Spatial and Temporal Analysis of Fatal and Injury Severity of Road Traffic Accidents in Santiago, Chile

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Abstract*– Chile´s capital, Santiago, presented over 91,000 traffic accidents between 2015 and 2018, yielding a total of 47,470 fatalities and severe injury outcomes. This study performed a spatial and temporal analysis of fatal and serious injury accidents to identify statistically significant spatial clusters using spatial statistical approaches at the global and local level. The results revealed that globally both fatality hotspots and spatial clusters of severe injury outcomes with high values tend to cluster over the studied period. Locally, the commune of Puente Alto presents the largest number of clusters with high injury severity index values in Santiago, while the commune of Quinta Normal has the largest clustering intensity of this index. Additionally, the communes of Maipú and Estación Central have the largest number of fatality hotspots among all communes in Santiago, and the highest average intensity of these hotspots are located in Puente Alto. Finally, a comparison between the spatial statistical approaches indicate that 85 locations exist in the city of Santiago, in which both spatial clusters of injury severity with high values and fatality hotspots coincide. The results of this study will aid local authorities, transportation professionals, and planners to improve traffic safety in Santiago.

Keywords-- traffic accidents, hotspots, fatality, injury severity, spatial autocorrelation, Chile

I. INTRODUCTION

Road traffic accidents and their social and economic consequences are a major burden for authorities worldwide [1]. Traffic accidents are also a major public health problem in Chile. The number of road traffic accidents has steadily increased from 58,000 accidents in 2010 to nearly 90,000 accidents in 2018. The number of annual deaths and injuries has not decreased from 1,500 and 60,000 victims, respectively, despite the enacting laws to prevent driving under the influence of alcohol, mandatory use of child car seats, maximum vehicle speed reduction to 50 km/hr in urban zones, among others [2]. In 2018, Chile had the highest fatality risk due to traffic accidents with 3.6 road deaths per 10,000 motorized vehicles among OECD country members. In addition, the economic cost of traffic accidents in 2018 represented approximately 3% of the GDP per capita [3]. These statistics reveal the critical priority of authorities in addressing this public health problem in Chile.

The Metropolitan Region of Chile has the highest number of traffic accidents nationwide. In 2018, over 30,000 traffic accidents were reported in this region, representing 34.4% of all accidents that occurred in the country that year. As a result of these accidents, 370 persons were killed and 16,092 victims were injured [2]. Santiago, Chile´s capital, is situated in the Metropolitan Region, and approximately 41% of Chile´s population (5.6 million inhabitants) reside in this city [4]. The number of traffic accidents in Santiago accounts for approximately 84% of all traffic accidents that occurred in the Metropolitan Region.

The objective of this study is to perform a spatial and temporal analysis of fatal and serious injury outcomes due to the occurrence of traffic accidents in Santiago, Chile between 2015 and 2018. This study detects statistically significant spatial clusters of these victims using global and local spatial autocorrelation with spatial statistical approaches such as Moran´s I and Getis-Ord Gi* statistics.

Multiple studies have employed different spatial statistical approaches to analyze clusters of traffic accidents. Some studies have performed spatial autocorrelation analysis of traffic accidents using the Moran´s I statistic [5, 6], the Getis-Ord Gi* statistic [7, 8, 9], or both [10, 11, 12, 13]. For example, [5] utilized Moran´s I statistic to detect spatial clusters of mortality from road traffic accidents in Iran. In another study, [6] used global and local Moran´s I spatial statistics to identify and measure the strength of spatial clusters of bicycle accidents in Chile. A spatial autocorrelation analysis was performed by [7] using Getis-Ord Gi* to identify hotspots of pedestrian-vehicle accidents and determine a correlation between the severity of these accidents with bus stop locations. Reference [8] analyzed cargo trucks on highway accidents to identify spatial clustering (hotspots) of crash attributes over time using Getis-Ord Gi*. Recently, [9] performed a spatio-temporal analysis of traffic crashes that involved microbuses and taxi-buses to identify emerging and disappearing hotspots and coldspots using Getis-Ord Gi* spatial statistic. In another study by [10], the authors assessed the spatial clustering and hotspots of road accidents based on severity using both Moran´s I and Getis-Ord Gi* statistics. Similarly, [11] identified spatial and temporal patterns of road accidents in Iran using spatial statistical approaches (Moran´s I and Getis-Ord Gi*). Reference [12] used Moran’s Index and Getis-Ord Gi∗ statistics to measure the spatial autocorrelation of vehicle crashes that occurred in Missouri in the United States. A spatial autocorrelation analysis of traffic accidents was performed by [13] based on a road safety risk index in Tunisia using Moran´s I and Getis-Ord Gi* statistics. Recently, [14] performed a spatial autocorrelation with Moran´s I and Getis–Ord Gi* to identify hotspot segments with high risk of heavy vehicle crashes in Malaysia. In this study, we performed a global and local spatial autocorrelation to identify spatial patterns of fatal and injury severity of traffic accidents in Santiago, Chile over time.

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II. METHODOLOGY

A. Injury Severity Index (ISI)

In this study, we employed a modified version of the injury severity index (*ISI*) proposed by [7], which is computed using (1).

$$ISI = 3.0\ Y_1 + 1.8\ Y_2 + 1.3\ Y_3 \quad (1)$$

where Y_1 is the total number of fatal accidents, Y_2 represents the total number of serious injury accidents, and Y_3 is the total number of slight injury accidents. *ISI* assigns more weight to accidents with fatal casualties than those with less severe injury outcomes. This index should be considered since traffic accidents with severe injury outcomes are seldom randomly distributed [10].

B. Spatial Autocorrelation

Spatial autocorrelation assesses the spatial relationship between features at certain locations and adjacent locations. A positive (negative) spatial autocorrelation implies that neighboring locations have similar (dissimilar) values [15]. Therefore, spatial patterns of fatal and serious injury outcomes do not arise randomly, and on the contrary, these patterns present noticeable clustering or dispersion.

This section describes the spatial statistics (Global Moran´s I, Local Moran´s I, and Getis-Ord Gi*) that are used to compute the spatial autocorrelation at the global and local level.

1) Global Moran´s I

The global Moran´s I statistic provides a single value that quantifies the overall spatial patterns (clustering or dispersion) of a certain variable over a geographic area using (2) [16].

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

Where w_{ij} is the spatial weight between locations i and j, x_i is the variable value at location i, x_j is the variable value at location j, $\bar{x}$ is the mean of the variable, n is the number of observations, and S_o is the sum of the weights w_{ij}.

The values of the global Moran´s I statistic range between -1 (spatial dispersion) and 1 (spatial clustering). Random spatial patterns arise for a Moran´s I value close to zero. The statistical significance of the Moran´s I statistic is examined with the Z-score and p-values (confidence level). A positive (negative) Z-score indicates that the contiguous features have similar (dissimilar) values [15].

2) Local Moran´s I

The local Moran´s I statistic identifies local spatial clusters of similar high and low, and atypical values using (3).

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j\neq 1}^{n} w_{ij}(x_i - \bar{X}) \quad (3)$$

Where w_{ij} is the spatial weight between locations i and j, x_i is the variable value at location i, $\bar{x}$ is the mean value of the variable, n is the total number of observations, and S_i is the sum of the weights (w_{ij}). This statistic classifies spatial clusters in four types described in Table I. These clusters are also associated with Z-score and p-values, which determine the statistical significance of the results. Note that in this study we are interested in identifying HH clusters of *ISI*, as in [6].

TABLE I
DESCRIPTION OF EACH TYPE OF SPATIAL CLUSTER

Type of spatial cluster	**Description**
High-High (HH)	High value locations surrounded by other locations with high values
Low-Low (LL)	Low value locations surrounded by other locations with low values
High-Low (HL)	High value locations surrounded by other locations with low values
Low-High (LH)	Low value locations surrounded by other locations with high values

3) Getis-Ord Gi*

The Getis-Ord Gi* statistic identifies high and low spatial associations among features at the local level [17]. This statistic employs (4), (5), and (6) to detect hotspots and coldspots, which represent concentrations of high values and low values in a study area, respectively [17].

$$G_i^*(d) = \frac{\sum_j w_{ij}(d) x_j - \bar{x} \sum_j w_{ij}(d)}{S \sqrt{\frac{n \sum_j w_{ij}{}^2(d) - \left(\sum_j w_{ij}(d)\right)^2}{n-1}}} \quad (4)$$

with

$$\bar{x} = \frac{\sum_j x_j}{n} \quad (5)$$

and

$$S = \sqrt{\frac{\sum_j x_j^2}{n} - (\bar{x})^2} \quad (6)$$

where x_j is the value of each location j, $w_{ij}(d)$ is the spatial weight matrix for all locations j within distance d from the crash at location i, and n is the total number of locations. Z-score and p-values show the statistical significance results and the identification of hotspots, coldspots, and outliers. Similarly to the local Moran´s I statistic, we will focus particularly on hotspots of fatalities road users as a result of traffic accidents in Santiago.

In this study, Z-score values greater than or equal to 1.65 (less than or equal to -1.65) with p-value < 0.10 represent a positive (negative) spatial autocorrelation. Additionally, note that the aforementioned spatial statistical methods employed spatial weights that were computed based on distances that included a minimum number of neighbors (contiguity level) equal to eight [18].

III. DATA DESCRIPTION

The digital maps with the location of the traffic accidents in Santiago, Chile for each year of the studied period were freely downloaded from the CONASET website [2]. A total of

91,218 traffic accidents occurred in Santiago between 2015 and 2018, of which 37,294 (40.9%) accidents presented at least one injured person, as shown in Fig. 1. This figure shows that both total number of accidents and those accidents with fatality and injury outcomes tend to increase over time. Fig. 2 presents the number of victims involved in these traffic accidents during the studied period, yielding a total of 911 (1.9%) deaths, 10,764 (22.7%) seriously injured persons, and 35,795 (75.4%) slightly injured victims.

Most accidents in Santiago were caused by the imprudence of the driver (e.g., inattentive driving, abrupt lanes changes, improper turns, etc.) with 38.8% of all accidents, followed by other causes with 33.3%, traffic signal disobedience with 12.2%, imprudence of the pedestrian with 6.2%, under the influence of alcohol with 4.9%, and loss of vehicle control with 4.6% (See Fig. 3). On average, vehicle collisions were the most frequent type of accident that arose in Santiago during the studied period with 53.6% of the total number of accidents, as depicted in Fig. 4. This figure also shows that pedestrian-vehicle collisions and impacts of vehicles with stationary objects represent 23.4% and 11.9% of all traffic accidents, respectively.

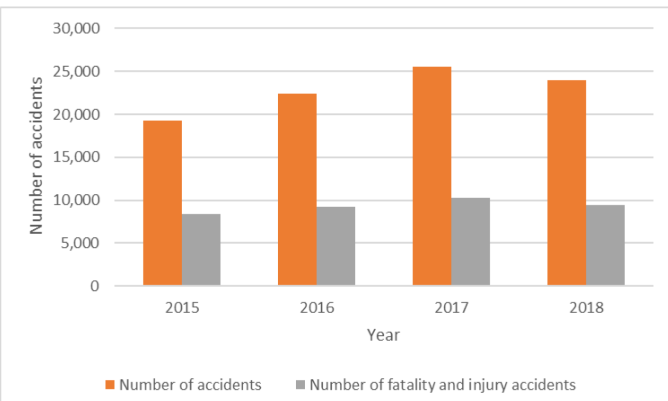


Fig. 1 Number of total traffic accidents and number of fatality and injury accidents in Santiago, Chile during the 2015-2018 period

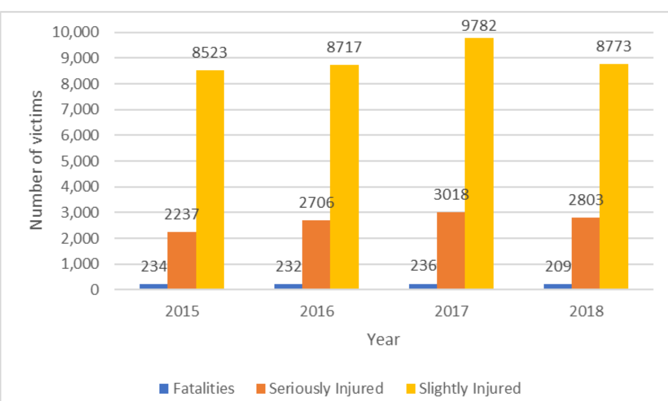


Fig. 2 Number of fatalities and injured victims in Santiago during the 2015-2018 period

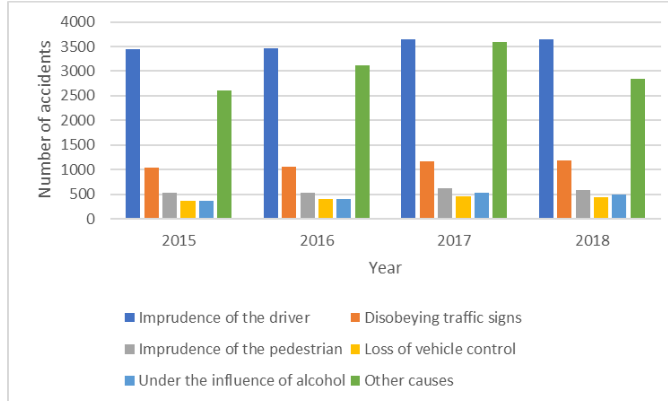


Fig. 3 Number of traffic accidents by contributing cause in Santiago during the 2015-2018 period.

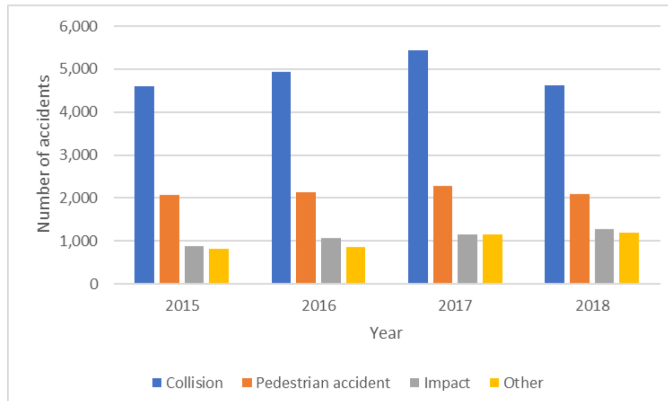


Fig. 4 Number of traffic accidents by type of accident in Santiago during the 2015-2018 period

IV. RESULTS

A. *Global Spatial Autocorrelation*

Tables II and III present a positive spatial autocorrelation at the global level for fatality accidents and *ISI*, respectively, computed with the global Moran´s I statistic. The results indicate that fatality accidents and *ISI* are spatially clustered for each year of the studied period at a significance level of 0.10 (90% confidence level). Therefore, fatality accidents and *ISI* tend to concentrate at certain geographic locations in Santiago that will be investigated in the following sub-sections using the local spatial autocorrelation using Getis-Ord Gi* and local Moran´s I statistics, respectively.

TABLE II
GLOBAL MORAN´S I RESULTS FOR FATALITY ACCIDENTS

Year	Moran´s I	Z-score	p-value
2015	0.0208	4.116	0.0000
2016	0.0079	1.653	0.0098
2017	0.0119	2.623	0.0087
2018	0.0127	2.489	0.0128

TABLE III
GLOBAL MORAN´S I RESULTS FOR INJURY SEVERITY INDEX (*ISI*)

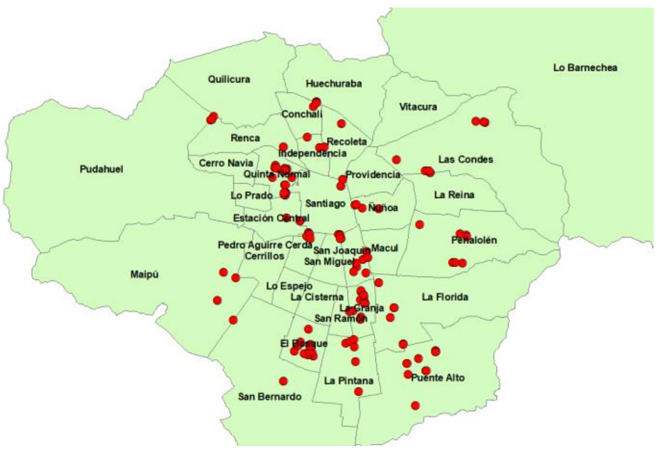
Year	Moran´s I	Z-score	p-value
2015	0.0225	4.463	0.0000
2016	0.0293	6.099	0.0000
2017	0.0119	2.642	0.0083
2018	0.0352	6.854	0.0000

B. *Local Spatial Autocorrelation*

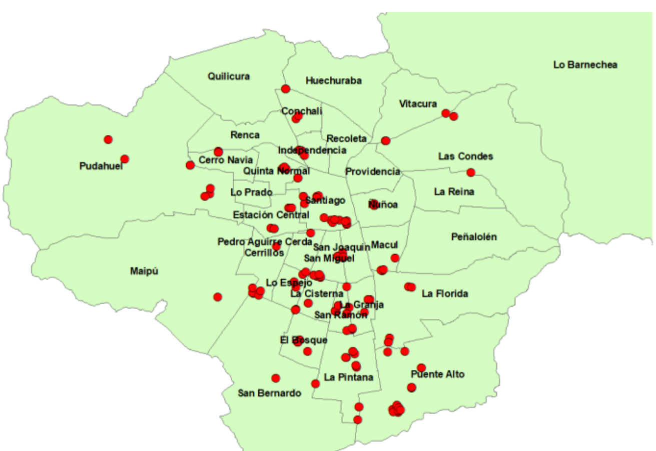
1) Local Moran´s I

Fig. 5 presents the local spatial autocorrelation results with the spatial clusters (HH) of injury severity using *ISI* for each year of the studied period. A total of 160, 180, 120, and 146 HH clusters of *ISI* are obtained during 2015, 2016, 2017, and 2018, respectively. These HH clusters tend to appear over time mainly towards the center of the city and to diminish in the outskirts of Santiago. All statistically significant HH clusters of *ISI* that arose during the studied period are shown in Fig. 6. This figure reveals that most of the spatial clustering of ISI have an intensity (Z-score) that ranges between 1.44 and 4.16.

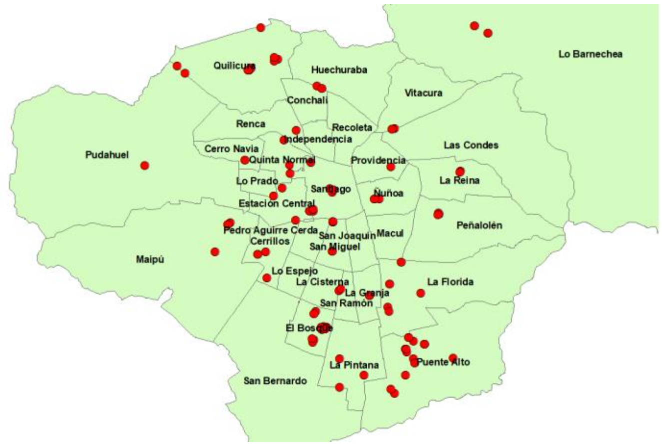
Table IV presents the top 10 communes with the greatest number of HH injury severity clusters during the 2015-2018 period and their average Z-score values. This table shows that the commune of Puente Alto has the highest number of HH clusters in Santiago, but Quinta Normal has the largest average HH clustering intensity of *ISI* with 3.56.



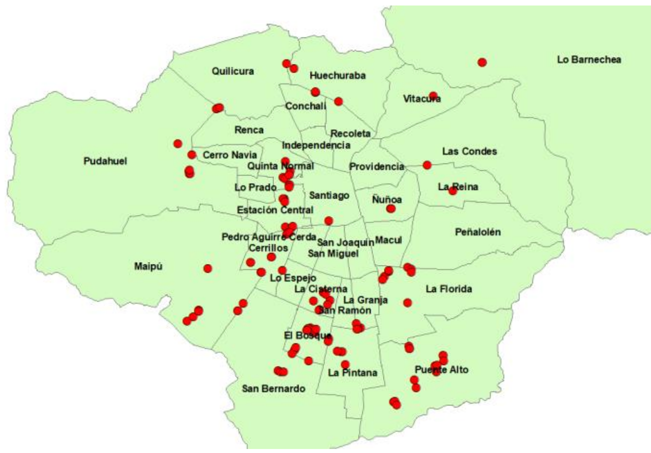
a) 2015



b) 2016



c) 2017



d) 2018

Fig. 5 HH clusters for *ISI* in Santiago per year of the 2015-2018 period

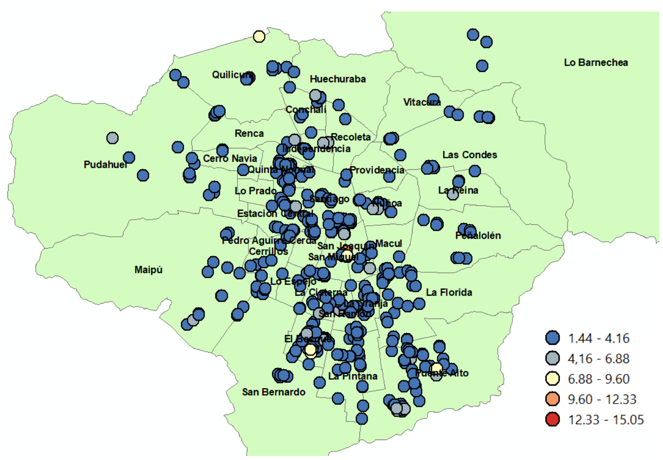


Fig. 6 HH clustering intensity of *ISI* in the 2015-2018 period

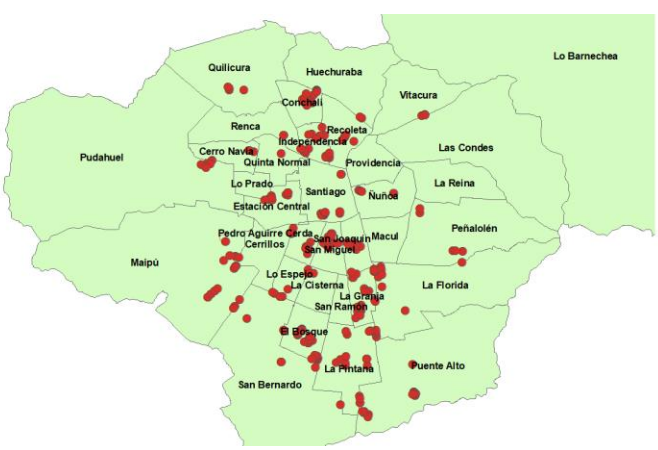
TABLE IV
TOP 10 COMMUNES WITH HIGHEST NUMBER HH CLUSTERS OF *ISI* IN THE 2015-2018 PERIOD

Commune	Year				Total	Average Z-score
	2015	2016	2017	2018		
Puente Alto	13	16	19	16	64	3.04
El Bosque	13	7	13	17	50	3.18
Quinta Normal	25	7	3	10	45	3.56
Santiago	3	20	8	1	32	2.84
La Pintana	7	13	3	5	28	2.59
La Florida	7	7	6	7	27	2.80
La Granja	15	6	3	2	26	2.42
Estación Central	6	11	2	6	25	3.08
Pudahuel	2	12	1	10	25	2.46
Cerrillos	0	6	6	12	24	1.68

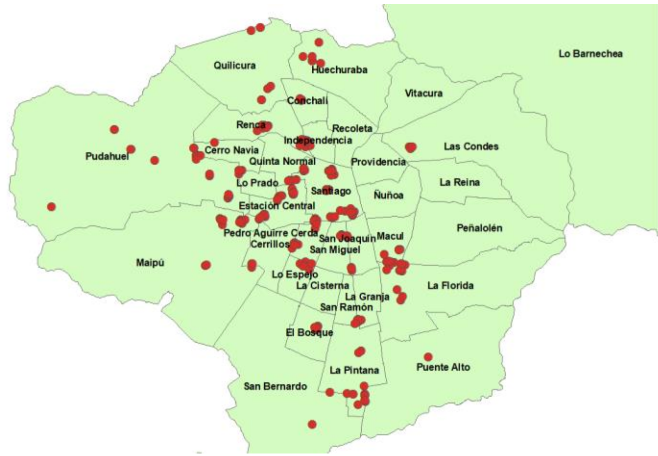
*2) Getis-Ord Gi**

Fig. 7 shows the hotspots of fatalities due to traffic accidents computed with the Getis-Ord Gi* statistic for each year of the 2015-2018 period. The total number of hotspots found in Santiago for the years 2015, 2016, 2017, and 2018 are 335, 288, 247, and 169, respectively. This figure shows that the number of fatality hotspots tend to decrease through time. Fig. 8 presents all statistically significant accidents hotspots that resulted in fatal outcomes between 2015 and 2018. Additionally, this figure shows the clustering intensity of these hotspots with Z-score values. Most fatality hotspots have intensity values between 2.73 and 4.18.

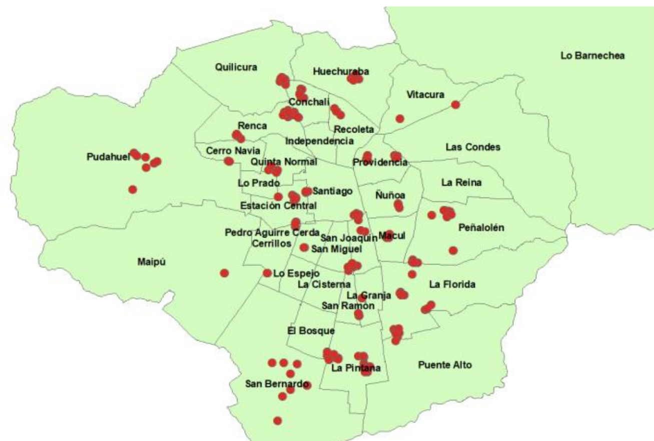
The top 10 communes with the largest number of fatality hotspots are presented in Table V. In this case, the communes of Maipú and Estación Central have the highest total number of fatality hotspots (81) during the studied period among all the communes in Santiago. However, Puente Alto have the strongest positive autocorrelation of these hotspots with an average Z-score of 4.82, meaning that fatal accidents have a very high clustering intensity in this commune.



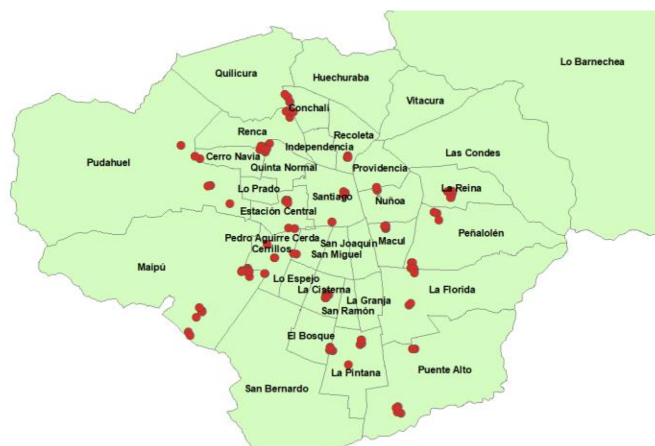
a) 2015



b) 2016



c) 2017



d) 2018

Fig. 7 Fatality hotspots in Santiago per year of the 2015-2018 period

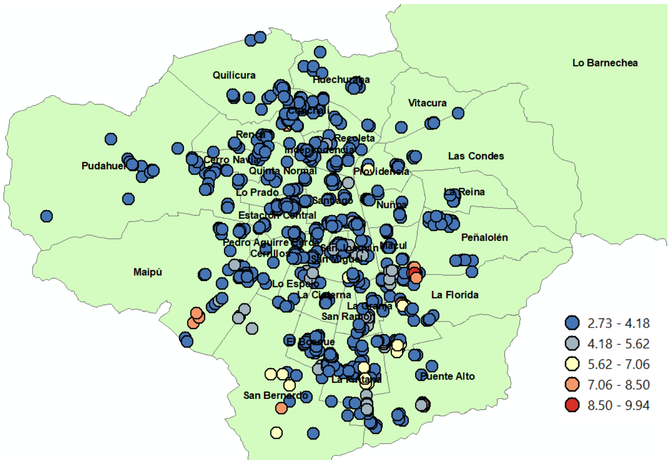


Fig. 8 Clustering intensity for all fatality hotspots in the 2015-2018 period

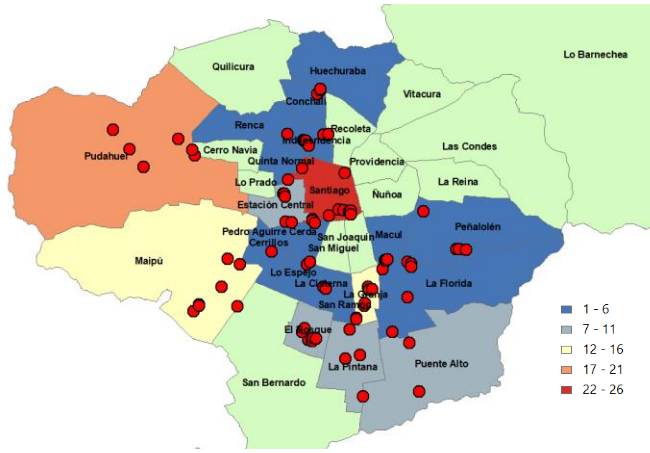


Fig. 9 Number of spatial coincidences of fatality hotspots and HH clusters of *ISI*

TABLE V
TOP 10 COMMUNES WITH HIGHEST NUMBER OF FATALITY HOTSPOTS IN THE 2015-2018 PERIOD

Commune	Year				Total	Average Z-score
	2015	2016	2017	2018		
Maipú	30	20	2	29	81	4.25
Estación Central	26	35	11	9	81	3.45
La Pintana	17	16	34	12	79	4.39
Santiago	24	40	8	5	77	3.68
Pudahuel	7	33	9	18	67	3.85
La Florida	17	14	23	5	59	4.61
Puente Alto	22	3	2	13	40	4.82
El Bosque	25	9	3	3	40	3.79
La Granja	26	8	6	0	40	3.65
Renca	5	13	14	5	37	3.90

3) Comparison between Moran´s I and Getis-Ord Gi statistics*

The communes with a large number of fatality hotspots coincide with most of the communes with high number of *ISI* HH clusters, suggesting that these communes have a high risk of clustering casualties and also severely injured victims as a result of accident occurrence. Fig. 9 depicts 85 (12%) locations throughout Santiago, in which the Getis-Ord Gi* statistic results are in agreement with the local Moran´s I statistic results. In other words, there are hotspots of fatality accidents that tend to occur also at locations with clusters of severe injury accidents given by *ISI*. In this case, the commune of Santiago presents the largest number of spatial coincidence (26) between *ISI* HH clusters and fatality hotspots, followed by Pudahuel with 19 and Maipú with 15.

V. DISCUSSION

The results of the spatial autocorrelation analysis performed in this study with the fatality and injury severity accidents aid authorities to prioritize those communes that are in need of crucial traffic safety measures. Overall, the global spatial autocorrelation results confirm that clustered patterns of fatal and injury severity of accidents exist in the city of Santiago for every year of the studied period. Higher global spatial clustering intensities are obtained for the *ISI* than for the fatality accidents, particularly in the years 2016 and 2018. Globally, this means that accidents with high *ISI* values have a tendency to cluster more than accidents with high fatality outcomes. In this case, the larger the Z score, the more intense the clustering of high values for both fatality and injury severity.

When regarding the spatial autocorrelation at the local level using local Moran´s I, a total of 606 HH clusters of injury severity index (*ISI*) was identified during the 2015-2018 period. These clusters represent traffic accidents with high *ISI* values surrounded by high *ISI* values, which should be considered in the traffic safety decision-making process. For example, the commune of Puente Alto presents the highest number of traffic accidents and also the largest number of HH clusters of *ISI* in Santiago during the studied period, perhaps because of the large population and high number of vehicles registered in this commune [4]. Nevertheless, Quinta Normal present an inferior number of HH clusters for *ISI* (45), but the highest clustering intensity of *ISI* of 3.56. Therefore, in this commune, the accidents with high risk of injury outcomes tend to cluster in space and time with a very large intensity. Additionally, other communes tend to increase the number of HH clusters of *ISI* every year. For example, El Bosque and Cerrillos are two communes that have increased their number of spatial clusters of injury severity accidents, and thus, a more in-depth analysis of the severe injury accidents that occurred in these communes should be performed.

The local spatial autocorrelation results with the Getis-Ord Gi* statistic indicate a total of 1,039 fatality hotspots were identified throughout Santiago between 2015 and 2018. Fortunately, the number of fatality hotspots have been decreasing over time from 335 in 2015 to 169 in 2018. However, the commune of Maipú not only has one of the highest total number of fatality hotspots in Santiago, but also had the highest number of these hotspots in the years 2015 and 2018. In addition, Puente Alto appears as the commune with the highest intensity of fatality hotspots in Santiago. Thus, both of these communes should be studied in more detail to determine the factors that contribute to the generation of these fatal hotspots.

When comparing the spatial agreements of fatality hotspots and HH clusters of *ISI*, the communes of Santiago, Pudahuel, and Maipú present the most spatial coincidence among both statistics. These two statistical spatial techniques present comparable results in identifying locations with spatial patterns of high *ISI* and fatality values. However, some differences may arise since the local Moran´s I and Getis-Ord Gi* statistics employ different criteria in determining clusters and hotspots, respectively [19]. These differences require further investigation.

VI. Conclusions

In this study, we performed a spatial autocorrelation analysis at the global and local level to identity spatial patterns of fatality and injury severity accidents in Santiago between 2015 and 2018. The global spatial autocorrelation reveals that the there is an overall spatial clustering of injury severity index (*ISI*) and fatality outcomes. The local spatial autocorrelation results identified communes with large number and high intensity values of *ISI* spatial clusters and fatality hotspots. Local authorities, transportation professionals, and planners should focus on the locations of the spatial clusters and hotspots of fatal and severe injury accidents that arise in different communes of Santiago, particularly in Estación Central, Maipú, Puente Alto, and Quinta Normal, to help improve traffic safety.

Future research should analyze the road infrastructure at those communes with high number of *ISI* clusters and fatality hotspots. Thus, countermeasures may be adequately intervened at the road level. Additionally, further research should include the analysis of fatality and seriously injured victims by considering different accident attributes such as type of accident (collisions, pedestrian accidents, etc.), contributing cause (loss of vehicle control, alcohol, speeding, etc.), time of the day, among others.

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