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Exploring spatial autocorrelation of traffic crashes based on severity

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ABSTRACT

As a developing country, Iran has one of the highest crash-related deaths, with a typical rate of 15.6 cases in every 100 thousand people. This paper is aimed to find the potential temporal and spatial patterns of road crashes aggregated at traffic analysis zonal (TAZ) level in urban environments. Localization pattern and hotspot distribution were examined using geo-information approach to find out the impact of spatial/temporal dimensions on the emergence of such patterns. The spatial clustering of crashes and hotspots were assessed using spatial autocorrelation methods such as the Moran's I and Getis-Ord Gi* index. Comap was used for comparing clusters in three attributes: the time of occurrence, severity, and location. The analysis of the annually crash frequencies aggregated in 156 TAZ in Shiraz; from 2010 to 2014, Iran showed that both Moran's I method and Getis-Ord Gi* statistics produced significant clustering of crash patterns. While crashes emerged a clustered pattern, comparison of the spatio-temporal separations showed an accidental spread in distinct categories. The local governmental agencies can use the outcomes to adopt more effective strategies for traffic safety planning and management.

Introduction

Traffic crashes usually increase as the population grows; in other words, fast urban growth and transport infrastructure improvement in developing countries are associated with more dependence on cars. In its turn, this issue results in a large number of road traffic deaths/injuries [1–3]. Traffic have significant impacts on the vehicular traffic flow, since they induce safety concerns and cause traffic delays [4].

Around 1200 thousand people all over the world are killed in vehicle-related crashes annually; between 20 and 50 million become disabled or wounded [5]. These damages are equal to 2.1% of the world's death rate and 2.6% of disability-adjusted life years (DALYs) lost. In this way, poor and middle-income nations annually share about 85% of the deaths and 90% of the DALYs lost due to the traffic crashes [6]. As a developing country, Iran has one of the highest crash-related death rates, with a typical rate of 15.6 cases in every 100 thousand people [7]. Investigations show that 25% of casualties in Iran is due to of unnatural deaths caused by traffic crashes [8]. Human failure is reported as the cause in more than 70% of crashes [9]. Greater reliance on cars and a better quality of life for the Iranian people are linked with the higher crash frequency occurred on the roads and their consecutive impacts [10]. This is estimated to cost more than 7% of the gross national product (GNP). Undesirable social and economic impacts of crashes impose large costs on the society [11].

While numerous studies have investigated spatiotemporal patterns of traffic crashes at different levels, and at area levels such as TAZ [12,13], and the road network with Kernel Density Estimation (KDE) [14–16] and Network KDE [17–19], little efforts have been so far taken for analyzing traffic crashes based on their severity. The novelty of this paper is its focus on different crash types rather than the aggregated crash number.

This paper concentrates on traffic crash patterns at TAZ level in Shiraz, the capital of Fars province, southwest of Iran. The study objectives are: (a) to pattern analyzing and cluster mapping of crashes for identifying hotspots respected to time in Shiraz, and (b) comparing the identified hotspots regarding to the crash type and its severity level.

The rest of the paper is as follows: Section – Literature Review, reviews some background studies; Section – Materials and Methods, introduces the materials and methods applied in this study; Section – Result, presents the main outcomes got from the spatio-temporal analysis of hotspots; and finally, the last section gives a discussion on the findings and draws some conclusions.

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Literature review

Transportation planners/managers are willing to detect risky zone in their attempts to enhance the road safety level by undertaking risk reduction programs [20,21]. The recognition of risky areas called "*safety black zones*" is the initial step in traffic safety analysis [22,23]. This stage could detect the priorities of investigation localities as the earliest action of the road safety management activities [24].

The spatiotemporal pattern of vehicular crashes and identification of hotspots have progressively been investigated in several researches. Analyzing spatial patterns of motorcycle crashes on Honolulu, Hawaii in 1990, Levine et al., found that most crashes occurred in vicinity of working sites instead of residential areas [25]. In fact, commercial and business areas are positively related with more fatal and injury crashes [26]. In contrast, Kim and Yamashita, discovered that the residential districts were more risky areas, especially during the peak hours [27]. Moreover, Levine et al., found that most deadly or severe injury crashes attributed to late night foolish driving occurred in remote suburban or rural areas instead of urban zones [25]. Scheiner and Holz-Rau studied the connection between the spatial distribution of road crashes and the place of residence in two case studies from Germany (North Rhine-Westphalia and Lower Saxony) [28]. They that the risk of being killed or seriously injured in a road accident is significantly lower for the residences of high-density cores than for the suburban and rural inhabitants.

The study by Wang and Abdel-Aty on the longitudinal crash data and intersection clusters for about 500 signalized intersections along corridors in Florida showed that there was a significant correlation between crash incidence in 2000 and 2002 [29]. A similar study undertaken by Huang et al., used a Bayesian spatial model in Florida for explaining the regional differences in crash occurrence risk after controlling for variables of travel distance and population density [30]. The results confirmed that regions with larger traffic volume, population and activity density were associated with a higher crash records. Higher truck traffic volume is correlated with more severe crashes, and the time spent on the journey to work is negatively associated with all kinds of crash risks. The study of spatial pattern of traffic crashes in Baltimore showed a high density in the central area and neighboring districts, as well as a distribution along the major arterial roads and intersections [31].

Li et al., conducted a GIS-based Bayesian analysis to discover the spatio-temporal pattern of motor vehicle crashes occurred in Harris County, Texas; and they found stability in high-risk segments using the data of four years [32]. Using data from a rural region in Pennsylvania and spatial correlation in road crash analysis, Aguero-Valverde and Jovanis, contributed to the method of crash studies [33]. The spatial correlation model showed to have higher conformity (R-square index) to the data than the Poisson lognormal model. Spatial correlation could also be able to decrease the bias accompanying the model misspecification [34]. Dai, determined crash clusters and some injury risk determinants in pedestrian–vehicle accidents by GIS on the urban districts of Atlanta metropolitan area [34]. The analysis found that high-activity corridors in suburban areas, where wide highways cross residential roads, considerably increased injury risks in crashes in comparison with other locations.

Using spatial autocorrelation functions in GIS, Erdogan et al., identified the crash hotspots in Afyonkarahisar, Turkey [35]. The study, in addition, showed the seasonal correlation among crashes mainly in crossroad of the villages and small towns. August and December were found to be the two most risky months of the year. Moreover, Fridays and weekends appeared to have higher number of crashes happened on a daily analysis. . Conventional quantitative methods and Gi* were integrated in a study of crash hotspots in Konya, Turkey. Hotspots were considered as those areas having either the largest 5% crash frequency or significant Gi* value. The analysis found that using two comparative approaches can enhance the precision of hotspot identification [36].

In other study, Blazquez and Celis, attempted to investigate the temporal pattern of kid's crash data from 2000 to 2008 by applying kernel density function in Santiago, Chile [37]. To this end, they used Moran's I index test for identifying the likely spatial autocorrelation on crash incidence during the day. Having used GIS to detect crash hotspots, Mitra, made an attempt to find out the intersection-level variables affecting the concentration of deadly injury crashes using a spatial regression model [38]. The research discovered that the role of spatial dependency is considerably significant when analyzing vehicle-related crash occurrence. Such spatial dependency was helpful for identifying statistically important clusters of crashes involving fatalities or severe/slight injuries.

The relationship between the crash frequency and socio-demographic characteristics of urban residents has been extensively investigated through the application of spatial autocorrelation techniques [39,40]. Safety concern is more serious for more underprivileged social groups and more deprived geographic areas. The areas with lower income level and job opportunity have higher crash rates relatively compared to the wealthy areas [30]. Explanatory variables such as highway length, road network density, and number of different types of vehicles are shown to be influential in crash level at a macro-scale comparison [41]. Numerous studies have found that crash incidence level is affected by roadway type; hence, arterial roads experience higher crash occurrence [42]. What matters are the spatial effects amongst adjacent samples over time or space that make traffic crash exploration complex [43].

It is believed that this matter often disturbs the independency assumption of statistical models. It is probable to have the correlation between one variable at a location and a dissimilar variable at the adjacent positions. Higher similarity shown through spatial arbitrariness suggests spatially-similar clusters in the two variables, whereas more dissimilarity indicates that the two variables are negatively associated [44]. In other words, traffic crash analyses should simultaneously consider the intervention of space and time in order to identify hotspots properly [12,14,24,45,46].

Materials and methods

Case study area

Shiraz, the capital of Fars province – as the case area for this study – is located in south of Iran and has a population of about 1′750′000 based on the report from the Iranian Statistical Centre [47]. The city covers an area of 17′889 ha with population density of 82 people per hectare. Shiraz faces with traffic problems especially with the intra-urban traffic crashes due to considerably increasing motor vehicle ownership and private car users. One of the significant sources of the intra-urban traffic crash growth is the increasing level of vehicle ownership and usage [15] and decrease in the trend of using other modes such as public transport and non-motorized transport by residents.

Furthermore, in Shiraz, urban development has poorly accommodated the requirements of vulnerable road users. Often motorized transport has been supplied, while choices of public transport and non-motorized modes have been rarely paid attention to. Thus, the rapid rate of the urban and population growth in Shiraz has led to the high proportion of traffic congestion throughout the metropolitan area and a growth in the number and severity of motor crashes. Fig. 1 shows Shiraz metropolitan area and its urban road networks consisting of main arterial roads.

Data

In most macroscopic traffic studies and planning processes, traffic data is aggregated and discussed in TAZ level [48]. A TAZ usually consists of one or more census blocks, block groups, or census tracts. As a geographical unit, TAZ represents the spatial location of trip origin and destination. Each TAZ is recognized by some socio-economic and land use properties that help estimation of the potential trip generation or attraction of that zone [49]. Defining TAZ is based on a set of criteria such as socio-demographic attributes and the likely number of trip generation. Since crash data is normally available in macro-level and less assigned to a particular geographic point, as the analysis unit, using TAZ is recommended [50,51].

According to Shiraz Municipality [52], there are 156 TAZs in Shiraz and every TAZ averagely includes about 11,400 residing population. The spatial TAZ border data were gained from the Transportation and Traffic Department of Shiraz Municipality. The land use, road network and population density data was obtained from Shiraz Municipality. The data on vehicle-related crash was obtained from Fars Road Police Database and was then categorized into injuries, fatalities and property damage only (PDO). All these types of data were required to discover the relationships between zone-based traffic crashes and their locational distribution throughout Shiraz metropolitan area as well as determining the similarities and differences among zones in terms of crash type.

Severity index

Severity is defined as the intensity level of property destruction or injury. Although a crash could result in different injuries of varying severity, the word "crash severity" denotes to the most severe injury caused by a crash [22]. Because of the huge difference in social cost among different crash severities, not all crash types can have an equal weighting, particularly where the traffic flow is non-homogeneous. Thus, for improving the accuracy of crash hotspot analysis, the crash severity should be considered since severe crashes are rarely distributed by chance [53–55]. In this study, for identification of the black zone, the severity index of the crashes for each zone is considered as following:

$$\text{Severity index} = \text{PDO} + 3\ \text{injuries} + 9\ \text{fatalities} \tag{1}$$

The weights for the above formula is taken from Iranian Ministry of Road and Urban Planning [56]. The advantage of integrating frequency and severity as offered by Severity Index could moderate the errors generated by not recording of less severe crashes [21].

Spatial autocorrelation

Spatial Clustering is the action of determining consistent groups of objects according to the amounts of their attributes [57]. Knox, defines the spatial cluster as a geographically restricted group of incidences of adequate size and concentration to be improbable to have appeared randomly [58]. Two types of clustering are generally known [59]: a) Global Clustering: providing a single index which sums up the locational pattern of the zone; and b) Local Clustering: analyzing sub-zones to find out whether that area embodies a cluster of low values (a cold spot)

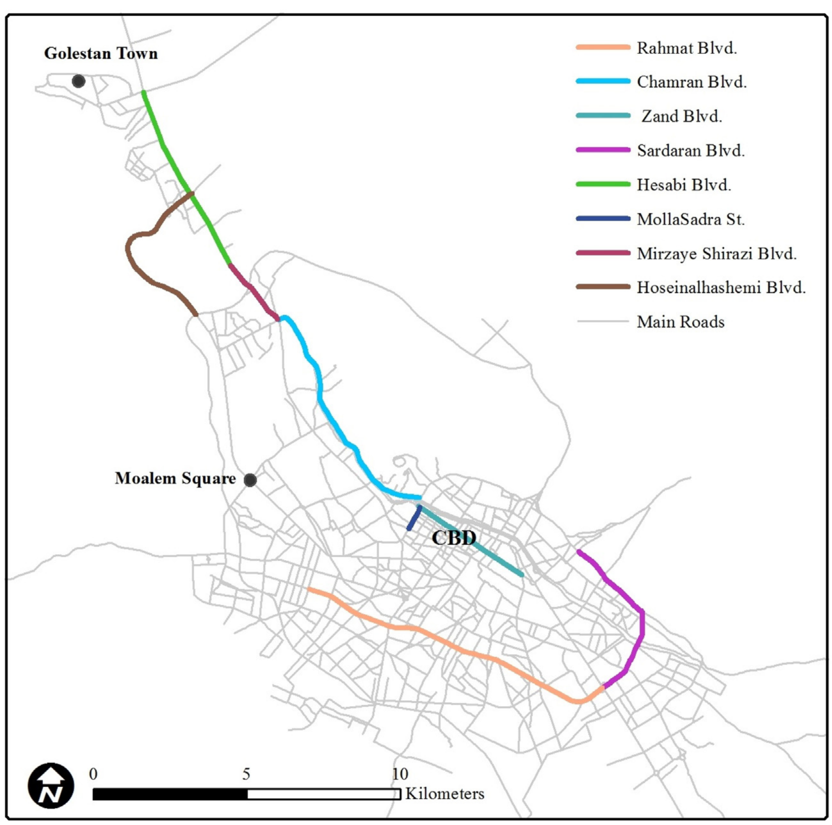

Fig. 1. Shiraz metropolitan area and its urban roads network consisting of main arterial roads.

or high values (a hot spot). Spatial autocorrelation discusses the fact that a variable at a place in space is associated with the value of the same variable in area vicinity [60]. This analysis can be conducted at both local and global levels using Moran's I statistic [61]. The outcome can be shown as two kinds of map including LISA cluster map and LISA significant map [62].

Moran's I statistics

Moran's global and local indices were utilized to determine the spatial concentration of crashes. Since this study discusses the association between spatial concentration and crash type, the following equation for Moran's I is drawn as following [63]:

The spatial pattern of crash data takes account of crash locations and their attribute values simultaneously by integrating the attribute resemblance and location adjacency into the single index of Moran's I [64]. The index can be described as following (Eq. (2)) [37]:

$$I = \frac{N\sum_{i=1}^{N}\sum_{j=1, j\neq 1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^{N}(x_i - \bar{x})^2} \forall_i = 1, \ldots, n \wedge \forall_j = 1, \ldots, n \quad (2)$$

In this formula, W_{ij} represents the elements of a spatial binary contiguity matrix and weights are the neighborhood relationships exist between location i and its adjacent location j,

$S_{0,}$ refers to the summation of all elements of W_{ij},

$x_{i,}$ represents the variable value at a specific location i,

$x_{j,}$ refers to the variable value at another location (i/j),

$\bar{x}$, is the average of the variable, and N is the total location number.

The Moran's I index values vary from −1 to +1. Greater positive values show greater degrees of spatial clustering of similar values, negative values show spatial spreading, and the value of zero shows a random distributed pattern of the feature. The Moran's I index is usually transformed to the Z score with a standard normal distribution (mean = 0, variance = 1). A positive Z score means that the adjacent features have similar values, while a negative Z score shows that the adjacent feature have dissimilar values [65].

The spatial Getis–Ord G_i^* statistic

Getis-Ord G is a technique for cluster analysis which discusses the location-related inclination in the attributes of spatial data [66]. Getis-Ord G can be regarded as the index of hot spot analysis and shows that the high or low values are clustered. Getis-Ord Gi* is a G statistic index. The value of the target feature is involved in analysis, which indicates where cold spots (representing low values clustered in a location) or hot spots (representing high attribute values clustered in a location) appear in the area. Hot spot appears where a feature has a high/low Z-score value; and it is bounded by the other features with high/low Z-score values. The G_i^* statistic is computed as following:

$$G_i^* = \frac{\sum_{j=1} w_{ij}x_j}{\sum_{j=1} x_j} \quad (3)$$

In this formula, G_i^* refers to the spatial autocorrelation statistic of an event i over n events. x_j refers to the value of the variable x at event j over all n events. G_i^* statistic is assumed to have the normal distribution. The output of the G_i^* function is a Z-score for every feature. The corresponding Z-score represents the statistical significance clustering features with either low or high values for a specific proximity. The subsequent Z-scores focus on the cluster areas spatially where the features have either low or high values. This measure works by observing each feature within the framework of adjacent features. Basically, the standardized G_i^* is a Z-score and is linked to statistical significance as following:

$$Z(G_i^*) = \frac{\sum_{j=1}^{n} w_{ij}x_j - \bar{x} - \sum_{j=1}^{n} w_{ij}^2}{s\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}} \quad (4)$$

The G_i^* statistic output is a map for spatial clusters location. Where the value of G_i^* is positive, high values are spatially dependent. In contrast, a negative value of G_i^* refers to the spatial dependence among low values. The confidence level and Z-score are signs of statistical significance and explain whether a feature belongs to a cold spot or hot spot or an outlier.

Four situations are recognized through LISA: 1) a cluster of zones with high–high rates, 2) a cluster of zones with high–low rates, 3) a cluster of zones with low–high rates, and 4) a cluster of zones with low–low rates. The selected objects show the significant zones with a significance level of 95% determined as a cluster with G_i^* statistic.

Comap

The Comap is a visualization technique allowing the discovery of spatial link between two geographically-based variables through conditional distribution patterns [67,68]. The Comap method is suitable for underlining differences in a traffic crash pattern using 'small multiples' of diagrams [69]. The time dimension can be divided into a group of time intervals and a spatial pattern can be then analyzed and explained for each time interval. For instance, Asgary et al. [70] applied the Comap technique in order for showing how distribution of fire incidents in Toronto, Canada have been changed over time.

Comap can subdivide crash data by the location and occurrence time. It can demonstrate spatial distribution variations of traffic crashes over time in a single visualization in order to explore time and location dependence [14]. In this study, Comap was applied to explain how the spatial distribution of crashes could change over time. The time scale level in this analysis is hour; thus, the temporal variations in the spatial distribution of crashes were investigated regarding to the different time of the day.

Result

Crash trend

In overall, car crashes have decreased over the studied period throughout metropolitan Shiraz area. Fig. 2 shows the total number of reported vehicle crashes with their severity level from 2010 to 2014. This figure includes only the reported crashes by police authority occurred on public roadway. The annual total, annual fatal and annual PDO crashes have declined between 2010 and 2014, but annual injury crashes have increased slightly at the same period.

Temporal distribution

On Fig. 3 the temporal distribution of crash type for the case study area during 2010 and 2014 is shown. From the spider plots (Fig. 3), PDOs were more probable to occur during the daytime whereas the lighting state were fine, while fatalities frequently occur during night time. In contrast, more injuries were probable to happen during the day, especially from 12 PM to 20 PM. It is evident that there are discrepancies in the distribution of crashes during the day. For instance, it is clear that the PDOs progressively increase from 8 AM to 14 PM, and clusters of PDOs appear at the northwest zones such as CBD area, *Chamran* road and *Golestan* town.

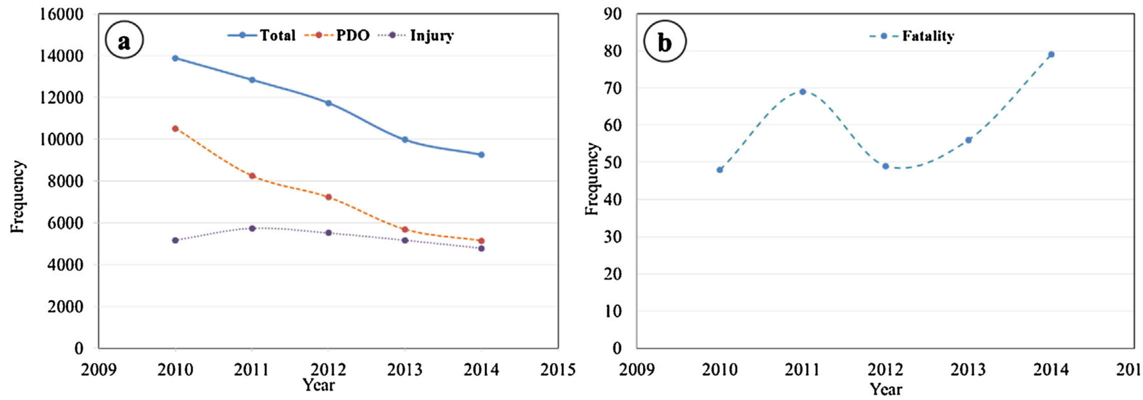

Fig. 2. Crash frequency trend in Shiraz from 2010 to 2014; a) total, PDO and injury crashes, b) fatality crashes.

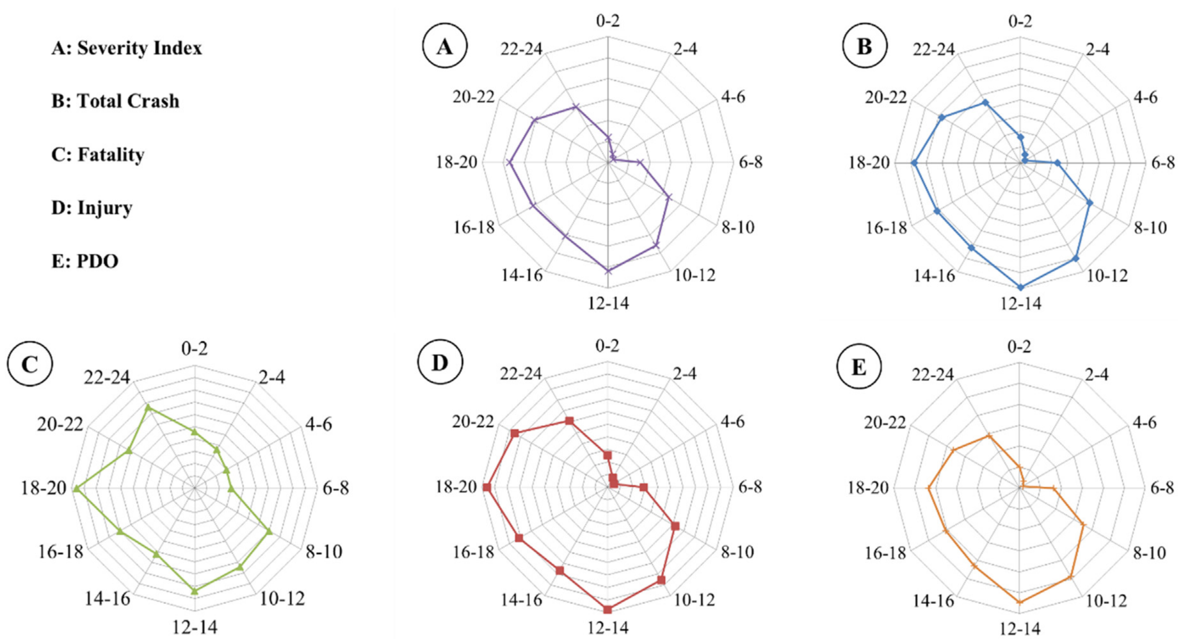

Fig. 3. The temporal distribution of different crashes.

Injuries have similar distribution pattern but their peak is between 6 PM and 8 PM. The hotspots appear at the northwest and the south during AM peak, but they partially are moving to city centre (*MolaSadra* Street and *Zand* Street) where evening social activities are concentrated.

Fatality crash does not show the same pattern of clustering as PDO or injury crash. It has a sharp increase from 6 AM to 10 AM during the day; then it is followed by a slow increase until 14 PM. It increases between 16 PM and 20 PM. It is evidently clustered during morning time in the northwestern part of the city, (Moalem Square) but moved to CBD area from 18 PM to 20 PM.

Hotspot analysis

Crash hot zones detection results in a list of areas which are prioritized for more in-depth explorations which may recognize crash patterns, causative factors, and potential policy and actions [24]. Three types of car crashes were studied and depicted on Moran I scatter plot: fatality, injury, PDO, in total and severity indices. The purpose was to determine whether these main crash types show a cluster, diffusion, or arbitrary distribution inside high risk zones of the studied area or not. Table 1 shows the Moran Statistic based on the crash type and its occurrence time. The Moran I value of 0.27 and Z-score of 11.1 ($p < 0.01$) for crash distribution confirms the clustered pattern and its autocorrelation. Note that Moran's index was based on location closeness and their attribute matches. The index was computed using straight-line distance and a confidence coefficient of 95% given the assumption of a normal distribution. The statistical importance of the global and local Moran's I according to their corresponding Z-scores showed that the spatial autocorrelation occurs in the zonal variables. The values of global Moran's I for all other variables except for "fatality frequency between 00:00 and 24:00," ranged between 0.18 and 0.30 (Z-score ranged 7.23 to 12.18) showing clustered spatial alignment at the significance level of 0.01.

The global Moran's I is the mean of the local Moran statistics. The local indices of spatial correlation (LISA) maps were generated and depicted for better clarification of the spatial clusters of traffic crashes (Fig. 4). In the figure, two LISA cluster maps are shown for each type of crashes, showing the positions of significant Local

Table 1
The Global Moran's I for crash frequencies in time of day to crash type.

Crash Type	Time of day		Moran's I	Z	P-value	Spatial Distribution
Total Crashes	00:00–24:00		0.27	11.1	0.01	Absolutely clustered
	AM	00:00–02:00	0.24	9.82	0.01	
		02:00–04:00	0.18	7.76	0.01	
		04:00–06:00	0.11	4.73	0.01	
		06:00–08:00	0.16	6.63	0.01	
		08:00–10:00	0.24	9.95	0.01	
		10:00–12:00	0.22	9.11	0.01	
	PM	12:00–14:00	0.26	10.58	0.01	
		14:00–16:00	0.24	9.77	0.01	
		16:00–18:00	0.29	11.73	0.01	
		18:00–20:00	0.28	11.55	0.01	
		20:00–22:00	0.29	11.95	0.01	
		22:00–24:00	0.27	11.26	0.01	
PDO	00:00–24:00		0.30	12.18	0.01	
Injury			0.18	7.23	0.01	
Fatality			0.04	1.98	0.05	Fairly clustered
Severity Index			0.24	9.7	0.01	Absolutely clustered

Moran's I statistics and classified by peak occurrence time period included 12:00–14:00 PM; 18:00-20:00 PM and the whole day (00:00-24:00).

The dark blue and dark red locations show spatial clusters (high enclosed by high, and low enclosed by low, respectively). In contrast, the light blue and light red indicate spatial outliers (high enclosed by low, and low enclosed by high, respectively). The matching significance map is shown in the right panel of each cluster/outlier map. Significance ($0.01 < p < 0.05$) is represented by darker shades of yellow, while the darkest matches to $p < 0.01$. It is obvious that the tighter significance standard excludes a few locations from the map.

Four sections of this scatter plot conform to two different kinds of spatial correlation. TAZs with local Moran I statistic in the upper right and lower left sections in the scatter plot were respectively characterized by the high–high and low–low type associations in each map. Instead, low-high and high-low associations embody negative spatial association or spatial spreading. The zones having local Moran value in their lower right and upper left sections were respectively shown as high-low and low–high types' correlation in each map. This means that the spatial cluster is linked to high–high patterns.

G statistics were used to determine the clustering of all types of crashes within 24 h. G statistics for the whole crashes are equal to zero which shows the presence of the clustering. The Getis Ord G* and it's associated Gi* Z score are used here for identifying hot and cold spots. A high positive value for a Gi* Z score means that a hotspot is encompassed in an area of a statistically significant cluster. Similarly, negative value of Gi* Z score shows a cold spot within proximity of a statistically significant cluster. Hot spots and cold spots with P-values less than 0.05 show a likelihood less than 5% of randomization; thus, confirming statistical significance (Fig. 5). Based on context knowledge and according to Figs. 4 and 5, the risky zones are identified as following (Table 2). There are four highways in Shiraz, acting as traffic passageways joining several urban areas; and these highways are non-homogeneous in terms of the traffic condition and road geometry. Details are discussed in the next section.

Discussion and conclusion

This paper studied traffic crash patterns at TAZ level in Shiraz in order to identify hotspots respected to time and to compare the identified hotspots in terms of crash type and severity index using spatial autocorrelation methods. Spatial statistic methods were applied for realizing the spatial variation of crashes over a definite time interval and comparing hotspots of crashes based on their type and severity index over TAZ and time, and thereby improving the identification of hazardous zones and time dependence.

Broadly speaking, the result of this study confirmed that hotspots generally appeared on arterial roadway which tend to have higher car speed/volume and more travel lanes (multi-lane roadway). The analysis showed that the majority of crashes occurred in a number of specific zones encompassing major arterial roads and specific urban activity centers. The results indicated that there were two critical areas in Shiraz requiring much more attention in safety plans. These are north-west fringe as the growing district and the main junction zone in the west that connects northwestern area to the central district and the other zones. This is in line with some other studies such as Flahaut [71] which found that physical environment and network configuration play a significant role in defining crash hotspots. Similarly, Wang and Kockelman, discovered that a higher mix of residences and commercial land uses is correlated with greater crash risk for residents [72].

The map also showed that those zones located at intersections that connect the other zones to each other were determined as clusters with high crash rates. Neighboring features have similar values. In Figs. 4 and 5, it is evident that there are four main risky corridors in Shiraz metropolitan area including north-west, *Rahmat* Blvd., south *Chamran* Blvd., and east *Sardaran* Blvd. However, each of these zones has different crash clustering pattern based on its road configuration or surrounding land use characteristics. Vehicle-related fatal crash clusters along arterials and relevant zones consist of network intersections that have cluster of fatal crashes. Arterial roads such as *Rahmat* Blvd and *Chamran* Blvd are characterized by their large number of motor vehicle. Previous studies confirmed that more vehicle lanes are associated with greater likelihood of crash occurrence [28,73]. The presence of recreational facilities and schools along arterials such as *Mirzaye Shirazi* and *Rahmat Blvd* are shown to be associated with crash occurrence [74].

The central district of Shiraz was recognized as a cluster with low–low rates probably because of its lower median speed of traffic flow. This contradicts the findings of Erdogan who found crash rates in urban areas higher than their counterparts in other areas [41]. In Shiraz, this trend is obvious for corridors connecting central district to the growing zones in the west (e.g. *Mirzaye Shirazi* Blvd.). On the other hand, CBDs have more pedestrian-vehicle collisions [75]. Road sections located in commercial areas

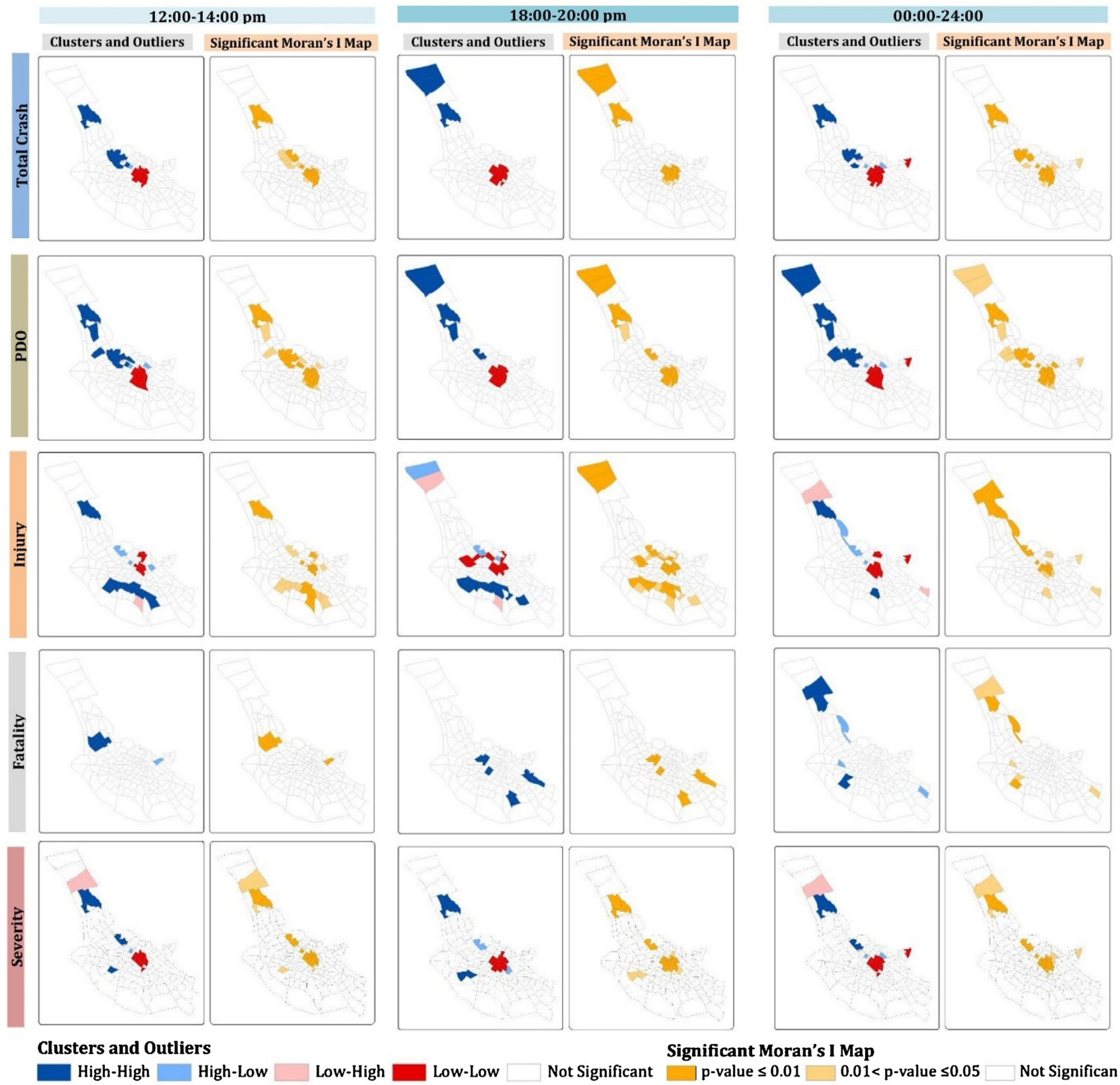

Fig. 4. The local indicators of spatial autocorrelation; cluster maps and significance maps.

(like CBD area) where a high percent of pedestrians appears are associated with a higher frequency of PDO crash occurrence due to the higher traffic congestion and the lower level of service (LOS). The hot spot zones are normally associated with the presence of the main trip generators such as hospitals, university education centers, shopping centers, etc. [76].

Higher crash rate and crash clustering in *Golestan* town show that suburban roadways are more risky for residents compared to the urban areas. This finding is similar to Ewing et al. [77] regarding to the correlation between urban sprawl and deadly crash rates. The explanation for this is probable because of the greater traffic speeds and many kilometers of driving in low-density fragmented areas for vehicle. Furthermore, increasing road capacity through opening new routes such as *Hosein-al-Hashemi* ring road (connecting *Golestan* Town to the western area) expanded the capacity and reduced traffic congestion; but, on the other hand, it has generated additional travel. One consequence of induced travel is imposing crashes due to higher speed and freer movement for drivers [78].

The existence of four-leg or three-leg intersections along *Chamran* Blvd., and *Rahmat* Blvd. potentially makes them risky for pedestrian crashes. This is in line with the work of Dumbaugh and Li [79]. In addition, poor lighting and darkness are the other factors affecting the rate of crash occurrence [80–83]. This is evident for those crashes occurred along these two roads at late evening. Intersections are spaces of high reciprocal actions between people and vehicle traffic. In addition, a crossroad may encounter high volumes of pedestrian passing the roads. This augments the probability of pedestrian related crashes occurred in crossroads [65]. In their research, Carter and Council, discovered that in urban areas approximately 40% of pedestrian crashes relates to intersection [84]. Higher volume of vehicle and pedestrian is

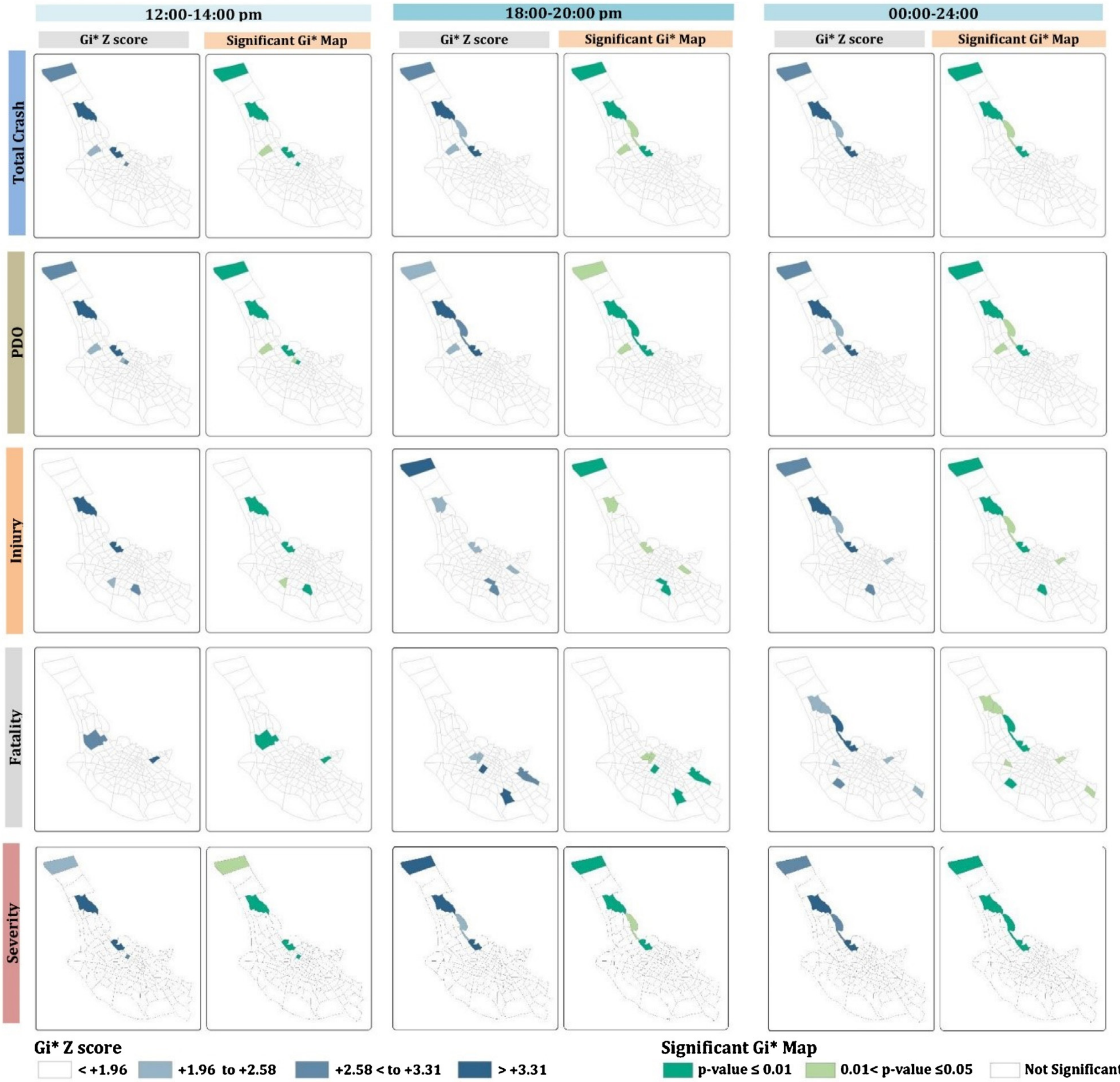

Fig. 5. The G_i^* Z Score and its significance level maps.

Table 2
Risky zones of the study area based on hotspot analysis.

Zone characterized by	Example	Total			PDO			Injury			Fatality			Severity Index		
		Peak AM	Peak PM	Whole Day	Peak AM	Peak PM	Whole Day	Peak AM	Peak PM	Whole Day	Peak AM	Peak PM	Whole Day	Peak AM	Peak PM	Whole Day
Road with high speed and non-homogeneous traffic flow	Rahmat Blvd.							✓	✓	✓		✓	✓	✓	✓	
High number of intersections	Mirzaye Shirazi Blvd.	✓	✓	✓		✓	✓	✓		✓			✓	✓	✓	✓
Inconsistency between road functional and the land use of adjacent environment	Chamran Blvd.	✓	✓	✓	✓	✓	✓	✓		✓				✓	✓	✓
Suburban and sprawled regions delaminated by highway road	Golestan Town		✓			✓	✓		✓							
Conflict between vehicle traffic and pedestrian flow	MolaSadra St. (CBD)	✓		✓	✓		✓					✓				

✓ = Identified as hotspot.

associated with greater probability of crashes at the uncontrolled crossings and intersections, especially in high-speed road as discussed by scholars such as Xu et al. [85]; Rosén et al. [86]; Tefft [87]; and Kröyer [88]. Therefore, to reduce future frequency of traffic crashes, TAZs with greater density of intersections must be taken into particular consideration.

This study was successful to identify the hotspot areas which require more attention in safety planning and budget allocation. In fact, the results could be as a way to plan strategies and regulations in the field of safety management in order to prevent from vehicle-related crashes. It is obvious that the patterns of different crash types in Shiraz vary in time and location, therefore a range of road safety rules and policies would be suitable.

Limitations and future research

Further research is needed to fully identify the spatial patterns of crash occurrence especially at outliers. There are several factors causing crash occurrence such as poor driving skill, inappropriate behavior of the users of transportation system, weather conditions, and improper design and configuration of roads. In order to classify crashes more carefully, both geometric and engineering attributes of roadway as well as behavioral and demographic characteristics should be considered. In fact, classifying is recommended based on the type of movement, crash location and socio-demographics. This study can be extended to explore how the characteristics of physical environment such as urban design, density, and land use diversity affect the movement patterns and consequently crash along the roads. A more in-depth study of driver and pedestrian's behavior is required to understand the real factors associated with crash occurrence in Shiraz. This study classified the crashes based on severity and categorized them regarding to the time of occurrence and relevant zone. Deeper classification is possible through qualitative research based on reviewing the police crash narratives. Micro–level research can be undertaken using additional information on demographic road design characteristics and the other environmental factors in order to discover the real causes of crashes in the case study area. This paper explored the crashes reported between 2010 and 2014; only those crashes that involved a motor vehicle. In fact, other types of collision were not included. The data also do not include crashes occurred in private spaces e.g. parking lots which are absent in the police authority report. The other limitation is that the unit of analysis was the crash aggregated at TAZ level. Considering that the behavior involved in crashes could lead to behavioral analysis in detail and considering socio-demographic characteristics, the data used for this study had its own limitations. Only instantaneous deaths/injuries reported on scene were recorded by the police authority; this means that the record does not include fatalities/injuries on the way to the medical centers or during hospital care. Therefore, it is required to consider hospital-based data in order to identify the real rate of crash-related death/injury. The analysis referred to the past four years and conditions which no longer exist due to the road safety actions taken within recent years.

Disclosure statement

The authors have no conflict of interest.

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