Spatio-Temporal Analysis of Public Transit Crashes in Viña del Mar and Valparaíso, Chile

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Abstract*– The conurbation of Viña del Mar and Valparaíso presented the highest number of public transit crashes in Chile with a total of nearly 350 fatalities and severely injured victims between 2014 and 2018. These crashes are caused mainly due to the imprudence of the driver yielding collisions between two or more moving vehicles, impacts with stationary objects, and falls of passenger from buses. This study performed a spatio-temporal analysis of traffic crashes that involved microbuses and taxi-buses to identify emerging and disappearing hotspots and coldspots during the study period. The results revealed that most crash hotspots due to the imprudence of the driver persisted in time in Viña del Mar, and crash hotspots due to signage disobedience sporadically appeared in Valparaíso. Hotspots of collisions and falls of passengers are types of crashes that emerged solely in Viña del Mar, as well as new, consecutive, and sporadic hotspots of severely injured victims. While morning historical hotspots emerged in Viña del Mar, consecutive, persistent, and sporadic hotspots of crashes appeared in the downtown area in both cities. The results of this study will aid authorities, transportation professionals, and planners make informed decisions about traffic safety.

Keywords—traffic crashes, hotspots, transit, Chile

I. Introduction

Every year approximately 1.3 million victims die as a result of traffic crashes worldwide. The number of fatalities due motorized crashes has decreased since 2010, except for Chile and the United States. Chile is the OECD member country that has the worst fatality rate with 11.9 per 100,000 inhabitants [1]. The number of road traffic crashes has presented a steady increase from 58,000 crashes in 2010 to nearly 90,000 crashes in 2018. Currently, the main external cause of death among Chileans is traffic crashes with approximately 1.600 deaths per year despite the recent 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]. This alarming statistic highlights the severity of this problem in Chile. In addition to the fatal losses due to traffic crashes in Chile, the estimated cost of traffic crashes in 2018 was approximately US$5.8 billion, which corresponds to 2.1% of the GDP per capita [3].

The conurbation of Viña del Mar and Valparaíso belong to the Region of Valparaíso, which is ranked second with the highest number of crashes after the Metropolitan Region [2]. Among all Chilean cities, Viña del Mar and Valparaíso present the highest number of crashes that involve public transit microbuses and taxibuses (from now on referred to as "public transit crashes"), followed by Concepción.

The objective of this study is to analyze crashes of public transit microbuses and taxibuses that occurred in the 2014-2018 period in the twin cities of Viña del Mar and Valparaíso from a spatial and temporal perspective. Thus, hotspots and coldspots of public transit crash attributes that persisted in time are identified. The results of this research will support authorities to develop efficient traffic safety programs for transit and to prioritize interventions by identifying high crash risk zones.

Studies have used different spatial techniques to identify hotspots of road crashes such as Nearest Neighbor Clustering [4], K-means [5, 6], and Kernel Density Estimation (KDE) [7, 8]. Studies have also employed spatial autocorrelation indicators to detect hotspots of road crashes [9, 10, 11, 12]. Additionally, researchers have conducted a spatio-temporal analysis of traffic crash hotspots [13, 14, 15]. For example, [14] conducted a spatio-temporal analysis to explore the traffic crash temporal evolution and to identify crash hot spots using Moran`s I and Getis-Ord Gi* spatial statistics. [13] performed a global and local spatial autocorrelation analysis of cargo trucks on Chilean highways to identify spatial clustering (hotspots) of crash attributes over time. In another study by [15], hotspots of traffic crashes involving elderly people in Seoul, Korea were analyzed spatial and temporally using emerging hotspot and space-time KDE analyses. In this study, a local spatial autocorrelation is performed using the Getis Ord Gi* index to identify public transit crash hotspots, and emerging hotspot analysis is conducted to classify these hotspots according to their temporal evolution.

II. Data Description

The public transit system of Viña del Mar and Valparaíso consists of approximately 2,096 buses that serve a population of 630,093 inhabitants through 100 routes [2]. A total of 3.586 road crashes occurred between 2014 and 2018 that involved public transit microbuses and taxibuses, of which 48.3% and 51.7% of these crashes occurred in Viña del Mar and Valparaíso, respectively. Fig. 1 presents 3,147 (87.8%) crashes that were successfully geocoded in a GIS environment.

Most of the crashes in both cities comprised two or more vehicles that collided as they were traveling, followed by impacts of vehicles with stationary objects, as shown in Fig. 2. As a result of these crashes, 2.103 victims suffered some type of injury during the studied period. Fig. 3 shows that more fatalities and injuries occurred in Viña del Mar than Valparaíso.

The main cause of public transit crashes in both cities was the imprudence of the driver (e.g., inattentive driving, abrupt lanes changes, improper turns, shoulder overtaking, etc.), which accounted for 75.4% and 58% of these crashes in Viña del Mar and Valparaíso, respectively (See Fig. 4). Additionally, this figure shows that more crashes occurred in Valparaíso due to other causes and the disobedience of traffic signals.

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Regarding the time of day, crashes in Valparaíso on average tend to occur at 8am, between 11am and 1pm, and between 5pm and 7pm. Whereas, Fig. 5 indicates that traffic crashes in Viña del Mar are mostly concentrated around noon and 6pm. On average, most traffic crashes in Viña del Mar tend to occur during weekdays (particularly Mondays), while over 50% of the crashes in Valparaíso occurred between Wednesdays and Fridays. On average, 145 and 154 public transit crashes arose every month in Viña del Mar and Valparaíso, respectively, with the highest number of crashes in March.

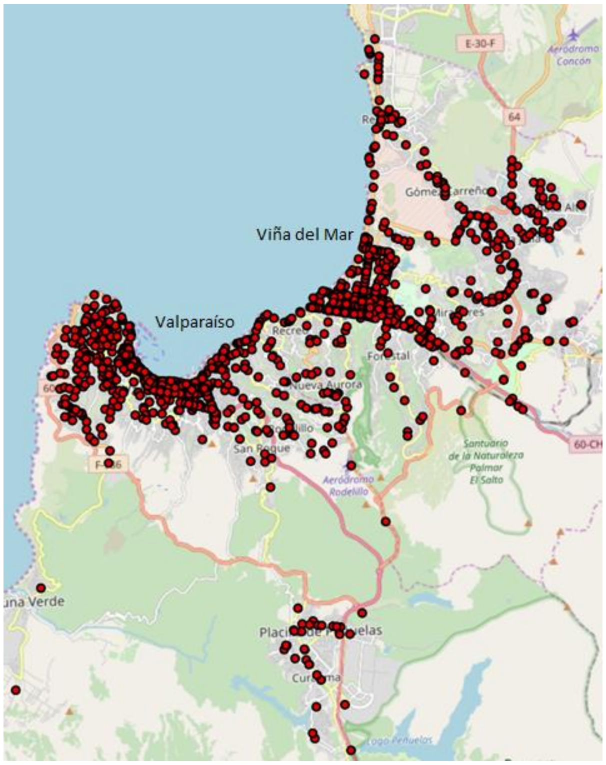

Fig. 1 Public transit crashes in Viña del Mar and Valparaíso that occurred during the period 2014-2018.

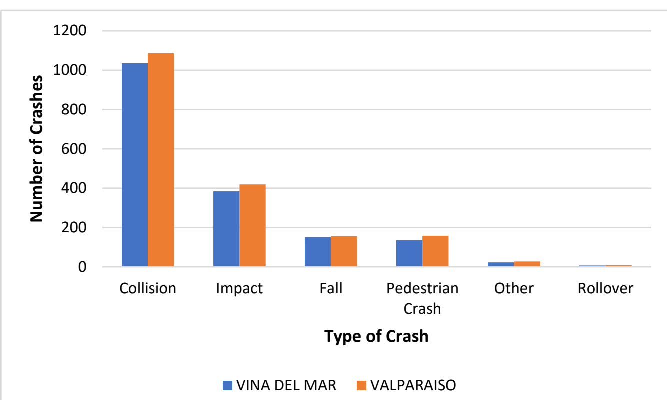

Fig. 2 Number of public transit crashes by type of crash in Viña del Mar and Valparaíso.

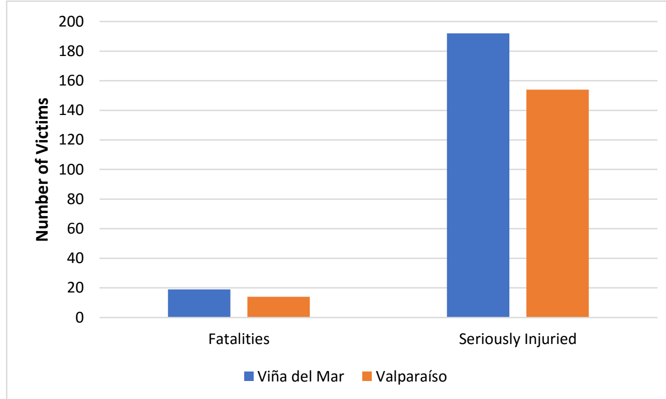

Fig. 3 Killed and seriously injured in Viña del Mar and Valparaíso due to public transit crashes.

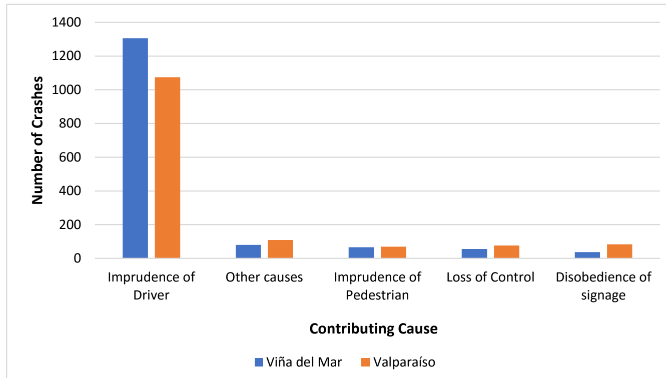

Fig. 4 Number of public transit crashes by contributing cause in Viña del Mar and Valparaíso.

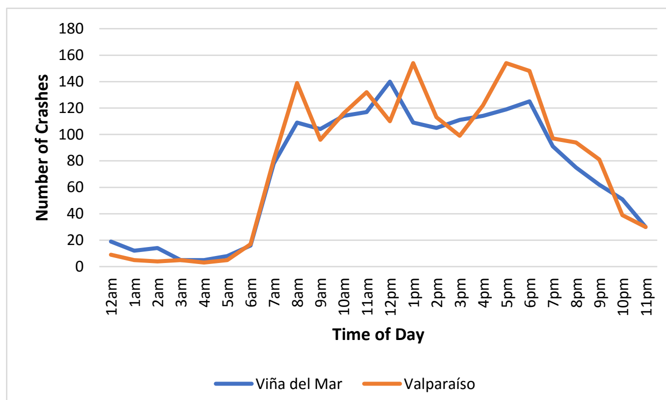

Fig. 5 Number of crashes per hour in Viña del Mar and Valparaíso.

Table I presents the variables associated to the public transit crashes analyzed in this study. These are grouped by contributing cause, type of crash, and time of day. Severely injured victims (summation of killed, and seriously and less seriously injured) are also examined.

TABLE I
PUBLIC TRANSIT CRASH VARIABLES

Variable Category	Variable
Severely injured	Summation of killed, and seriously and less seriously injured
Contributing causes	Imprudence of the driver
	Imprudence of the pedestrian
	Loss of control of vehicle
	Signage disobedience
	Other causes
Type of crash	Collision of two or more moving vehicles
	Impact with a stationary vehicle
	Fall of passenger from a bus
	Pedestrian run-over
Time of day	Morning (6am-11:59am)
	Afternoon (12pm-5:59pm)
	Night (6pm-11:59pm)

III. METHODOLOGY

Tobler´s first law of geography states that "everything is related to everything else, but near things are more related than distant things" [16]. The principle of spatial autocorrelation is based on this law, in which assesses the spatial relationship between attributes at certain locations and surrounding locations. If the spatial correlation is higher (lower) than expected, then neighboring locations have similar (dissimilar) values and the spatial autocorrelation is positive (negative) [17]. Therefore, spatial patterns of crashes demonstrate distinct clustering or dispersion and are not generated by random.

In this study, spatial autocorrelation analysis was performed with the Emerging Spatio-temporal Hotspot Analysis tool from ArcGIS software to identify the clustering tendency of public transit crashes by evaluating spatial-temporal cubes. These cubes consist of bins with information that horizontally represent the location and vertically the time series, as depicted in Fig. 6 [18]. Each bin is assigned with total number public transit crashes that occurred in a certain time slice o interval, and empty bins are filled with zero values.

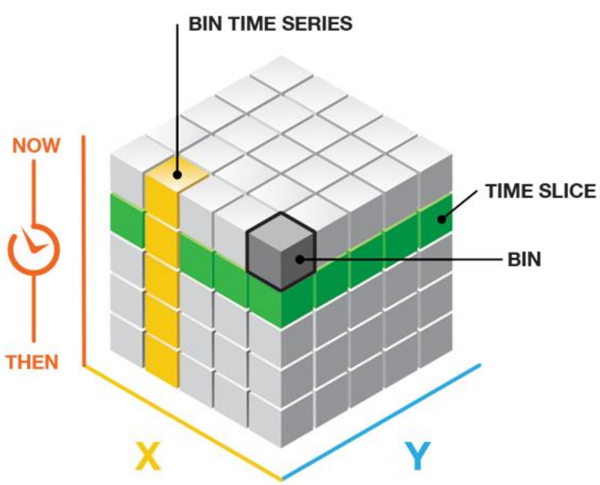

Fig. 6 3D representation of time-space bins [18].

Getis-Ord G_i* statistic was used to identify the location and level of spatial clustering of bins (aggregated public transit crashes) in combination with the Mann-Kendall statistic to assess the trend through time series at each location [19, 20]. Getis-Ord G_i* index obtains the concentration of high values (hotspots) and low values (coldspots) of a study area by using (1), (2), and (3) [21].

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

with

$$\bar{x} = \frac{\sum_j x_j}{n} \quad (2)$$

and

$$S = \sqrt{\frac{\sum_j x_j^2}{n} - (\bar{x})^2} \quad (3)$$

where x_j is the attribute 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 are yielded as output information for each bin when using the G_i* statistic to indicate standard deviation and statistical probability, respectively. Table II presents the classification of hotspots and coldspots according to Z-score and p-values [18]. Note that a positive (negative) spatial autocorrelation is identified with Z-score values of 1.65 or greater (-1.65 or less) with p-value <0.10.

TABLE II
HOTSPOT AND COLDSPOT CLASSIFICATION ACCORDING TO Z-SCORE AND P-VALUES

Z-Score	p-value	Category
< -2.58	0.01	Coldspot, 99% confidence level
-2.58 – 1.96	0.05	Coldspot, 95% confidence level
-1.96 – -1.65	0.10	Coldspot, 90% confidence level
-1.65 – 1.65	-	Not significant
1.65 – 1.96	0.10	Hotspot, 90% confidence level
1.96 – 2.58	0.05	Hotspot, 95% confidence level
> 2.58	0.01	Hotspot, 99% confidence level

Once the hotspots and coldspots are identified per bin for each time interval (time-space cubes), these are classified into the temporal trend categories listed in Table III. These categories represent fluctuations between emergences and disappearances of hotspots and coldspots over time.

IV. RESULTS

First, time-space cubes were obtained for each analyzed variable by aggregating the public transit crashes in 268 m x 268 m bins and using a time-step interval of 4 months (i.e., 15 bins per location for the complete study period). These values were determined by testing bin sizes between 100 m and 400 m, and time-step intervals between 1 and 6 months. Different distance bands were also tested to examine the proximity between each crash and its neighboring crashes (i.e., distance at which spatial autocorrelation is maximized). A distance band of 1,498.3 meters yielded the best results for all crash variables analyzed in this study.

TABLE III
TEMPORAL TENDENCY CATEGORIES OF STATISTICALLY SIGNIFICANT HOTSPOTS AND COLDSPOTS (BASED ON [18])

Tendency	Definition
No identified tendency	None of the temporal tendencies specified in the other categories.
New hotspot (coldspot)	Hotspot (coldspot) appeared only during the last time interval.
Consecutive hotspot (coldspot)	More than 90% of the bins appeared continuously as hotspots (coldspots)
Intensifying hotspots (coldspot)	At least 90% of the time intervals have presented hotspots (coldspots) and clustering intensity has been increasing over time.
Persistent hotspot (coldspot)	At least 90% of the time intervals have presented hotspots (coldspots) and no increasing or decreasing tendency exist.
Diminishing hotspot (coldspot)	At least 90% of the time intervals have presented hotspots (coldspots) and clustering intensity has been decreasing over time.
Sporadic hotspot (coldspot)	Hotspots (coldspots) appear only during certain time intervals.
Oscillating hotspot (coldspot)	Some hotspots appear for certain time intervals and some coldspots appear for certain time intervals.
Historical hotspot (coldspot)	At least 90% of the time intervals have presented hotspots (coldspots), except for the last time interval.

Subsequently, the spatial autocorrelation results are analyzed through time, and statistically significant hotspots and coldspots are classified according to the temporal tendency categories described in Table III. The following subsections present the results for each analyzed crash variable.

A. Injury severity

Fig. 7 shows a 3D visualization of bins with hotspots of public transit crashes that yielded severely injured victims in Viña del Mar and Valparaíso. This figure indicates that few hotspots appeared in Valparaíso, while some hotspots emerged in the center of Viña del Mar near the Pacific Ocean in recent years. No coldspots are identified for this variable.

The emerging spatio-temporal hotspot analysis for each bin yielded three types of severely injured hotspots (New, consecutive, and sporadic hotspots) only in Viña del Mar, as illustrated in Fig. 8. These results suggest that most crashes did not persist in time since the majority of the hotspots are classified as sporadic hotspots. The few hotspots that appeared in the center of Valparaíso, as shown in Fig. 7, are not classified into any of the temporal trend categories.

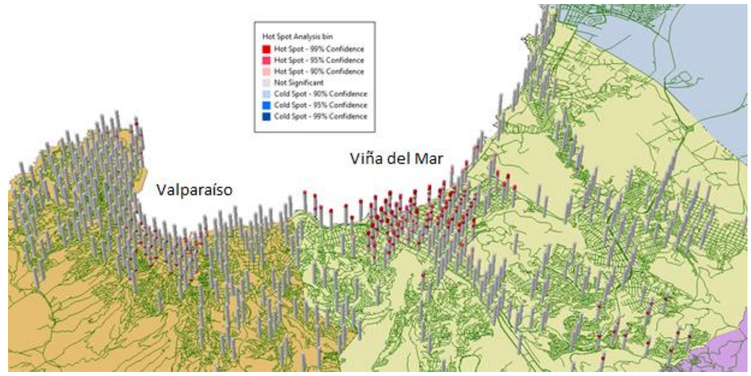

Fig. 7 3D visualization of hotspots of severely injured victims.

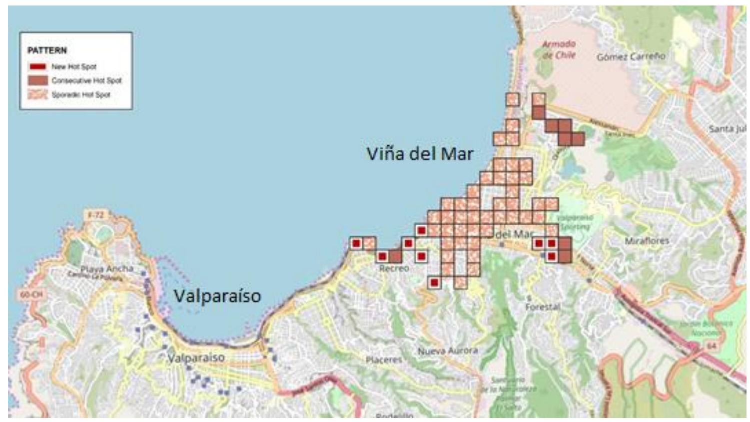

Fig. 8 Temporal trends of hotspots of severely injured victims.

B. Contributing causes

Fig. 9-11 present the 3D visualization hotspots and coldspots associated to public transit crashes caused by the imprudence of the driver, signage disobedience, and other causes, respectively. These figures suggest that more crash hotspots are perceived in Viña del Mar due to the imprudence of the driver, whereas crash hotspots due to the signage disobedience and other causes are observed only in Valparaíso. Neither hotspots nor coldspots were identified for crash variables related to the imprudence of the pedestrian and loss of control of vehicles.

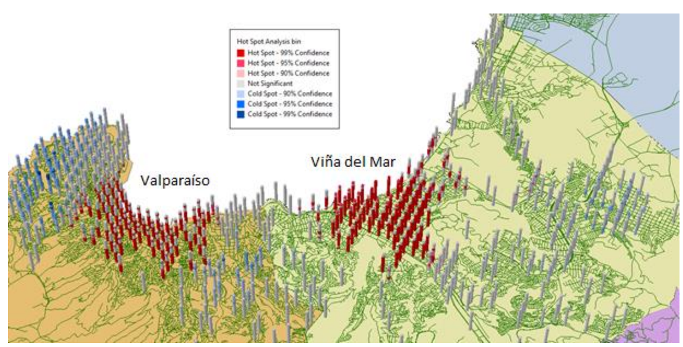

Fig. 9 3D visualization of crash hotspots and coldspots due to imprudence of the driver.

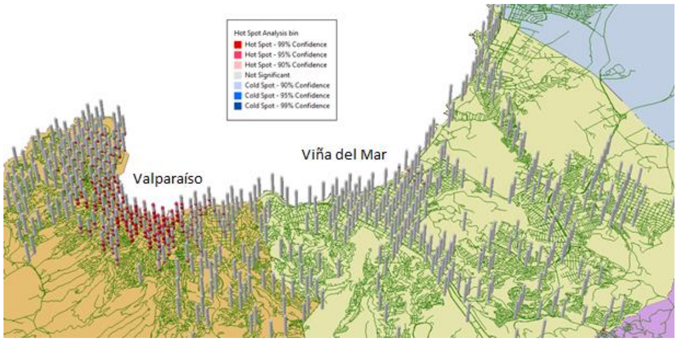

Fig. 10 3D visualization of crash hotspots due to signage disobedience.

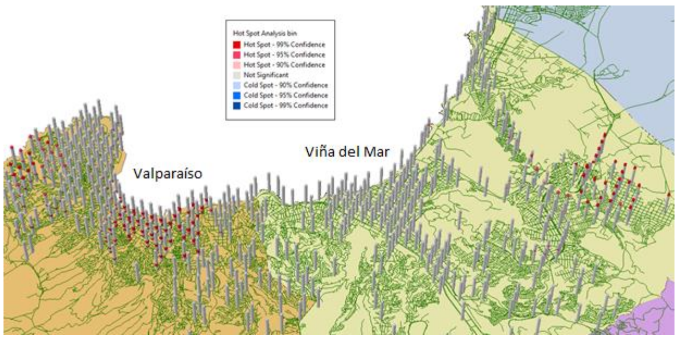

Fig. 11 3D visualization of crash hotspots due other causes.

Fig. 12 shows that while persistent crash hotspots due to the imprudence of the driver arose in the center of Viña del Mar, a group of sporadic coldspots are present near the Gómez Carreño neighborhood in Viña del Mar, and consecutive, intensifying, and sporadic coldspots appear on the hills of Valparaíso. Fig. 13 indicates that sporadic crash hotspots due to signage disobedience are only observed downtown Valparaíso. New crash hotspots due to other causes are perceived only on the hills of both cities, as shown in Fig. 14.

Fig. 12 Temporal trends of crash hotspots and coldspots due to imprudence of the driver.

Fig. 13 Temporal trends of crash hotspots due to signage disobedience.

Fig. 14 Temporal trends of crash hotspots due to other causes.

C. *Type of crash*

Fig. 15 suggests from the 3D visualization that more hotspots of colliding vehicles appeared in Viña del Mar than in Valparaíso. However, the results of the temporal tendency analysis in Fig. 16 yielded only few persistent hotspots in Viña del Mar, and only coldspots emerged in Valparaíso. In Valparaíso, hotspots for this variable persisted only 8 out of 15 bins during the 2014-2018 period, and thus, these hotspots were not classified into any spatio-temporal category.

Fig. 17 reveals that hotspots of falling passengers from buses prevailed in Valparaíso. However, new and sporadic hotspots appeared only in Viña del Mar (See Fig. 18). Hotspots in Valparaíso did not meet any temporal criterion of the emerging hotspot categories. Notice that no hotspots and coldspots were obtained for public transit crashes that resulted in impacts of vehicles with stationary objects and pedestrian run-overs.

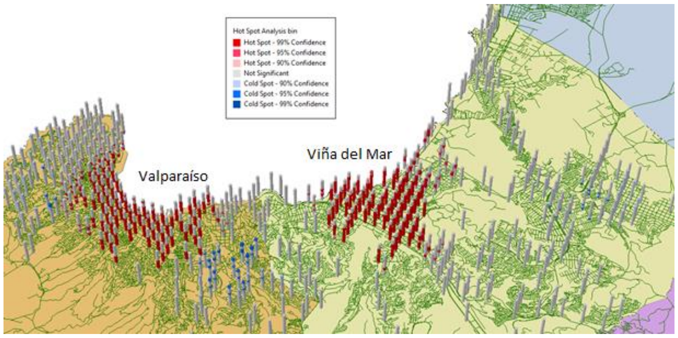

Fig. 15 3D visualization of crash hotspots and coldspots that resulted in collisions

Fig. 16 Temporal trends of crash hotspots and coldspots that resulted in collisions.

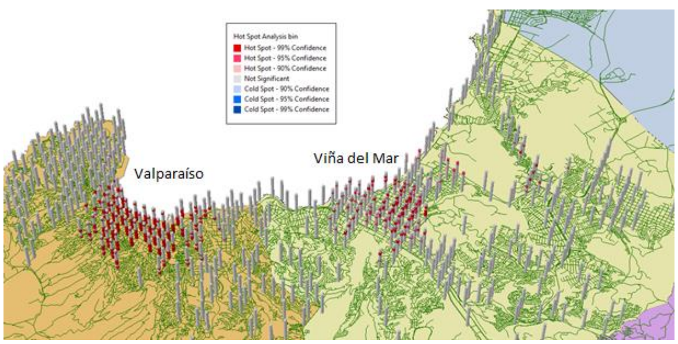

Fig. 17 3D visualization of crash hotspots that resulted in the falls of passengers

Fig. 18 Temporal trends of crash hotspots and coldspots that resulted in falls of passengers.

D. Time of day

More hotspots of morning and afternoon crashes persisted over time in Viña del Mar than in Valparaíso, particularly in the center of the cities, as shown in Fig. 19 and 20, respectively. Fig. 21 shows that only three historical hotspots of crashes emerged in the morning in Viña del Mar, while Fig. 22 presents that consecutive, persistent, and sporadic hotspots arose in Viña del Mar and Valparaiso during the afternoon. The latter figure also shows that only one new coldspot and some sporadic coldspots are perceived on the hills of Valparaíso. Note that hotspots and coldspots did not emerge for public transit crashes during the evening between 6pm and 11:59pm.

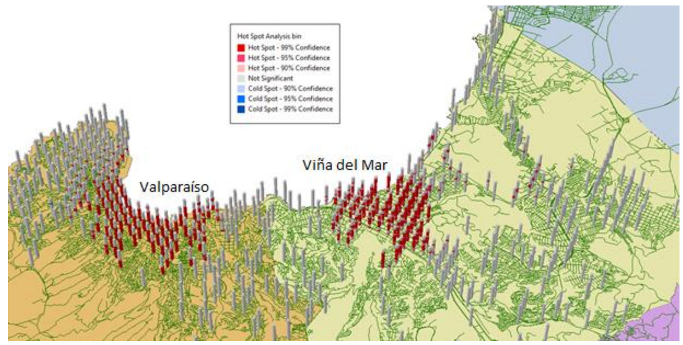

Fig. 19 3D visualization of crash hotspots that occurred during the morning.

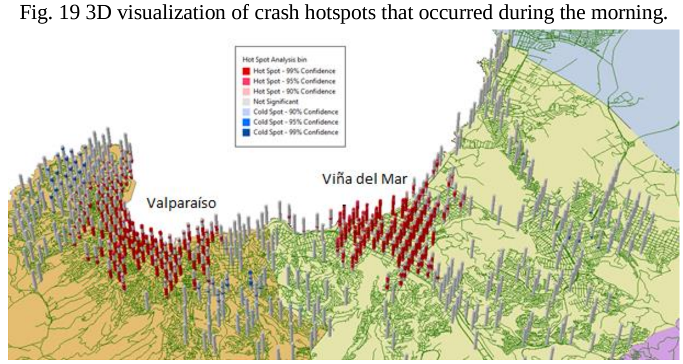

Fig. 20 3D visualization of crash hotspots that occurred during the afternoon.

Fig. 21 Temporal trends of crash hotspots that occurred during the morning.

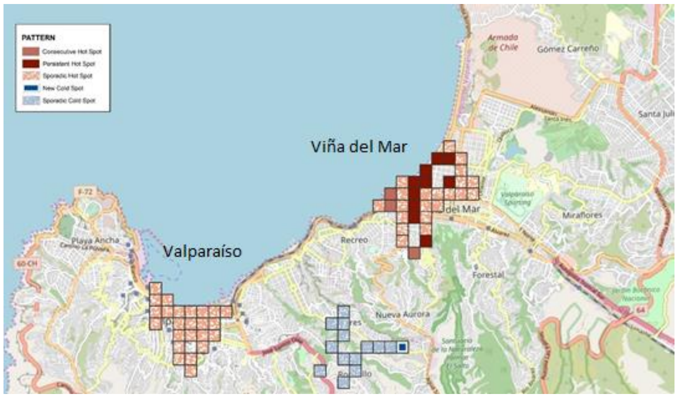

Fig. 22 Temporal trends of crash hotspots and coldspots that occurred during the afternoon.

V. Discussion

The results of the spatio-temporal analysis performed in this study for different public transit crash variables helps to identify critical zones that require urgent traffic safety measures. For example, in Viña del Mar, local authorities should prioritize those crash locations identified as new and consecutive crash hotspots that resulted in severely injured victims. These have either recently emerged with high values of the crash attributes surrounded by high values of crash attributes or more than 90% of the bins have continuously emerged as hotspots.

In addition, hotspots caused by the imprudence of the driver that resulted in collisions have persisted over time in the center of Viña del Mar, particularly in the afternoon. These crash hotspots may have appeared because of the high flow of pedestrians and vehicles in commercial areas during that time of the day and noting that approximately 70% of the bus routes traverse this part of the city [22]. Police monitoring and surveillance is mandatory, in order to increase traffic safety and raise awareness of appropriate driving behaviors.

New crash hotspots that emerged on the hills of Valparaíso and Viña del Mar due to other causes should be analyzed in more detail to determine specifically each of these causes and why they have appeared in the last time interval. Sporadic crash hotspots caused by disobeying traffic signals appeared in downtown Valparaíso during the afternoon, which coincides with the highest number of crashes during this time period and approximately 63% of the bus routes. These hotspots emerged only during certain time intervals, and perhaps these may not require urgent countermeasures. Both new and sporadic hotspots of crashes that resulted in falls of passengers arose only in Viña de Mar. These hotspots also need to be examined with caution. Overall, the results of this study imply that hotspots of certain public transit crash variables are more prone to occur over time in Viña del Mar than in Valparaíso.

Although many persistent hotspots and coldspots are observed with different crash variables, these do not fulfill the 90% requirement described in the temporal tendency category. Thus, these hotspots and coldspots do not belong to any of the spatio-temporal categories described in Table III. For example, although hotspots of morning crashes are illustrated in the 3D visualization for Viña del Mar and Valparaíso, these were statistically significant in approximately 80% and 50% of continuous time intervals, respectively. Perhaps additional temporal trend categories are required, in order to highlight this type of crash hotspots. Similarly, more hotspots of crashes that resulted in falls of passenger are visualized in 3D in Valparaíso than in Viña del Mar. However, no statistically significant hotspot is obtained in Valparaíso from the emerging spatio-temporal hotspot analysis.

VI. Conclusions

This study performs a spatiotemporal analysis of traffic crashes that involves microbuses and taxibuses in the cities of Viña del Mar and Valparaíso, Chile. Different crash variables are analyzed to determine locations of hotspots and coldspots and their emergence or disappearance during the 2014-2018 period. These variables are grouped into severely injured victims, contributing causes, type of crash, and time of day.

The results suggest that most public transit crash hotspots that persisted over time in Viña del Mar occurred due to the imprudence of the driver causing collisions between two or more moving vehicles mainly. Whereas, in Valparaíso, sporadic hotspots of crashes emerged because the driver disobeyed the traffic signals. Both hotspots in these cities occurred during the afternoon in the downtown area, in which a large flow of vehicles and pedestrians exists in commercial areas during this time of the day. Authorities should pay close attention to the hotspots of crashes that are yielding fatalities and seriously injured persons in the center of Viña del Mar during the studied period.

Further research is required to analyze high crash risk locations near bus stops, commercial areas, etc. in more detail, in order to implement adequate safety measures.

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