motorcycles were registered throughout the country with approximately 9.6 motorcycles per 1,000 inhabitants (INE, 2016). Motorcycles are deemed as an economical and convenient transport mode with respect to congestion, fuel consumption, 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 (2016) 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 (2014) 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

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deep learning framework was developed to predict motorcycle crash severities, which were related to rider ejection, two-way roads, curved roads, and weekends (Das et al, 2018). Lee et al (2018) 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 impacts the proportion of motorcycle crashes. Lastly, Chung and Song (2018) 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.

Other researchers have studied the spatial problem using statistical methods such as spatial autocorrelation to identify spatial clusters of crashes. For example, Dezman et al (2016) 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 (Soltani and Askari, 2017). In another study, Pour et al (2018) applied spatial autocorrelation to detect any dependency between time and location of vehicle-pedestrian crashes in Melbourne. Blazquez et al (2018) performed a spatial autocorrelation of cargo trucks on Chilean highways at the global and local level. Yet another study was performed by Aghajani et al (2017) to identify spatial and temporal patterns of traffic crashes, and to determine hotspots of fatal and injury outcomes in Iran.

The authors are not aware of any study performed in Chile that employs spatial autocorrelation methods to analyse recurrent spatial clustering of motorcycle crashes through time. The objective of this study is to employ spatial statistical indicators to distinguish significant patterns of motorcycle crashes at the commune level in Chile, and to assess whether a spatial dependence of such patterns exists with respect to the main crash attributes (e.g., type of crash, relative location, contributing factors, and weather) that 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 (Mitra, 2009). First, the global Moran´s I index was employed to test the general spatial autocorrelation of the main crash attributes 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 these crash attributes. The following subsections describe each statistic.

2.1 Global Spatial Autocorrelation

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 Equation 1.

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_o \sum_{i=1}^{n}(x_i - \bar{x})^2} \quad \forall\ i,j \qquad (1)$$

where x_i is the variable value at a particular location i, $\bar{x}$ 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.

2.2 Local Spatial Autocorrelation

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 (1995). 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 (Meng, 2016). The local Moran´s I index is expressed by Equation 2.

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

where x_i is the variable value at location i, $\bar{x}$ 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 (Manepalli et al, 2011). This study will focus on identifying locations of clusters of motorcycle crashes with particularly high crash attribute values.

3 DATA DESCRIPTION

The 2011-2015 crash database employed in this study was provided by the National Commission of Traffic Safety (CONASET, acronym in Spanish). A total of 18,826 motorcycle crashes were successfully aggregated into 343 communes, as shown in Figure 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. Note that over 40% of the motorcycle crashes occurred in the Metropolitan Region during the studied period, where most of the Chilean population resides in the capital city, Santiago. Figure 2 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.

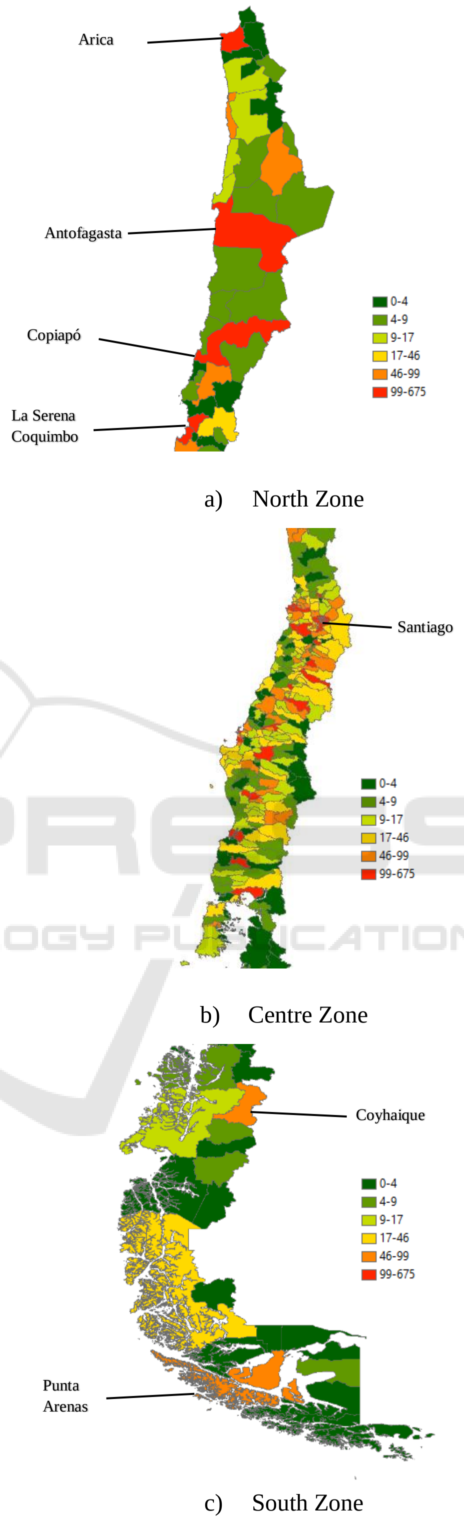


Figure 1: Motorcycle crashes for the 2011-2015 period aggregated at the commune level for the a) North Zone, b) Centre Zone, and c) South Zone.

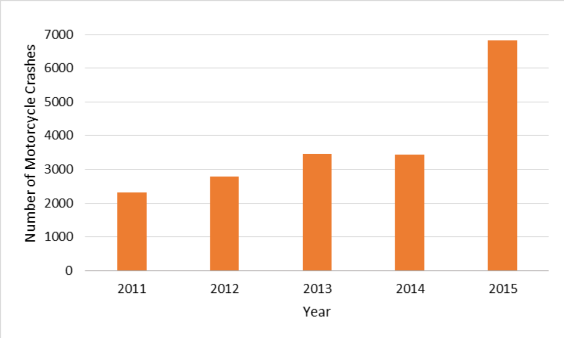


Figure 2: Number of motorcycle crashes for the 2011-2015 period.

The main attributes of the motorcycle crashes were classified into six groups (type of injury, type of crash, relative location, contributing factors, type of zone, and weather conditions), as shown in Table 1. This table indicates that 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 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 (80%), and young adults between 19 and 33 years of age (42.6%). Approximately 22% (4,089) motorcycle crashes occurred between 6 pm and 9 pm. Friday is the day of the week with the largest occurrence of motorcycle crashes, which accounted for 16.3% of all studied crashes. On average, almost 60% of the crashes occurred between January and June with the highest number of motorcycle crashes arising in March (2,069).

4 RESULTS

An incremental spatial autocorrelation analysis was first performed to obtain a distance threshold or bandwidth value for each analysed crash attribute 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. Both global and local spatial autocorrelation analyses employed these distance thresholds, as shown in the following subsections. Additionally, notice that in both spatial autocorrelation, 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 attributes.

Table 1: Number of motorcycle crashes for each analysed variable per year.

Variable	**2011**	**2012**	**2013**	**2014**	**2015**
Type of injury					
Fatalities	29	78	72	75	151
Seriously Injured	146	285	349	334	1336
Slightly Injured	2127	2647	2588	6569	5339
Type of crash					
Collision	1150	1393	1811	1826	4508
Impact	579	649	854	899	779
Pedestrian crash	318	410	431	407	370
Rollover	156	170	217	175	950
Relative location					
Straight section	1250	1513	1850	1783	3660
Curved section	138	162	242	265	461
Intersection with signage	654	822	967	1019	1877
Intersection without signage	111	123	147	148	324
Contributing factors					
Imprudence of driver	866	1079	1756	1433	2428
Imprudence of pedestrian	242	296	312	357	467
Loss of control	225	282	272	309	1900
Driving under influence alcohol	197	213	237	244	748
Other causes	420	533	639	732	944
Type of zone					
Urban	1962	2341	2903	2928	5868
Rural	353	445	560	517	949
Weather conditions					
Sunny	2154	2323	2907	2799	5939
Drizzly	8	41	28	38	34
Foggy	5	15	23	19	16
Rainy	55	133	150	180	332
Cloudy	93	272	351	408	495

4.1 Global Moran´s I

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 attributes 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 attributes. For example, motorcycle crashes that occurred at intersections with traffic signals presents a stronger positive spatial pattern with an average Moran´s I value of 0.088 during the five years of the study than any other analysed attribute in the table.

With respect to the type of injury, victims that were seriously injured have the lowest clustering intensity with an average Moran´s I value of 0.021 compared to the remaining attributes. 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.

Regarding the type of crash, collisions between moving vehicles present a global positive autocorrelation of 0.053 and are clustered during the five years of the 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 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 were 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 contribution cause related to driving under the influence of alcohol shows the largest clustering intensity (0.064) among the other contributing factors, as in the results of Blazquez et al (2015). 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, 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.

Table 2: Results of recurrent global spatial autocorrelation of motorcycle crashes.

Variable	**Average Moran´s I**	**Standard Deviation Moran´s I**	**Number of Clustering Years**
Type of injury			
Fatalities	0.073	0.029	5
Seriously injured	0.021	0.019	3
Slightly injured	0.050	0.041	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

4.2 Local Moran´s I

As aforementioned, the local Moran´s I statistic identifies high and low value clusters, and spatial outliers. This subsection presents the local spatial autocorrelation results regarding the location of motorcycle crash clusters of high attribute values surrounded by high attribute values (High-High local spatial pattern, HH).

The number of HH spatial clusters for each analysed motorcycle crash attribute 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 segments with straight sections, followed by roads with curved sections and fatality outcomes. Overall, HH clusters appeared in four or five years of the studied period. However, motorcycle crashes that resulted in rollovers on rainy or cloudy days along rural areas present a low existence or lack of clustering of HH values over time, concurring with the global spatial autocorrelation results.

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. Also 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 number 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.

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.

Figures 3-8 present spatial clusters at the commune level for each analysed motorcycle crash attribute 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 regions of the country (Region of Valparaiso, Metropolitan Region, and regions of 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.

Figure 3 shows the HH clusters of fatality outcomes that persisted for the whole studied period in the communes situated in the Metropolitan Region, the Region of Valparaiso, and the Region of O´Higgins. Whereas HH clusters of seriously or slightly injured victims are recurrent for less number of years and only in some communes of these regions.

Similarly to the results presented in Table 3, Figure 4 shows that collisions represent the largest number of HH spatial clusters among other types of crashes. These clusters are mostly located in communes of the Region of Valparaiso and Metropolitan Region. Notice that rollover-related crash HH clusters are not shown since such clusters in all communes were positive and significant for less than three years.

Figure 5 presents the recurrent HH clusters of motorcycle crashes with respect to their relative

Table 3: Number of HH spatial clusters of motorcycle crash attributes that arose during the 2011-2015 period.

Variable	**Year**					**∑HH**
	2011	**2012**	**2013**	**2014**	**2015**	
Type of injury						
Fatalities	54 (46.4)	46 (44.9)	52 (48.4)	51 (58.4)	50 (61.5)	253
Seriously Injured	46 (31.5)	0	23 (33.0)	31 (38.4)	49 (44.7)	149
Slightly Injured	55 (44.7)	39 (20.8)	20 (12.8)	48 (45.7)	61 (56.4)	223
Type of crash						
Collision	57 (41.6)	45 (31.3)	53 (33.6)	24 (59.8)	45 (42.5)	224
Impact	61 (32.6)	30 (70.3)	31 (80.7)	38 (52.2)	4 (72.3)	164
Pedestrian crash	62 (28.4)	12 (4.4)	7 (11.6)	54 (45.4)	49 (45.3)	184
Rollover	10 (23.4)	0	7 (16.3)	14 (5.9)	25 (39.6)	56
Relative location						
Straight section	61 (34.7)	50 (38.2)	58 (37.1)	68 (35.9)	50 (53.7)	287
Curved section	35 (41.2)	50 (39.4)	60 (37.4)	51 (53.2)	57 (55.0)	253
Intersection with signage	30 (83.3)	34 (63.8)	39 (52.2)	39 (75.1)	34 (84.1)	176
Intersection without signage	34 (42.5)	35 (37.5)	39 (54.8)	40 (52.1)	35 (77.6)	183
Contributing factors						
Imprudence of driver	51 (44.5)	44 (17.1)	43 (37.5)	55 (58.9)	47 (20.2)	240
Imprudence of pedestrian	30 (24.3)	48 (39.7)	53 (43.1)	56 (53.5)	53 (58.3)	240
Loss of control	27 (13.3)	50 (61.2)	56 (36.9)	53 (49.1)	59 (53.7)	245
Driving under influence alcohol	25 (12.1)	55 (31.3)	45 (15.1)	54 (56.2)	53 (54.6)	232
Other causes	48 (62.9)	38 (38.4)	42 (21.3)	49 (63.9)	29 (44.3)	206
Type of zone						
Urban	56 (46.9)	4 (13.3)	24 (11.3)	51 (5.9)	60 (20.8)	195
Rural	0	8 (9.8)	5 (5.1)	49 (39.1)	61 (20.4)	123
Weather conditions						
Sunny	50 (49.6)	41 (42.5)	47 (36.2)	48 (52.4)	54 (53.1)	240
Drizzly	0	57 (48.1)	62 (50.7)	52 (59.5)	55 (57.2)	226
Foggy	0	30 (26.4)	17 (41.9)	48 (44.2)	55 (35.2)	150
Rainy	19 (43.2)	0	0	21 (52.5)	16 (61.4)	56
Cloudy	40 (72.8)	0	0	0	36 (59.9)	76

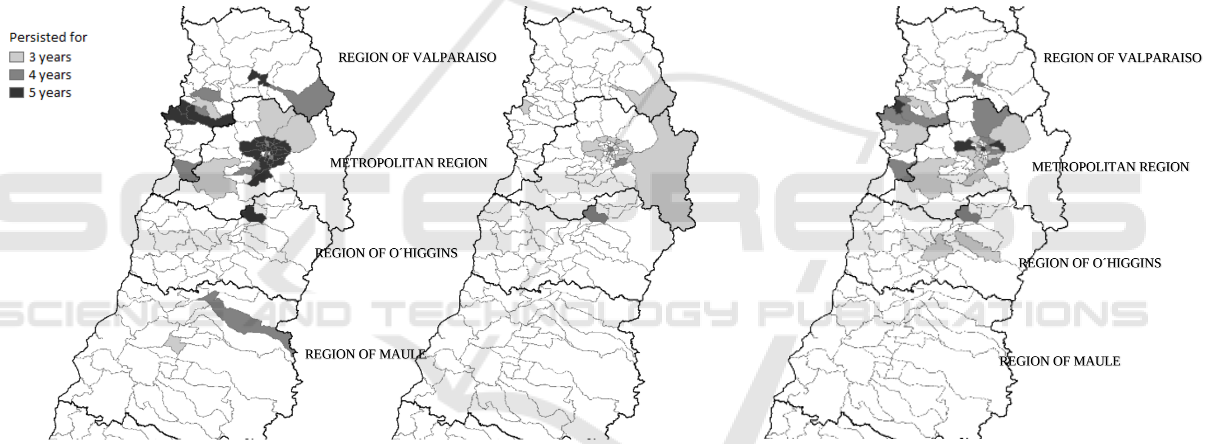
Note: Average local Moran´s I values are shown in parenthesis.

location at the commune level. 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, and for all types of relative locations. Conversely, recurrent HH clusters appeared in many communes in the centre of the Metropolitan Region (coinciding with the city of Santiago) along straight and curved road sections.

Communes in the four regions shown in Figure 6 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 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 a few communes in the city of Santiago and Region of Valparaiso. HH clusters appear in a lesser degree a a result of other causes.

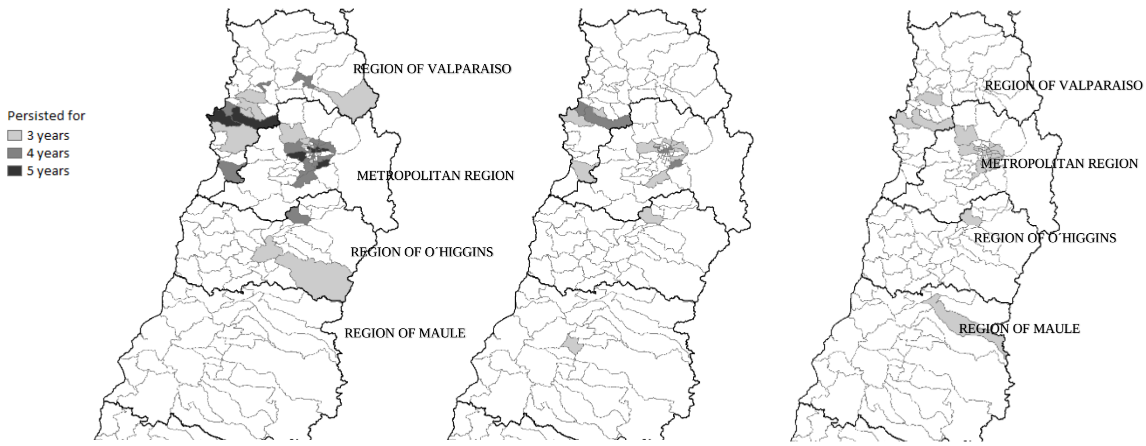
Recurrent spatial clustering of crashes that occurred in urban areas are recurrent for 3 or 4 years during the studied period in communes of the regions of O´Higgins and Maule, as shown in Figure 7. No HH clustering of crashes in rural zones was perceived in any commune for three or more years.

Regarding the weather conditions, Figure 8 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, however for three and four years of the studied period.



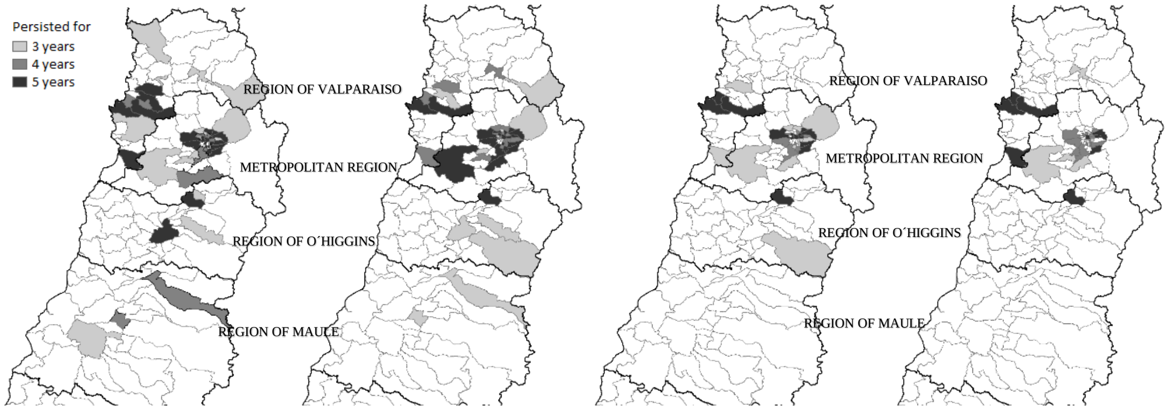
a) Fatalities b) Seriously injured c) Slightly injured

Figure 3: HH spatial clusters for each type of injury.



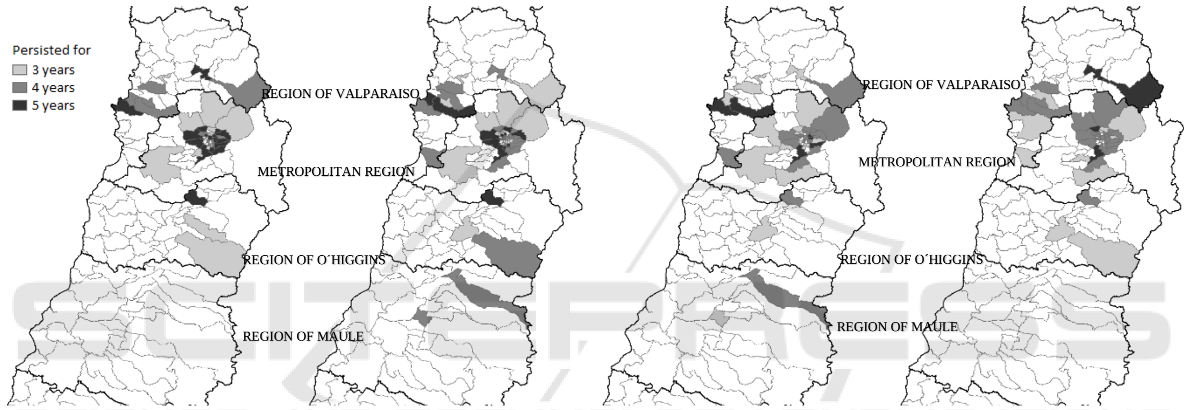
a) Collision b) Impact c) Pedestrian crash

Figure 4: HH spatial clusters for each type of crash.



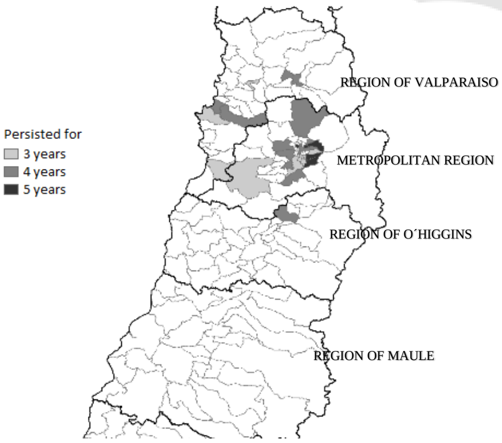
a) Straight section b) Curved section c) With signage d) Without signage

Figure 5: HH spatial clusters for the relative location of motorcycle crashes.



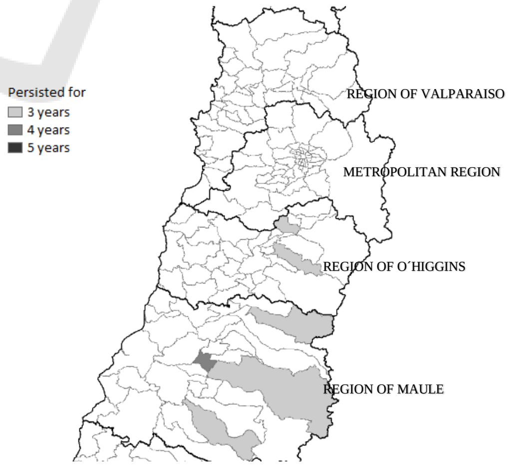
a) Driver´s imprudence b) Pedestrian´s imprudence c) Loss of control d) Alcohol of driver

Figure 6: HH spatial clusters for the contributing factor attribute.



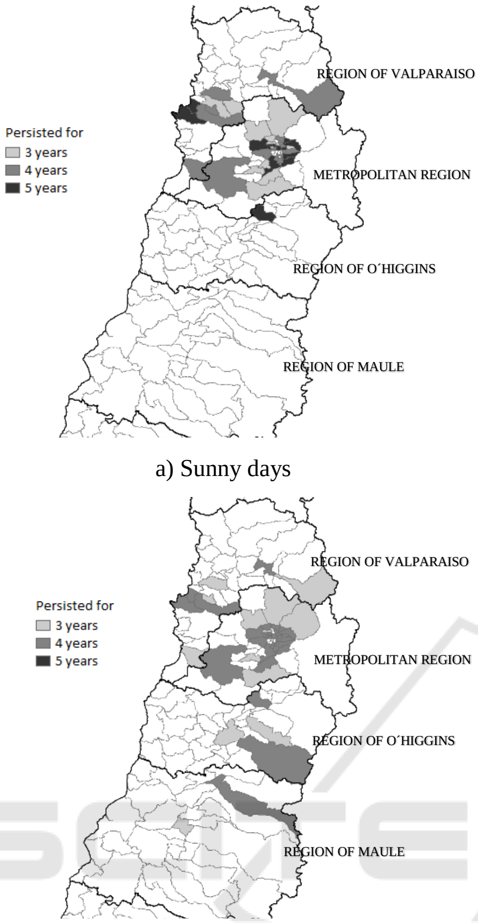
e) Other causes

Figure 6 (continued): HH spatial clusters for the contributing factor attribute.



a) Urban zone

Figure 7: HH spatial clusters of crashes in urban zones.



b) Drizzly days

Figure 8: HH spatial clusters for weather conditions.

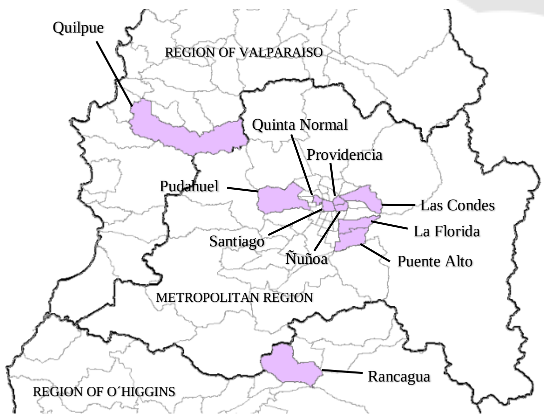


Figure 9: Communes with the largest number of HH attribute clusters during the 2011-2015 period.

The top ten Chilean communes with the largest number of HH for the 23 analysed crash attributes in the five-year period are shown in Figure 9. This figure shows that 8 out of these 10 communes with the most number of HH crash attributes are located in the Metropolitan Region. The communes in the regions of O´Higgins and Valparaiso (Rancagua and Quilpue, respectively) are located in the vicinity of the Metropolitan Region. 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 65.5% of the total number of motorcycles nationwide are registered in these three regions, which are more prone to be exposed to traffic crashes.

Table 4 presents the average value of the local Moran´s I index and average Z score in parenthesis for recurrent crash attributes for the ten communes depicted in Figure 9. Those communes with no values indicate that that particular variable was significant for less than three years. Therefore, HH crash clusters are not present for those vehicles that rolled over in rural areas on cloudy or foggy days for any of the ten analysed communes. HH clusters only exist for the attributes associated to urban areas and rainy days in Rancagua and Santiago, respectively.

Overall, Santiago has the highest intensity of HH clusters in 13 of the crash attributes when compared to the rest of the communes, similarly to the findings in Blazquez and Celis (2013) and Blazquez et al (2016). 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 (INE, 2017). Authorities and CONASET should prioritize the promotion and education of the community about road safety in this commune.

5 CONCLUSIONS

In this study, the global Moran´s I index was employed to detect overall spatial autocorrelation of motorcycle crashes in Chile at the commune level. In addition, a local spatial autocorrelation was performed with Anselin´s local Moran´s I to identify statistically significant crashes that are recurrent during the 2011-2015 period. Six groups of motorcycle crash attributes were examined in the autocorrelation analysis. Certain crash attributes tend to be located closer together than randomly over time.

Table 4: Number of HH spatial clusters of motorcycle crash attributes per commune that persisted for three or more years during the 2011-2015 period.

Variable	Commune									
	La Florida	Las Condes	Ñuñoa	Providencia	Pudahuel	Puente Alto	Quilpue	Quinta Normal	Rancagua	Santiago
Type of injury										
Fatalities	96.9 (4.3)	107.2 (4.2)	118.1 (4.2)	117.2 (4.4)	62.4 (4.2)	162.5 (4.2)	84.3 (4.1)	56.8 (4.3)	120.0 (4.0)	207.1 (4.2)
Seriously Injured	83.2 (2.8)	42.3 (2.7)	41.3 (2.8)	-	102.8 (2.6)	80.4 (2.5)	-	-	50.2 (2.7)	48.7 (2.7)
Slightly Injured	62.9 (3.7)	71.5 (3.4)	138.3 (3.8)	85.8 (3.8)	41.4 (3.4)	147.5 (3.8)	42.9 (2.9)	36.0 (3.9)	85.8 (3.7)	113.7 (3.3)
Type of crash										
Collision	66.6 (3.5)	58.6 (3.6)	96.2 (3.7)	81.7 (3.6)	30.9 (3.5)	124.7 (3.6)	79.3 (3.7)	38.4 (3.8)	84.7 (3.0)	141.1 (3.5)
Impact	35.5 (3.4)	82.1 (3.4)	72.9 (2.7)	86.7 (3.6)	26.5 (3.3)	71.1 (3.7)	105.7 (3.6)	-	73.0 (3.2)	180.4 (3.6)
Pedestrian crash	51.9 (3.6)	105.8 (3.5)	40.3 (3.6)	108.7 (3.5)	58.8 (3.6)	117.4 (3.5)	41.7 (3.4)	27.2 (3.7)	62.8 (3.5)	149.6 (3.5)
Relative location										
Straight section	88.0 (3.7)	74.4 (3.7)	108.6 (3.8)	91.9 (3.7)	49.4 (3.6)	163.2 (3.7)	73.7 (3.7)	48.1 (3.6)	95.5 (3.6)	134.4 (3.6)
Curved section	88.0 (3.8)	86.1 (4.0)	87.9 (3.9)	114.2 (4.1)	50.2 (3.8)	129.1 (3.8)	91.1 (3.9)	52.7 (4.0)	84.1 (3.5)	176.0 (3.8)
Intersection with signage	106.2 (12.4)	132.5 (15.6)	122.3 (14.3)	128.5 (15.0)	80.8 (9.4)	169.9 (19.8)	108.3 (12.9)	41.0 (4.8)	136.7 (16.0)	216.5 (25.2)
Intersection without signage	88.5 (10.3)	53.3 (6.3)	151.2 (17.6)	83.2 (9.7)	84.2 (9.8)	88.8 (10.4)	46.7 (5.6)	84.6 (9.9)	84.6 (9.9)	117.3 (13.6)
Contributing factors										
Imprudence of driver	61.4 (3.4)	64.2 (3.6)	58.2 (3.3)	82.1 (3.4)	32.5 (3.4)	68.5 (3.4)	71.8 (3.7)	38.5 (3.4)	97.5 (3.2)	153.7 (3.1)
Imprudence of pedestrian	96.0 (4.2)	98.0 (3.8)	104.1 (4.0)	103.1 (4.1)	50.7 (3.7)	142.1 (4.1)	75.0 (3.7)	43.3 (3.9)	86.3 (3.5)	187.1 (4.1)
Loss of control	58.9 (3.9)	124.0 (4.2)	111.7 (3.8)	137.5 (3.7)	69.1 (4.2)	174.8 (4.2)	38.1 (3.8)	42.4 (4.4)	70.8 (4.0)	194.6 (4.2)
Driving under influence alcohol	75.9 (3.7)	105.3 (3.7)	103.9 (3.6)	98.5 (3.6)	44.8 (3.5)	111.3 (3.7)	69.4 (3.7)	58.3 (3.6)	95.7 (3.5)	149.3 (3.5)
Other causes	74.3 (3.2)	59.9 (3.4)	122.3 (3.3)	76.5 (3.4)	92.4 (3.4)	93.4 (3.2)	109.4 (3.4)	32.0 (3.4)	67.2 (3.3)	62.8 (2.9)
Type of zone										
Urban	-	-	-	-	-	-	-	-	57.0 (2.6)	-
Weather conditions										
Sunny	96.2 (4.0)	98.1 (4.1)	71.9 (4.0)	84.6 (4.4)	78.7 (3.9)	161.8 (3.9)	72.9 (4.5)	52.5 (4.0)	94.7 (3.9)	133.5 (3.9)
Drizzly	113.3 (4.7)	122.5 (4.5)	136.0 (4.7)	133.4 (4.6)	74.6 (4.6)	171.5 (4.5)	104.0 (4.5)	65.5 (4.7)	129.0 (4.2)	235.8 (4.5)
Rainy	-	-	-	-	-	-	-	-	-	62.3 (2.3)

From a global perspective, the results indicate that crash attributes associated with intersections with traffic signals as a relative location, collisions, and fatality outcomes are spatially autocorrelated for the whole study period with the largest intensities among the remaining analysed attributes. In addition, driving under the influence of alcohol on drizzly days strongly clustered during four years of the study period.

The findings from the local spatial autocorrelation technique revealed similarities and differences among the communes. The communes with the largest number of HH clusters are portrayed, indicating the persistence and intensity of this clustering for each group of crash attributes. In particular, communes located in city of Santiago are smaller in size and closer together, and present high number of spatial clustering of motorcycle crashes. In addition, the presence and persistence of HH spatial clusters of crash attributes in the communes located in the Region of Valparaiso, Metropolitan Region, Region of O´Higgins, and Region of Maule are particularly distinguished.

Overall, a large number of HH clusters of collisions due to the loss of control are present on sunny days in the aforementioned regions. Most motorcycle crashes also tended to spatially cluster along straight and curved road segments. Drivers tend 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 Chung and Song (2018).

There is a considerable increase in the use of motorcycles nationwide in the last few years, particularly in the centre part of Chile. However, the number of motorcycle crashes has also presented a dramatic increase. Future research should prioritize those communes with high clustering of motorcycle crashes, in order to implement specific interventions that help improve traffic safety.

The Road Coexistence Law became effective in November of 2018 with the aim of equating road spaces and imposing an equality among all transport modes (motorised vehicles, bicycles, pedestrians, etc.). This law enforces road users to become aware of their rights and obligations when travelling, and thus, increasing road safety. Further investigation is required to analyse the impact of this law in the traffic crashes that involve motorcycles.

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