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GIS-based spatiotemporal analysis for road traffic crashes; in support of sustainable transportation Planning

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ABSTRACT

Road traffic crashes pose a significant challenge worldwide, necessitating increased efforts to reduce them and promote sustainable transport systems. This study aimed to investigate spatiotemporal road traffic crashes and their causes in the State of Qatar by identifying hot spots of crashs and exploring whether they were primiarly attributed to behavioural practices and/or the geometrical design of roads and intersections. The study employed various methods, including Time-Space Cube analysis, Geographically Weighted Regression (GWR), Emerging Hot Spot analysis, and Spatial Autocorrelation analysis, with historical traffic crash data from 2015 and 2019. The findings indicated that crashes were mainly concentrated in the central-eastern region of Qatar and are related to driver behaviour. The analysis also revealed that crashes during the weekdays in 2019 were more strongly clustered than in 2015, suggesting a probable systematic cause of crashes. The results provide valuable information for policymakers to target high-incidence locations, prioritize interventions and develop more effective measures and policies to reduce crashs and promote a sustainable transportation system in Qatar. Overall, this study highlights the importance of continued research and policy development in this area and could potentially be applicable and transferable to similar regions.

1. Introduction

Road crashes are significant global issue, leading to thousands of human fatalities and injuriesand incurring substantial human and material costs. In order to reduce the number of road traffic crashes and resulting human fatalities and injuries, many countries implemented different traffic and road safety practices (Abdel-Aty et al.; Abulibdeh, 2022). Road crashes injuries cost many countries huge economic losses – estimated at 1% – 5% of their Gross Domestic Product (GDP) annually. According to the World Health Organization (WHO), road crashes are the leading cause of death among children and young people worldwide (Chen et al., 2019).

The United Nations (UN) has included road safety in its Sustainable Development Goals with two targets: 1) to halve global deaths and injuries from road traffic crashes by 2030, and 2) to provide access to safe, affordable, and sustainable transport systems for all. The Second Decade of Action for Road Safety 2021–2030 aims to reduce road traffic deaths and injuries by at least 50% through a Safe Systems framework based on the Vision Zero approach. Although human error is inevitable, the Safe Systems framework provides multiple levels of protection to create a "forgiving" system and prevent severe outcomes (Rossi et al., 2019).

Qatar formulated its National Road Safety Strategy 2013–2022 based on the UN Global Plan for the Decade of Action. The strategy aimed to provide "a safe and sustainable road transport system that protects all road users from death and serious injury". It set a target of reducing its annual number of road crash fatalities and serious injuries by half to 130 and 300 respectively by 2022 (Chen et al., 2019). To achieve the road safety targets, Qatar's Road Safety Action Plan provides set of initiatives or projects to be implemented by stakeholders over five years (Consunji et al., 2018).

In accordance with the recommendations of the UN Decade of Action, Qatar established a National Traffic Safety Committee to coordinate and monitor the road safety-related activities of all the stakeholders. However, the implementation of road safety interventions

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Table 1
Transport Mode Share (Source: MoTC).

Nationality & Day of Week	Mode of Travel							
	Car Driver	Car Passenger	School Bus	Company Bus	Taxi	Public Bus	Walk	Other
Citizen Weekday	49.9%	41.8%	4.6%	0.2%	0.2%	0.0%	2.8%	0.5%
Citizen Weekend	45.9%	46.2%	0.2%	0.0%	0.1%	0.0%	7.3%	0.3%
Resident Weekday	49.0%	24.5%	9.8%	5.4%	2.5%	0.3%	7.1%	1.4%
Resident Weekend	43.2%	39.0%	1.5%	2.3%	2.8%	0.4%	9.8%	1.0%

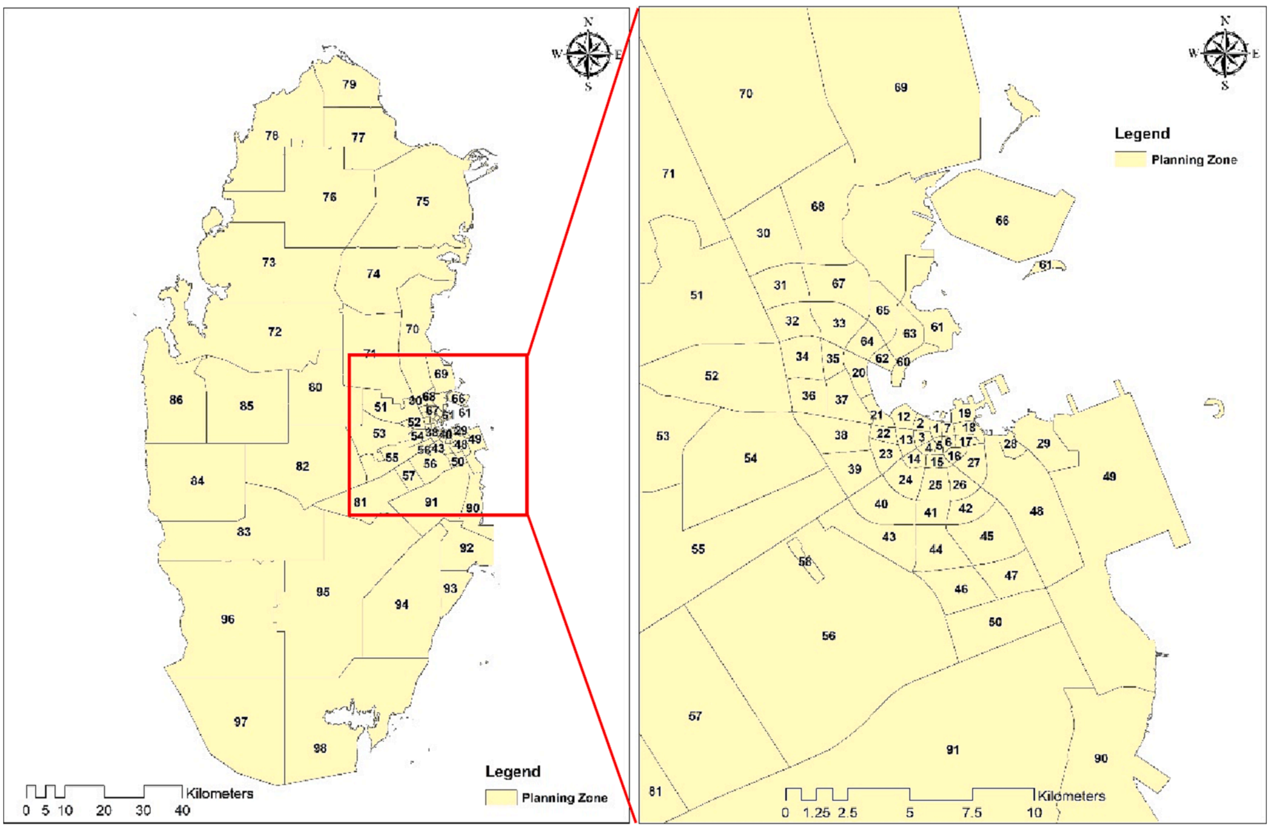


Fig. 1. Municipal zonal boundaries of the country.

Table 2
Road crash frequency 2015–2019 and the percentage change during the period.

Police-Reported Motor Vehicle Traffic Crashes						
	2015	**2016**	**2017**	**2018**	**2019**	**% Change (2015, 2019)**
Fatal	194	155	159	154	134	−31%
Serious	548	666	579	530	608	11%
Slight	5,129	5,284	5,319	5,474	5,805	13%
Total	**5,871**	**6,105**	**6,057**	**6,158**	**6,547**	12%
Police-Reported Motor Vehicle Traffic Crashes Casualties						
Fatality	227	178	177	168	154	–32%
Serious Injury	693	871	742	683	778	12%
Slight Injury	7,488	8,028	7,962	8,116	8396	12%
Total	**8,408**	**9,077**	**8,881**	**8,967**	**9,328**	11%
Other National Statistics						
Vehicle Kilometers Traveled (VKT) (in millions)	30,936	33,097	34,818	36,306	43,593	41%
Resident Population	2,335,068	2,520,621	2,614,626	2,662,845	2,712,959	16%
Registered Vehicles	1,352,979	1,447,478	1,522,733	1,587,815	1,655,676	22%
Licensed Drivers	1,234,350	1,340,271	1,441,594	1,538,407	1,625,339	32%

by various stakeholders may be affected by competing and short-term focused objectives. In addition, there is limited understanding of the full transport-related risks and harms, particularly at larger spatial and temporal scales, which exacerbates the situation.

Road crashes vary spatially and temporally (Ziakopoulos and Yannis, 2020); (Loo and Anderson,). Therefore, it is important to consider spatial dependence and heterogeneity in investigating the effects of road safety and suatainable transporation systems variables and attributes on

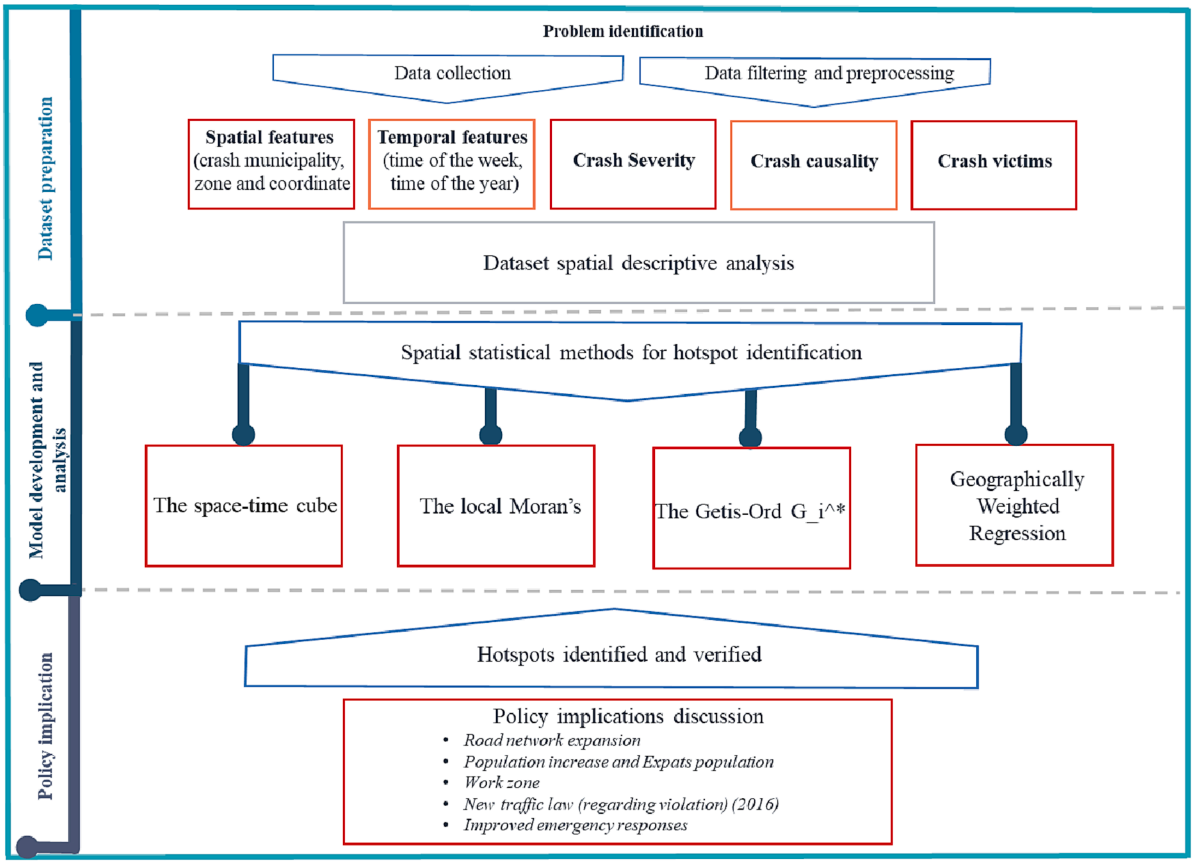


Fig. 2. Research methodology outline.

Table 3
Variable used for spatiotemporal analysis of crashes.

Variables	Description (Values)
Year	Year of crash
CrashSeverity	Severity of the crash; Fatal, Serious, Minor
Date	Date of the crash in the Gregorian Calendar
DayofWeek	Day of the week; Sun, Mon, Tue, Wed, Thu, Fri, Sat
CauseCrash	Police reported the cause of the crash
Municipality	Municipality where the crash occurred
Zone	Zone number of where the crash occurred
Driver_Fatality	Total number of driver fatalities during the crash
Passenger_Fatality	Total number of passenger fatalities during the crash
Pedestrian_Fatality	Total number of pedestrian fatalities during the crash
Driver_SeriousInjury	Total number of driver seriously injured during the crash
Passenger_SeriousInjury	Total number of passenger seriously injured during the crash
Pedestrian_Serious Injury	Total number of pedestrian seriously injured during the crash

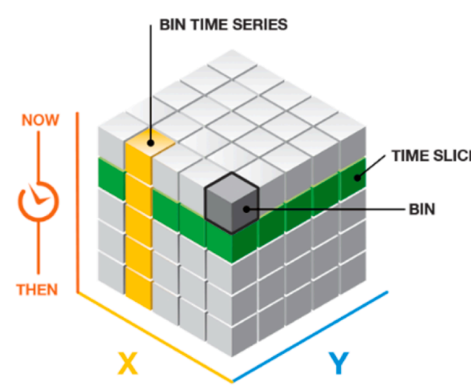


Fig. 3. Diagram of Space-time cubes. (ESRI, 2023) https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/learnmor-ecreatecube.htm#ESRI_SECTION2_4518F0A12E194690AA986118D508E9F7.

specific areas and how neighboring areas may influence them. Additionally, understanding the evolution of traffic crashes and identifying hotspots is crucial for achieving traffic safety and informing transportation planning, resource allocation, decision making, and policy implications. However, road safety interventions are often limited to technical specialists who may be shaped by their cultural and institutional contexts. This may result in the prioritization of conventional practices, such as road network expansion, over effective measures to reduce crash risk, such as travel demand management. To address this issue, it is important to foster a multidisciplinary and collaborative approach to road safety that takes into account the social, economic, and environmental factors that influence road use and traffic crashes. This can help ensure that interventions are evidence-based, context-sensitive, and effective in achieving their intended goals.

Properly designed and constructed road infrastructure is critical to the safe and efficient transportation of goods and people. Properly designed and constructed roads can significantly reduce the number of accidents and fatalities on the roads (Alarifi et al., 2018; Alharbi et al., 2022). Well-designed and constructed road infrastructure is essential for ensuring road safety (Mannering and Bhat, 2014). It can significantly reduce the risk of accidents, injuries, and fatalities on the road, and provide safe and accessible facilities for all road users. For example, well-designed roadways can reduce driver confusion, provide clear guidance to drivers, and prevent accidents caused by inadequate or

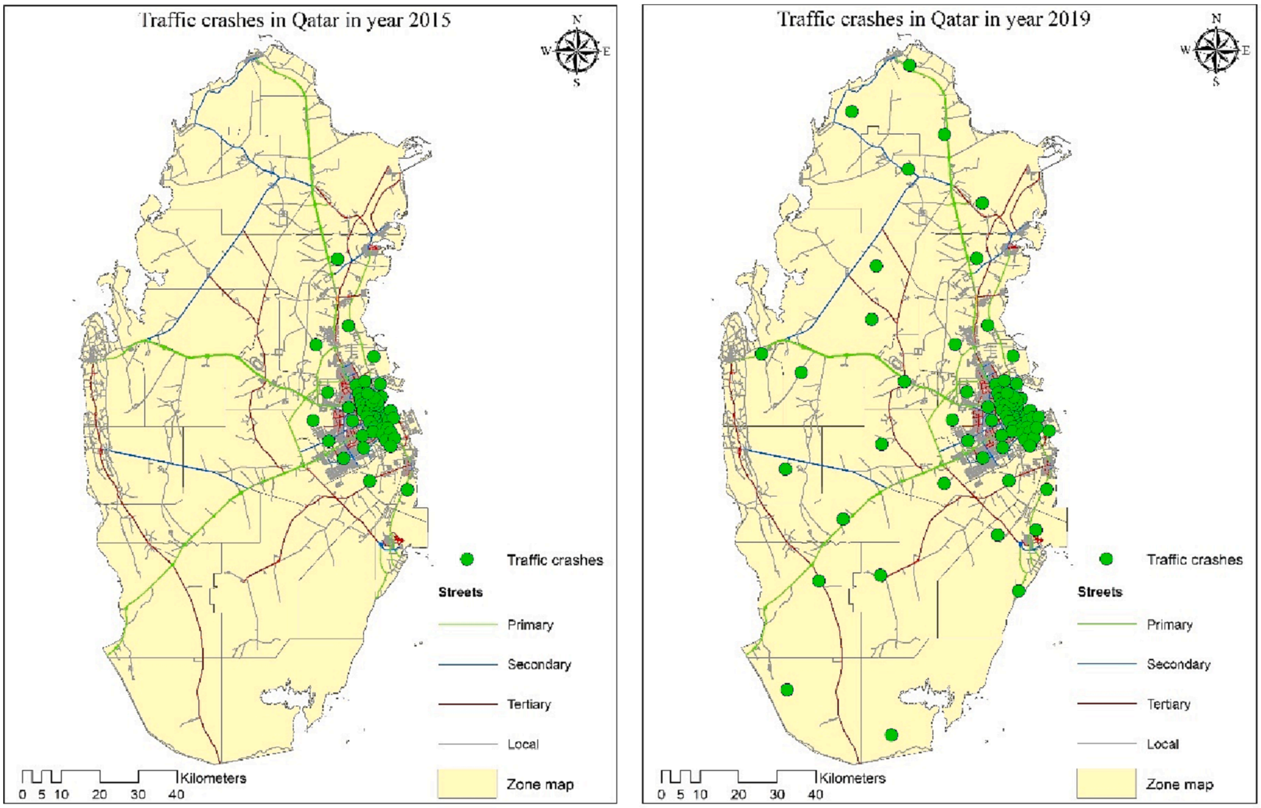


Fig. 4. The study area shows traffic crashes distribution in Qatar in 2015 and 2019.

unclear road markings and signs.

Addressing road safety is a complex and multi-faceted policy issue that requires more attention Despite previous studies on road traffic crashes in Qatar, there has been a lack of emphasis on the spatial dimension of the phenomenon. Therefore, this study aims to analyze the spatial and temporal evolution of road traffic crashs in order to identify the emerging, intensifying, diminishing, consecutive, sporadic, and persistent hot spots over time and space. The study also seeks to investigate geographical patterns of these crashes at a zonal level as well as their causes. By taking into account the spatial and temporal variation of road traffic crashes, the study intends to inform the prioritization of interventions for more effective allocation of resources and to facilitate the integration of road safety measures with other urban transport policies. The results of this study will be useful for the National Traffic Safety Committee and other similar agencies with multiple stakeholders, as they can use them to formulate well-targeted action plans, and monitor and evaluate their effectiveness in tackiling road safety issues. All the crashes considered in this study are presented in absolute numbers rather than rates, in line with Qatar's targets.

2. Literature review

Traffic crashes and road safety have the potential to severely restrict the economic and social development of many countries. Several studies have been conducted to explore the risk factors associated with road safety and road crashes (Al-Kindi et al., 2020; Al-Mistarehi et al., 2022; Amoh-Gyimah et al.; Atubi, 2012; Balakrishnan et al., 2023) and road safety measures (Bao et al., 2017; Benlagha and Charfeddine, 2020; Bina et al., 2021; Brunsdon et al., 1996). Furthermore, these studies have employed or developed a variety of spatial and mathematical methodologies to examine crash analysis and predict the causes of crash, mitigation, and road safety site prioritization problems (Bu et al., 2018; Cai et al., 2019; Cai et al., 2019). The spatial analysis of traffic crashes encompasses a wide range of topics such as identifying clustering patterns of traffic collisions, mapping, and visualization of crash counts, investigating the effects of risk factors, and recommending targeted countermeasures. Factors, such as the local environment, the road segment environment (urban and rural segments), and road infrastructure (Wang et al., 2016); (Flahaut, 2004) are critical contributores to the occurrence of traffic crashes.

2.1. Spatial units of analyzing crashs

Studies on traffic crashes and road safety have explored various spatial units of analysis, ranging from community size (Chen et al., 2019a; Cheng et al., 2019b; Daniels et al., 2019) to state level (Atubi, 2012), with studies investigating different road safety indicators such as crash counts, crash rates, and injury severity rates. Spatial units used in such studies include road segments, road intersections, zonal units, and regional areas such as counties (El-Basyouny and Sayed, 2009; Elvik, 2021; Erdogan, 2009), cities (Moeinaddini et al., 2014), and metropolitan areas (Bu et al., 2018). Early approaches to spatial analysis in investigating traffic crashes and road safety focused on straight road segments and intersections with researchers seeking to understand visual patterns of heightened concentration or investigate the impact of segments on crash counts and density (Page and Meyer, 1996; Thomas, 1996). Intersections are significant contributers to the number of traffic crashes, with intersection location, size, geometry, and traffic parameters all playing significant roles (Ghofrani et al., 2022; Gilardi et al., 2020; Gomes et al., 2017; Guo et al., 2010).

Zonal units, including census-based, traffic-based, or administrative-based boundaries (Ziakopoulos and Yannis, 2020; Huang et al., 2010; Huang et al., 2020; Jonathan et al., 2016; Kang et al., 2018; Kang et al., 2020); have also been used as spatial units in investigating traffic crashes and road safety. Traffic Analysis Zones (TAZs) are traffic-related zone systems that have been created in the US and used in many countries to collect trip and traffic statistics and data. Zonal factors, such as Vehicle Miles Traveled (VMT), can be shared by both segments and

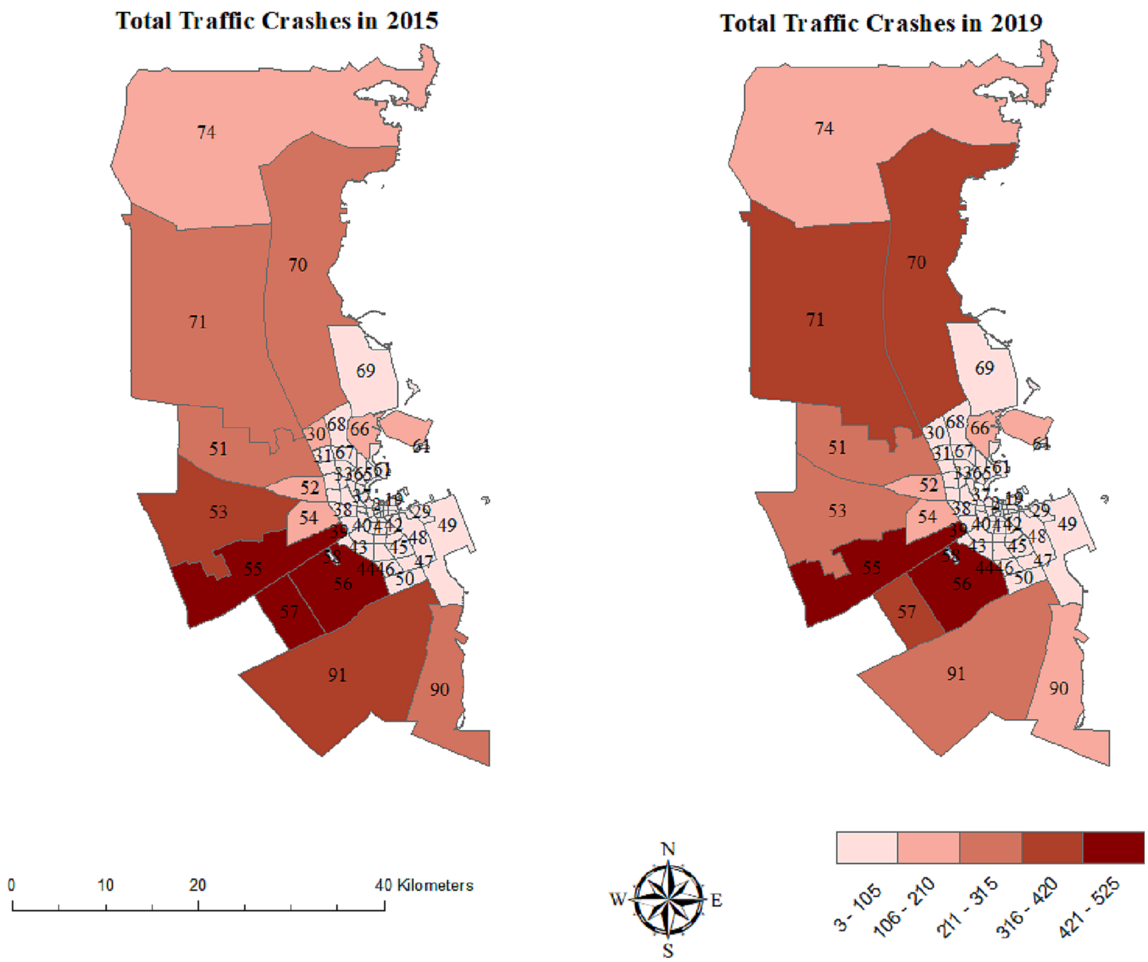


Fig. 5. Distribution of crashes at zone level.

intersections within the same zone (Ziakopoulos and Yannis, 2020; Guo et al., 2010; Xie et al., 2013). At the zonal level, both observed and unobserved heterogeneity can influence crash frequency at intersections and segments within these zones (Lee et al., 2017; Kim et al., 2017; Lascala et al., 2001; LaScala et al., 2004; Lee and Abdel-Aty, 2018).

Some studies have integrated different spatial units in investigating traffic crashes and road safety, while others (Lee et al., 2017) have used a more rigid ruleset of spatial units, such as fixed-distance grid structures and multiple grid sizes (Cai et al., 2018; Cai et al., 2019). However, relying on a single spatial unit might be improper for certain areas depending on the spatial distributions of safety-related parameters (Zeng and Huang, 2014; Alarifi et al., 2018). It is crucial to understand the strength and limitation of each spatial unit in conducting effective analysese and developing targeted interventions to improve raod safety (Kim et al., 2006; Ossenbruggen et al., 2009). The choice of spatial unit in investigating traffic crashes and road safety varies, with different units offering different insights.

2.2. Geospatial statistical models to investigate crashs

Various spatial modeling approaches have been utilized to investigate spatial traffic crashes and road safety. Furthermore, several tools have been developed and applied to predict spatial traffic crashes and road safety indicators (Mannering and Bhat, 2014; Mansour et al., 2022; Martínez-Ruiz et al., 2013; Miaou and Lord, 2003). These models and tools investigate spatial correlation and unobserved heterogeneity. Different geospatial statistical models have been used to examine the spatial autocorrelation or heterogeneity of the factors that contribute to traffic crashes and road safety. These models include Getis-Ord-Gi*, Generalized Linear Models (GLMs), Moran's I, and Geographically

Table 4
Overview of the number of crashes, fatalities, and serious injuries, in the zones with the highest crashes numbers in 2015 and 2019.

Variable		Number crashes	Number of fatalities	Number of serious injuries
2015	Zone 55	391	34	35
	Zone 56	478	28	48
	Zone 57	452	19	77
	Zone 71	234	17	43
	Zone 70	215	21	37
2019	Zone 55	524	11	37
	Zone 56	470	10	49
	Zone 57	334	4	56
	Zone 71	319	10	51
	Zone 70	332	13	69

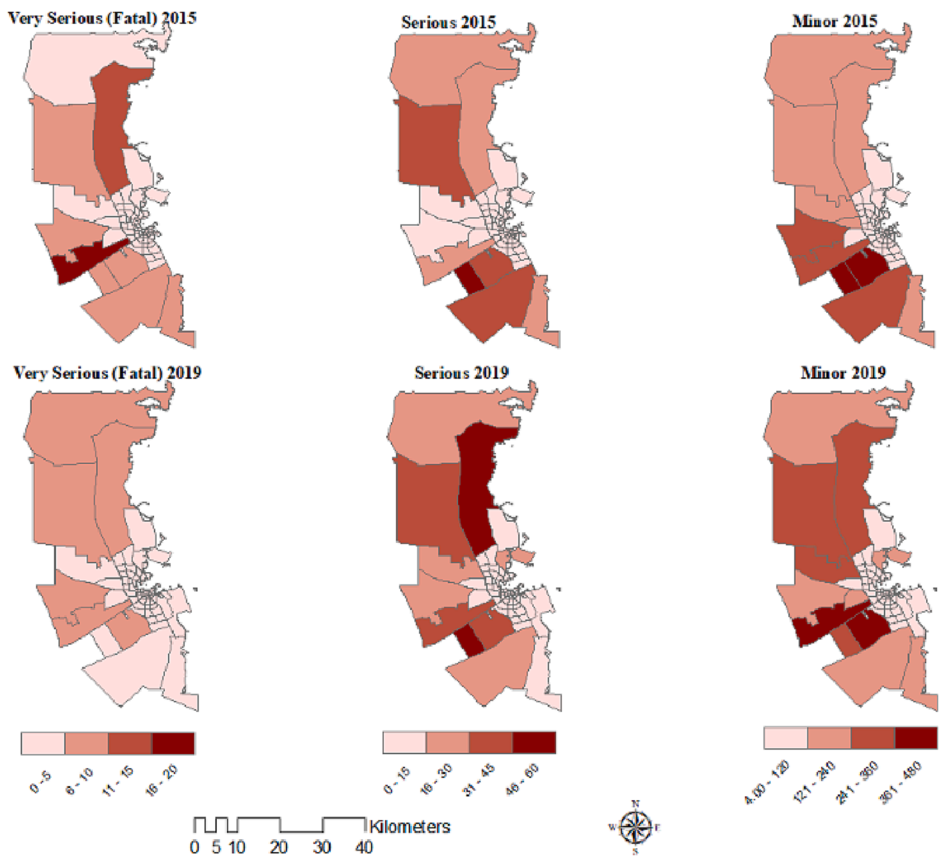


Fig. 6. Distribution of severity of crashes in 2015 and 2019.

Weighted Regression (GWR), conditional autoregressive priors (CAR) models Local and Global Moran's I statistics (Moeinaddini et al., 2014; Mollalo et al., 2020; Noland and Quddus, 2004), autoregressive priors (SAR) models (Quddus, 2008; Zeng and Huang, 2014; Gilardi et al., 2020) among others. GLMs models, for example, were used because they assume that crashes are random, independent, and sporadic countable events (El-Basyouny and Sayed, 2009). GWR was used to investigate traffic crashes because this method considers spatial variations of explanatory variables on traffic crashes, adding descriptive and explanatory power to the spatial analysis and providing intuitive results (Pirdavani et al., 2014).

2.3. Crash hotspots analysis

The spatial analysis of road traffic crashes is crucial in identifying hotspots and informing road safety interventions. Studies in different countries, such as Germany, China, USA, and Colombia have investigated the spatial distribution of traffic crash risk and hotspots using various methods, including time–space cubes, spatial autocorrelation, and Bayesian maximum entropy. Scheiner and Holz-Rau (Scheiner and Holz-Rau, 2011) found that the risk of being killed or seriously injured in a traffic crash was higher in suburban and rural areas compared to high-density cores in Germany. Cheng et al. (Cheng et al., 2019b) identified a hotspot for road traffic crashes in the Northeast part of Wujiang's major urban area in China, while Dezman et al. (Dezman et al., 2016) found that crashes mainly occurred in the high-density center of Baltimore in the USA. Saha (Saha et al., 2018) investigated bicycle crashes in Florida, USA and found that they were spatially dependent and clustered, and not randomly distributed. Fox et al. (Fox et al., 2015) used Bayesian maximum entropy methods to identify pedestrian mortality hotspots in Cali, Colombia and distinguish between persistent and transient hotspots. Kang et al. (Kang et al., 2018) investigated the spatiotemporal characteristics of elderly people's traffic crashes in Seoul, finding that the hotspots varied depending on whether the elderly people were drivers or victims. Soltaniand and Askari (Soltani and Askari, 2017) analyzed the spatiotemporal patterns, hotspot distribution, and autocorrelation of traffic crashes at the TAZ level using different geoinformation approaches in an unspecified location. These studies show that spatial analysis can inform targeted interventions and improve the allocation of resources to tackle road safety issues effectively.

After conducting an intensive literature review on road safety and traffic crashes, it has been found that studies in this field have utilized various spatial units of analysis, such as road segments, intersections, and Traffic Analysis Zones (TAZs). Understanding the strengths and limitations of each spatial unit is essential for developing effective targeted interventions. Geospatial statistical models, including Getis-Ord-Gi*, GLMs, Moran's I, GWR, and CAR models, have been employed to investigate spatial traffic crashes and road safety. These models account for spatial autocorrelation and heterogeneity of factors that contribute to traffic crashes and road safety. The findings of different studies from different countries using different methods reveal that traffic crash risk varies across areas, and spatial analysis can effectively identify hotspots and inform targeted interventions to tackle road safety issues.

3. Materials and methods

3.1. Study area

The study focuses on road safety and traffic crashes in Qatar, a small Gulf country with an area of11,571 km^{2}located in the Arabian Gulf Sea (Abulibdeh, 2021c). Qatar has a booming economy and massive infrastructural mega-projects due to its large natural gas reserve and its National Vision 2030, as well as hosting the Fifa World Cup in 2022 (Soltani and Askari, 2017; Tamakloe and Park, 2022; Theofilatos and

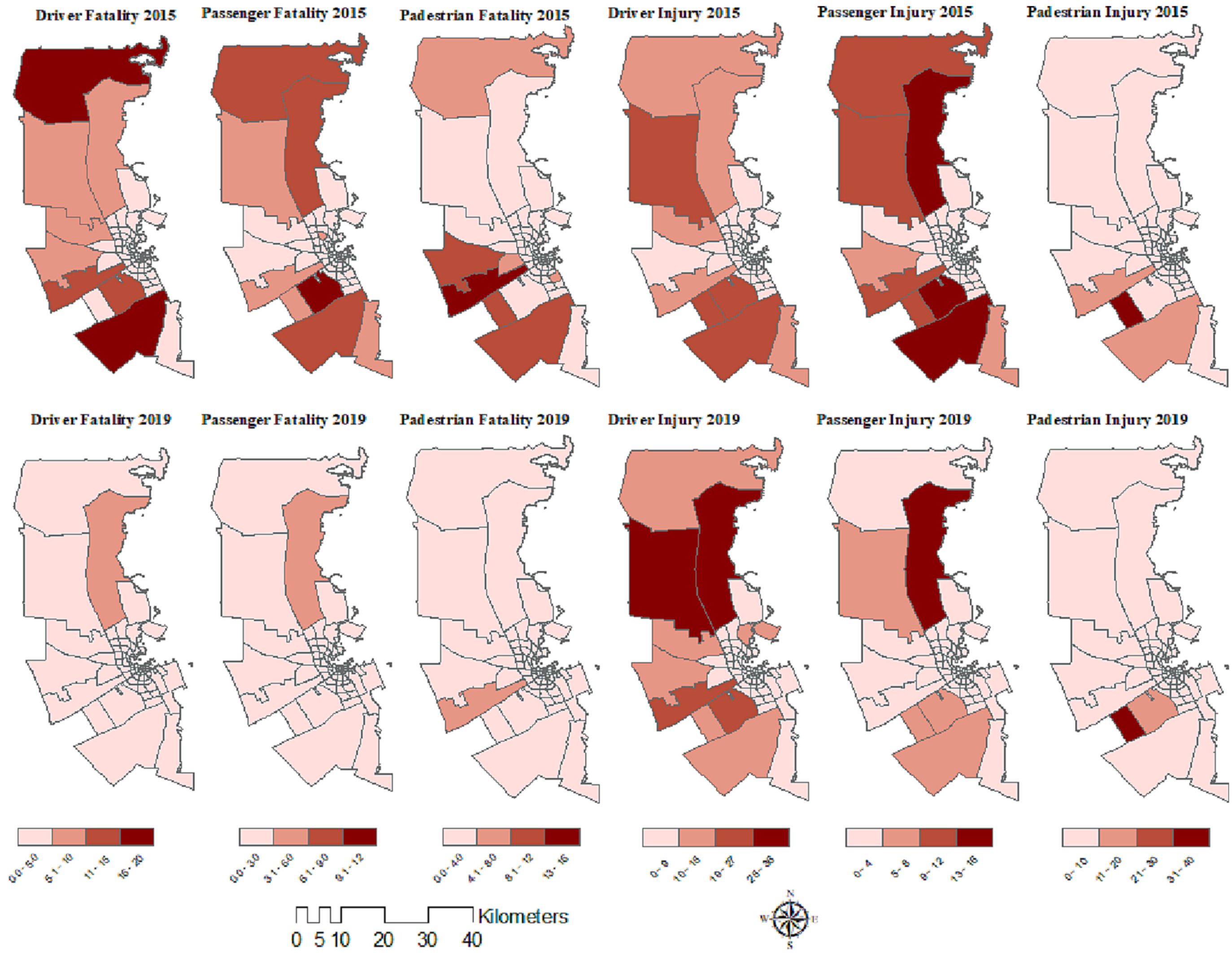


Fig. 7. Crash casualty type by zone in 2015 and 2019.

Yannis, 2014; Zaidan and Abulibdeh, 2020). The country has a large population of foreign workers and a low-density urban fabric with mostly single-use developments (Saha et al., 2018; Al-Awadhi et al., 2022). Developments in Qatar have attracted a large number of foreign workforce influx or ex-pats, making up more than 80% of the total population (Kang et al., 2018; Abulibdeh, 2022). Moreover, throughout the State of Qatar, residents are forced to drive to reach their destinations due to several reasons. As a wealthy nation, its people are more willing to own their vehicles rather than use public transport, thus, in general, private cars are the dominant transport choice as shown in Table 1. The capital city, Doha, is the most populated with 40% of the total population, and has seen major residential developments in the past few years in areas such as Al Daayen, Umm Salal, Al Rayyan, and Al Wakra (Thomas, 1996; Timmermans et al., 2019; Abulibdeh, 2019). The study's geographical scope is limited to Qatar, and Fig. 1 shows the municipal boundaries on the zonal level of the country.

The road network in Qatar is more concentrated in the capital city of Doha and less so further away. To provide an overview of the state of road crashes at a national level, Table 2 below summarizes the frequency of road crashes in 2015 and 2019, along with the percentage change during the period.

The data presented in Table 2, which shows the road crash frequency 2015–2019, and the percentage change during the period, indicates that despite the spatial VKT and demographic (population, the number of vehicles, and licensed drivers) variables increasing between the two years, fatal crashes and fatalities decreased over the same period while other injury crashes increased as expected. Typically, crashes are expected to increase with the increase of these variables. Furthermore, it is noteworthy that when taking into account the underlying distributions (populations and VKT), all types of crash rates have decreased between 2015 and 2019. The decrease in the fatal crashes and fatalities could be attributed to the effectiveness of the Qatar National Traffic Safety Strategy and the Action Plans by its stakeholders that commenced in 2013 (Charlton and Fotheringham, 2009).

3.2. Methodology

This study employs a range of advanced spatiotemporal analytical techniques to examine road safety and traffic crashes in the State of Qatar. These techniques include Time-Space cube analysis, GWR, and spatial autocorrelation analysis. The study uses historical traffic crash data reported from 2015 to 2019 to identify high incidence locations of road traffic crashes, and to present the spatial pattern changes between these two years. Additionally, the study assesses the statistical significance of the crash locations. Fig. 2 provides a flowchart outlining the research methodology employed in this articleThis study uses comprehensive spatiotemporal analytical methods to investigate traffic crashes and road safety in the State of Qatar. These methods namely are; Time-Space cube analysis, GWR, and spatial autocorrelation analysis. Historical traffic crash data reported from 2015 and 2019 were used in to

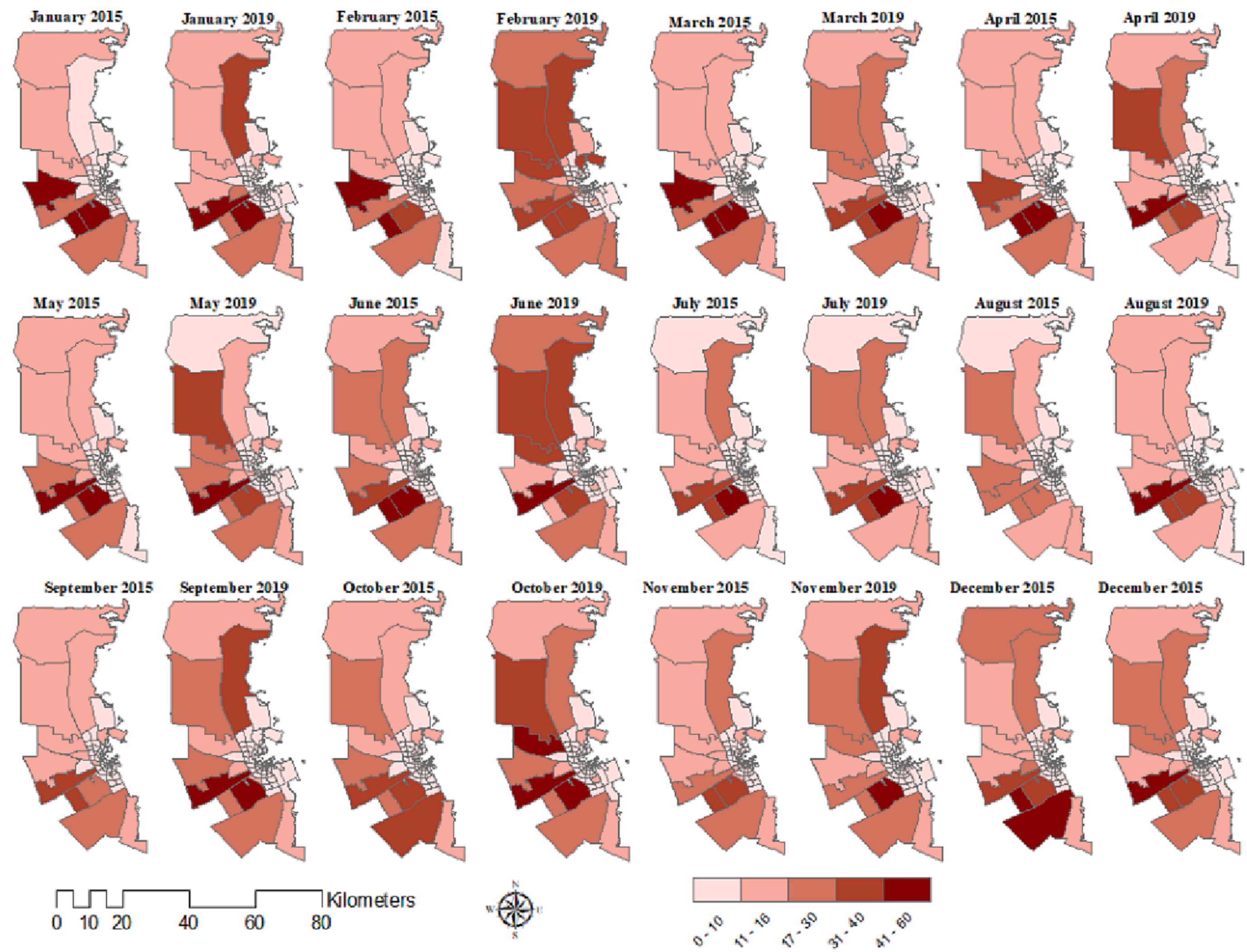


Fig. 8. Road Traffic Crash distribution in 2015 and 2019 by month.

identify the high incidence locations of road traffic crashes and present the spatial pattern changes between these two years, and identify the statistical significance of the crash locations. Fig. 2 outlines the flowchart of research methodology implemented in this study.

3.3. Data description

This study utilizes crash data pertaining to traffic crashes that occurred across the entire state of Qatar, and were exclusively reported to the General Directorate of Traffic (GDT). In this context, a crash is defined as an event involving the movement of at least one road vehicle on a road, which results in death, injury to a person, or property damage. The crash data used in this research was sourced from the GDT database, as well as publicly available sources such as the Planning and Statistics Authority. It is important to note that the crash data considered in this study is limited to those resulting in fatality or injury, with property-damage only crashes excluded. The crash database includes a total of 12,418 crashes reported for both 2015 (47%) and 2019 (53%), with 328 (3%) resulting in fatality, 1156 (9%) resulting in serious injury, and the remaining 10,934 (88%) resulting in slight injury. Table 3 provides a list and description of the variables used for the analysis.

In line with the National Road Safety Strategy's goal, the approach to finding hotspots is based on the aggregation of fatal and serious injury crash frequency. It thus emphasizes maximizing the system-wide benefits of safety intervention targeted to the hotspots rather than from an individual road user's equity perspective.

3.4. Analysis methods

This study includes a general descriptive analysis to provide an overview of the spatial and temporal variations in crash frequency across the study area. The space–time cube analysis was then used in this study to visualize the distributions of traffic crashes over time and space on the zonal level. Furthermore, the GWR, global Moran's I, and the Getis-Ord Gi* were used to characterize the intrinsic spatial pattern of traffic crashes in the State of Qatar. These methods are well-known and well-established geospatial statistics tools in the GIS literature for understanding the spatial patterns of any geographical phenomenon (Abulibdeh, 2021b). These models are used to investigate the statistical significance and the spatial aggregation characteristics of these crashes. The spatiotemporal crash hotspot location is identified by the location that has a high crash frequency and is surrounded by other locations with a high frequency of crash rates. The spatial autocorrelation analysis is employed to identify consistent groups of traffic crashes according to their attributes. These methods are essential in understanding the spatial patterns of any geographical phenomenon and are widely used in geospatial statistics.

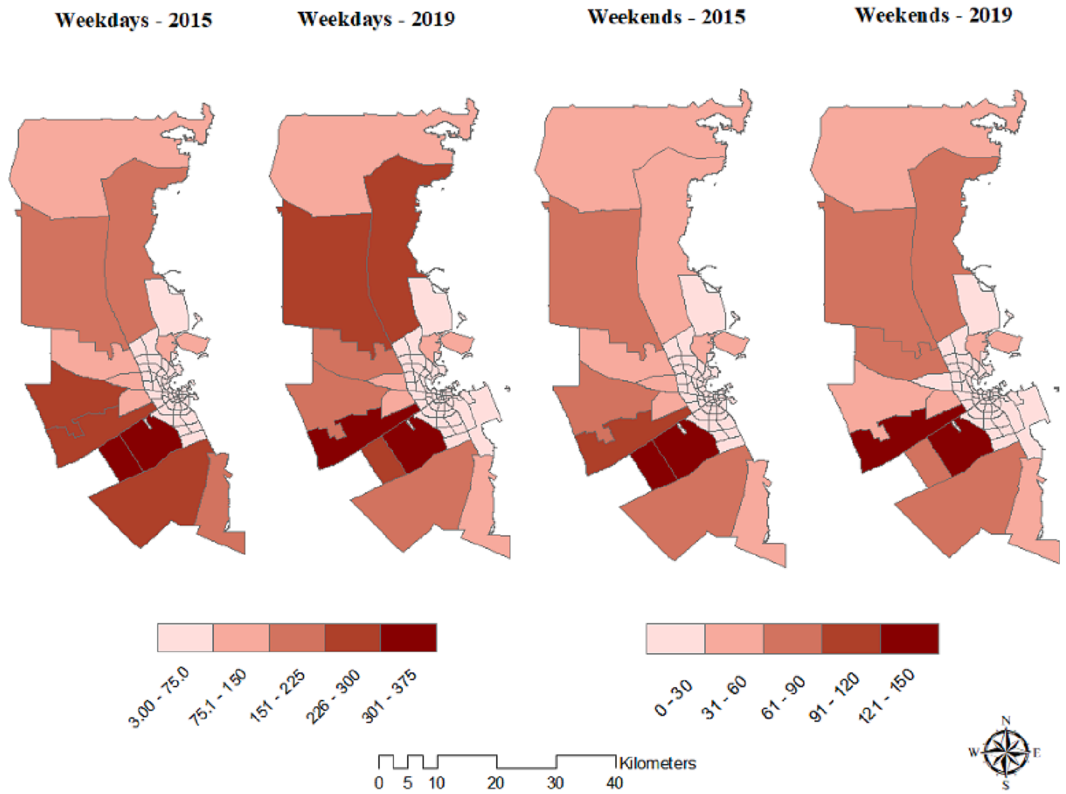


Fig. 9. Temporal variation of crashes in 2015 and 2019 – Weekends vs Weekdays.

3.4.1. The space–time cube model

The space–time cube model was used in this study to show the spatiotemporal distribution of traffic crashes at Qatar's road network. This method is a 3D geo-visualization technique that map the spatio-temporal traffic crash data in a cub, where the x-axis and the y-axis represent the two-dimensional spatial range while the z-axis denotes time. A bin time series is obtained through spatial positioning and the bin time sequence will consist of a unit cube (column) and will be a longitudinal column (Cheng et al., 2019b) (Fig. 3). We used ArcGIS 10.8.2 Space Time Pattern Mining Tools toolset (ESRI, 2022) to first create space time cube by aggregating points. The resultant netCDF cube was then used in the emerging hot spot analysis tool to identify trends in the clustering of point densities in the cube. The spatial time-seriese trend analysis is performed to see if the events increased or desreased through time. This trend analysis is performed using Mann-Kendall trend test on each location with data as an independent bin. The Mann-Kendall test is calculated using the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\left(x_j - x_i\right) \tag{1}$$

Where n is the number of data points, xi and xj are the data values in time series I and j (j > i), respectively. $sgn(x_j - x_i)$ is the sign function as

$$sgn\left(x_j - x_i\right) = \begin{cases} +1, if\left(x_j - x_i\right) > 0 \\ 0, if\left(x_j - x_i\right) = 0 \\ -1, if\left(x_j - x_i\right) < 0 \end{cases} \tag{2}$$

The variance is composed as

$$\mathrm{V(S)} = \frac{n(n-1)(2n+5) - \sum_{k=1}^{m} t_{k\,(t_k-1)(2t_k+5)}}{18} \tag{3}$$

The time step in the z-axis bin is one month and hence the bin includes twelve-time steps January to December. Each column contains a number of points that represents the geographic traffic crashes that occur within the unit time step. Therefore, the changes in geographical traffic crash over time can be visualized in the bin time series. This model was used to detect the changes in the geographical location of the crash to identify the emerging, intensifying, diminishing, consecutive, sporadic, and persistent hot spots over time and space. The time–space cube analysis quantitatively and qualitatively characterizes the traffic crash situation of each zone from a spatiotemporal perspective.

3.4.2. The local Moran's I

The local Moran's *I* is a measure of the spatial autocorrelation analysis method used in this study to investigate the spatial distribution and clustering of the traffic crashes and determine whether these crashes have spatial agglomeration characteristics. Spatial data are described as highly correlated if patterns for the configuration of these data can be identified and if likely values are spatially close to each other, and conversely, they are defined as random or independent if no patterns can be identified (Huang et al., 2020); (Kang et al., 2020). This method depends on the covariance relationship of the statistical correlation coefficient. The mathematical formulation of the local Moran's *I* method is as the following (Cheng et al., 2019b); (Abulibdeh, 2021b):

$$I_i = \frac{x_i - \overline{X}}{S_i^2} \sum_{j=1, j\neq i}^{n} w_{i,j}\left(x_j - \overline{X}\right) \tag{4}$$

Where x_i is attribute for feature I, $\overline{X}$ is the mean of the corresponding attribute, $w_{i,j}$ is the spatial weight between feature I and j, and:

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n} \left(x_j - \overline{X}\right)^2}{n-1} \tag{5}$$

Where n equating to the total number of features.

The value of the Moran's *I* test must be between −1 and 1. The value greater than 0 represents a positive relationship at spatial distribution and more clustering of the traffic crashes, while the value of 0 represents a random distribution at the spatial aspect (complete spatial

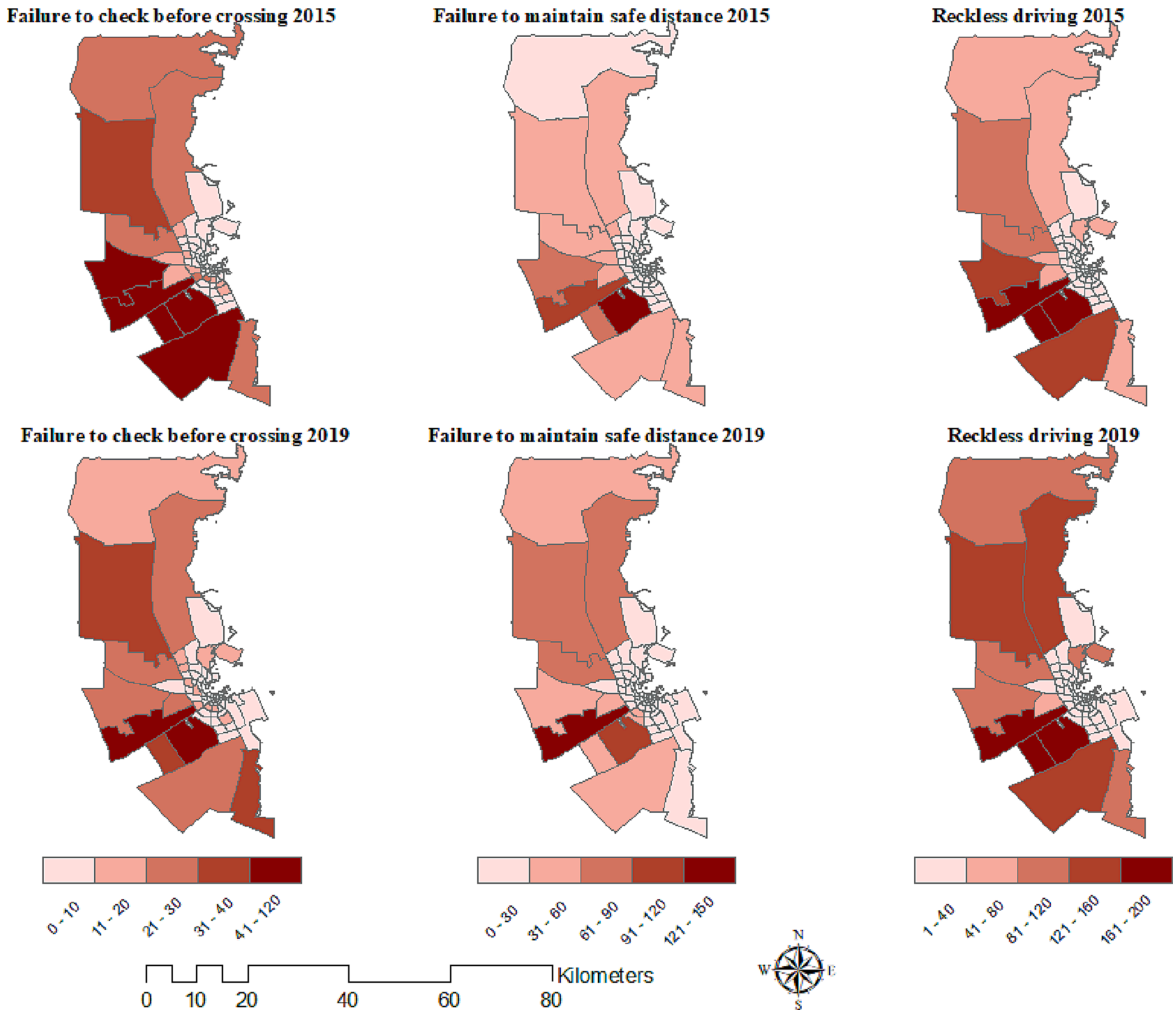


Fig. 10. The main cause of crashes as indicated in crash reports in 2015 and 2019.

randomness) (Abulibdeh, 2021b). The value less than 0 represents a negative relationship and denotes that the same area has a large difference in attributes (random pattern). Moran's *I* index is also associated with a Z-score and p-value. The z-score quantifies the degree of deviation (i.e., the dispersion or clustering around Moran's *I* value). The z-score value can be positive or negative, where a positive value denotes that the adjacent features have similar values while the opposite applies to the negative value of the Z-score. The P-value gives indications of the statistical significance of clustering outputs. The significant relationship denotes that the value of the variable at a specific location depends on the values at the neighboring locations and vice versa (Al-Kindi et al., 2020); (Prasannakumar et al., 2011).

3.4.3. *The Getis-Ord* $\mathbf{G_i^*}$

The Getis-Ord G_i^* is used to statistically test the spatial distribution pattern of the traffic crashes at the zonal level. We use this method to identify the hot spots (high values clustered in an area) and the cold spots (low attribute values clustered in an area) of these crashes and hence to determine whether these crashes tend to be spatially clustered (dependent) or random. Getis-Ord G_i^* consider that if any geographical area is identified as a hot spot for traffic crashes, then other areas adjacent areas should exhibit high traffic crashes as well. Therefore, this method can be considered as an index of local spatial autocorrelation analysis. The Getis-Ord G_i^* is associated with a Z-score and p-value as well for each geographical zone. The large Z-score values denote that the clustering of the traffic crashes value is more intense in this zone (hot spot). These values indicate if zones with either low or high crash rates tend to be clustered over space. Mathematically, the Getis-Ord G_i^* is computed according to the following formula (Abulibdeh, 2021b):

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2\left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{6}$$

where n is the traffic crash rate value, x_j is the property value for feature jth element, w_{ij} is the spatial weight between zone i and zone j and $\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}$ is the mean of the variable. This distance-based weight matrix is based on the inverse distance between locations i and j (i.e., 1/dij).

3.3.4.4. *The GWR.*

The GWR model was used in this study to further assess the spatial association between traffic crashes and the contributing variables in each geographical zone and to solve the spatial heterogeneity. This method is a type of linear regression for investigating spatially varying relationships. Furthermore, it assumes non-stationary

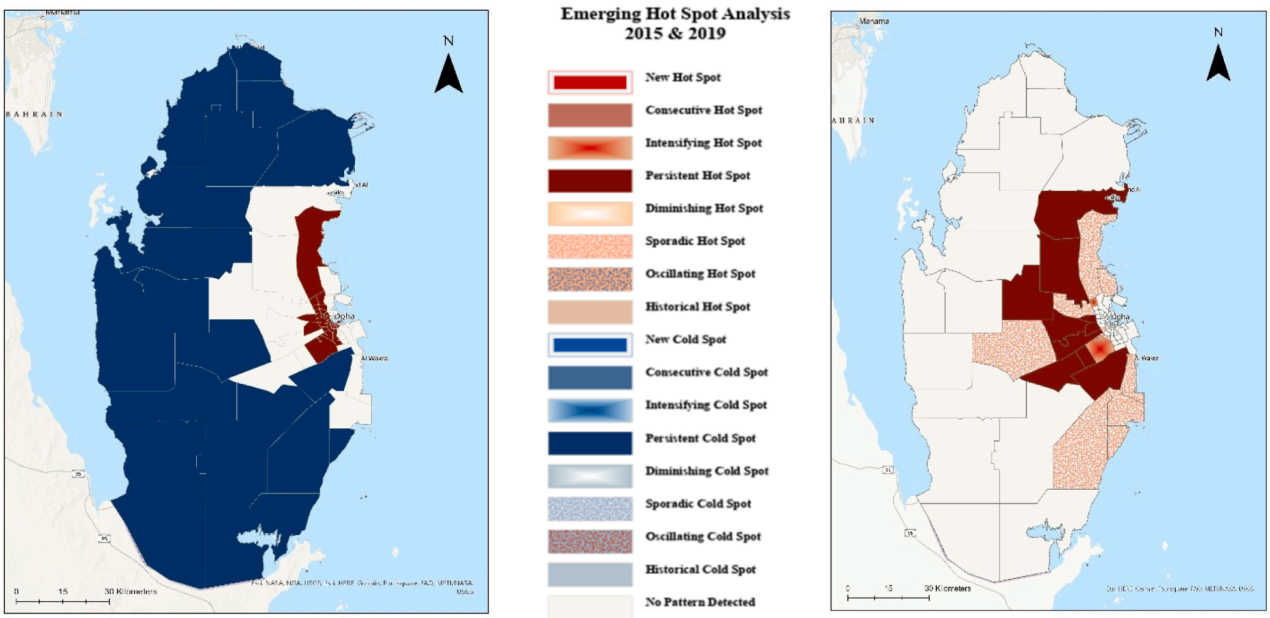


Fig. 11. Time-Space cube analysis showing the traffic crashes emerging hot spot in 2019 compared with 2015.

correlation and the regression parameters vary over space (Xu et al., 2017; Yan et al., 2015; Yoon and Lee, 2021). Mathematically, the model is represented as the following (Mollalo et al., 2020); (Fotheringham and Oshan, 2016):

$$y_i = \beta_{i0} + \sum_{j=1}^{m} \beta_{ij} X_{ij} + \varepsilon_i, i = 1, 2, \cdots, n \tag{7}$$

where at zone i, y_i is the value of traffic crashes rate, β_{i0} is the intercept, β_{ij} is the j^{th} regression parameter, X_{ij} is the value of the j^{th} explanatory parameter and ε_i is a random error term. In a matrix form, parameter estimates for each explanatory variable and at each zone is given as follows (Mollalo et al., 2020; Fotheringham and Oshan, 2016):

$$\widehat{\beta}(i) = (X' W(i) X)^{-1} X' W(i) Y \tag{8}$$

where $\widehat{\beta}$ denotes the vector of parameter estimate (m × 1), X demonstrates the matrix of selected explanatory variables, W(i) is a diagonal matrix of spatial weights (n × n) and is constructed from the weights of each observation depending on its distance from the location i and is calibrated based on a locally weighted regression, and y represents the vector observations of traffic crashes rates (m × 1).

6. Results and findings

4.1. Descriptive analysis

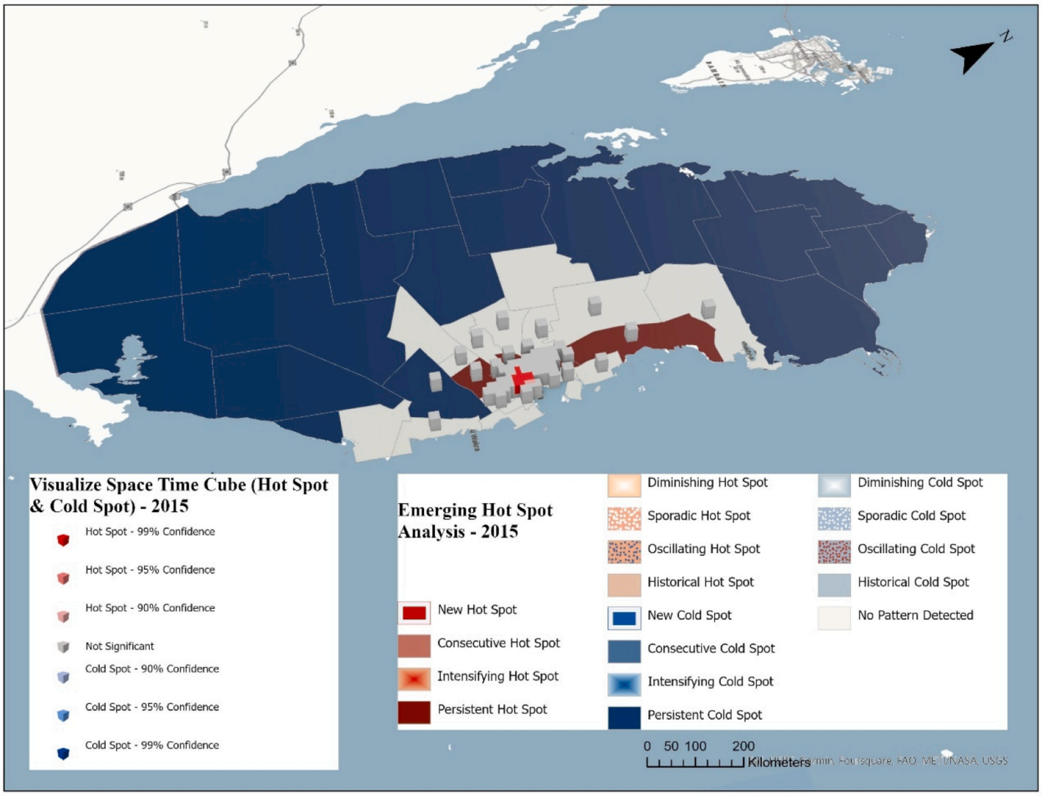
Fig. 4 depicts the distribution of road traffic crashes in Qatar in 2015 and 2019. The data reveals a concentration of crashes in Doha and its surrounding areas, which is not unexpected given that this region is the most populous and has an extensive road network.Conversely, the crashs beyond Doha and its vicinity are infrequent (less than60 crashes/year) and are typically confined to roads that connect these areas to Doha. As a result in this study zonal level analysis will focus on zones within Doha and its surrounding zones.

Upon zooming into the area of interest, Fig. 5 highlights that the crash frequency in the zones located north and west of Doha has increased in 2019 compared to 2015. These zones have experienced substantial growth during this period with new residential and commercial areas popping up continuously over the years. These areas also witnessed extensive road network expansions such as the main Doha expressway that runs from north to south. Table 4 provides an overview of the zone with the highest occurrence of crashes, fatalities, and serious injuries from 2015 to 2019.

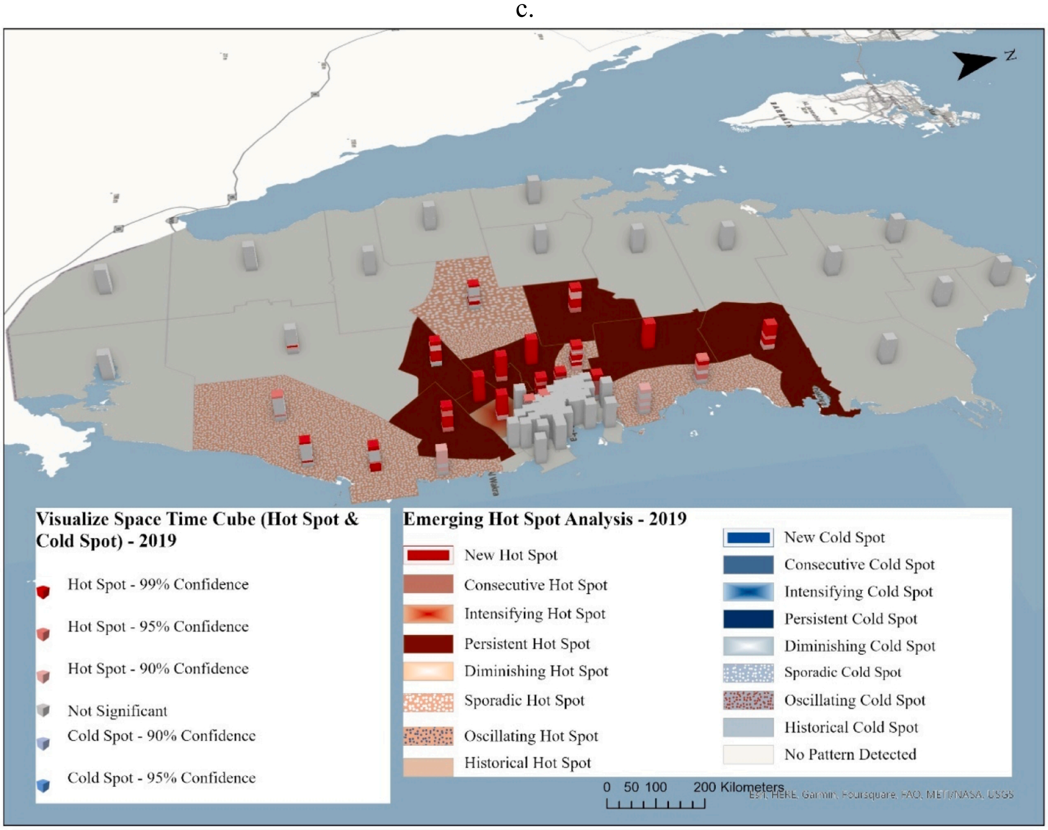
Conversely, the zones situated to the south of Doha experienced a decrease in the frequency of crashes in 2019. This inclinecan be attributed to the land transport blockade by Saudi Arabia in 2017. Qatar shares its only land border crossing with Saudi Arabia and prior to the blockade, there was a significant amount of trade between the two countries. However, with the border closed, freight transport shifted to mainly, air and sea transport.

Looking deeper into the type of crashes at a zonal level, it is clear from Fig. 6 that the number of fatal crashes in 2019 decreased dramatically (-31%) from those in 2015. Zones in the immediate north and west of Doha especially saw fewer fatal crashes as these areas become more developed over the years. Fatal crashes are generally linked to high-speed crashes which are alleviated as population density increases and demand for travel increases forcing lower speed on the road (congestion) (Ziakopoulos and Yannis, 2020). Further explanation of the decrease in fatal crashes in 2019 could be the advancement in emergency response services since 2015. Indeed this is plausible especially since the overall number of crashes increased over the period from 2015 to 2019 but fatal crashes particularly decreased over the same period. The potential fatal crashes thus shifted to serious crashes as emergency response services address the situation more swiftly.

Fig. 7 and Fig. 8 illustrate the distribution of crashes by type of casualties and per month, respectively. The fatalities involving drivers and passengers are concentrated in the northern areas, while pedestrian fatalities occur more frequently in the southwestern part of Doha.. As explained above the fatality crashes have decreased and thus fatalities. Pedestrian crash casualties make up more than 20% of all victims consistently over the years. Pedestrian crashes tend to be concentrated in the southwest area of Doha which is characterized by low-income residences for labor workers. Loukaitou-Sideris et al (Loukaitou-Sideris et al., 2007) observed a similar pattern: high pedestrian crashes in regions with lower income levels when other risk factors are controlled. The majority of the other crash victims are located in the northern zones



c.



d.

Fig. 11. (*continued*).

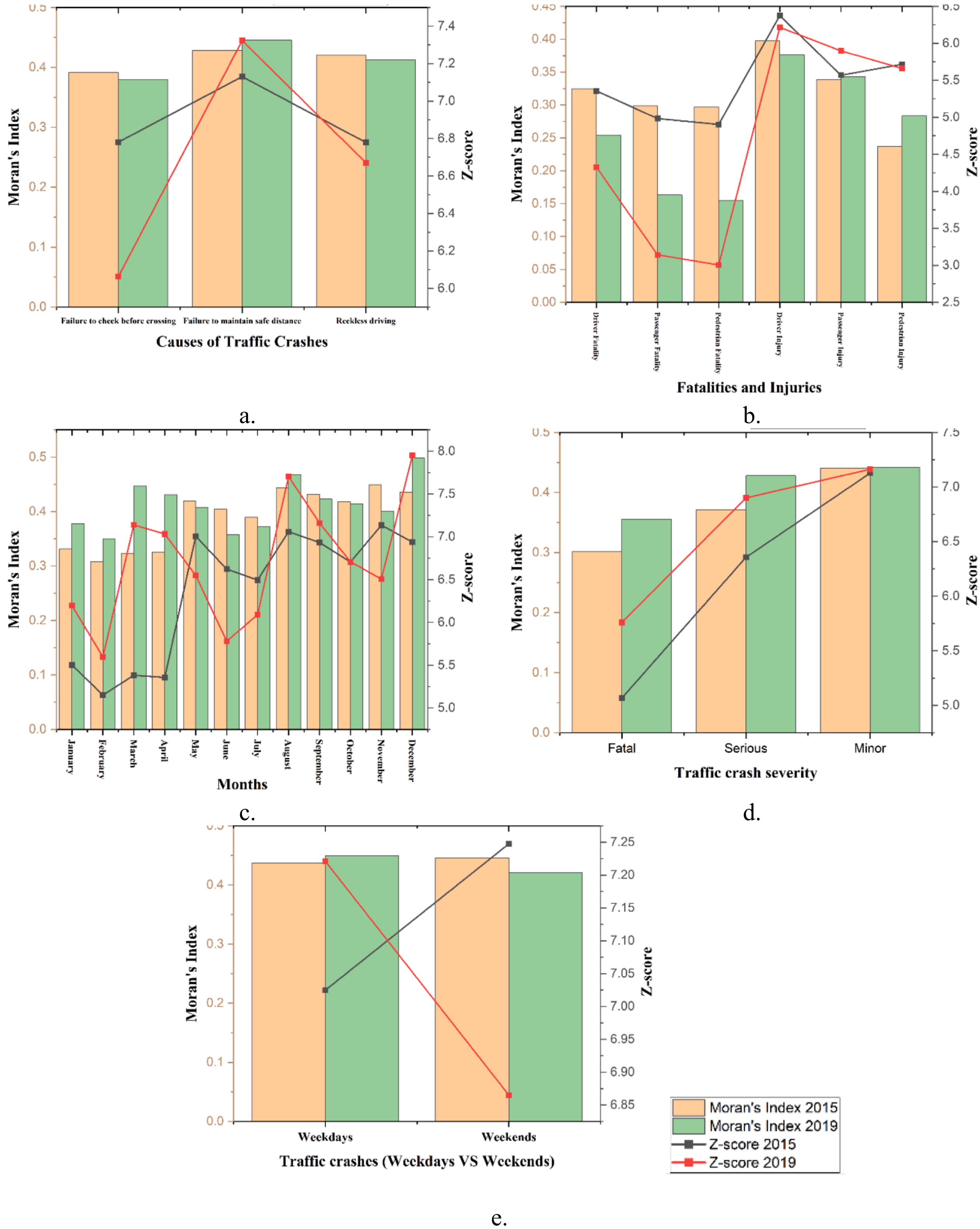


Fig. 12. Moran's index.

of Doha that underwent significant expansion between 2015 and 2019.

Timmermans et al (Timmermans et al., 2019) examined the time series trend for crashes in Qatar and identified a clear pattern of variation over different months and seasons. In Qatar, the weather conditions vary from mild and pleasant winter in December – February to humid and extreme heat reaching above 45 °C during summer (June – August) (Abulibdeh, 2021a). Such variation in weather makes a big difference in the volume of pedestrians on the road. The autumn (September-November) and winter seasons are characterized by foggy and misty weather, and while rainfall is rare, autumn is the season when it is most likely to occur. These weather conditions are conducive to pedestrian movement, which peaks during the winter months.

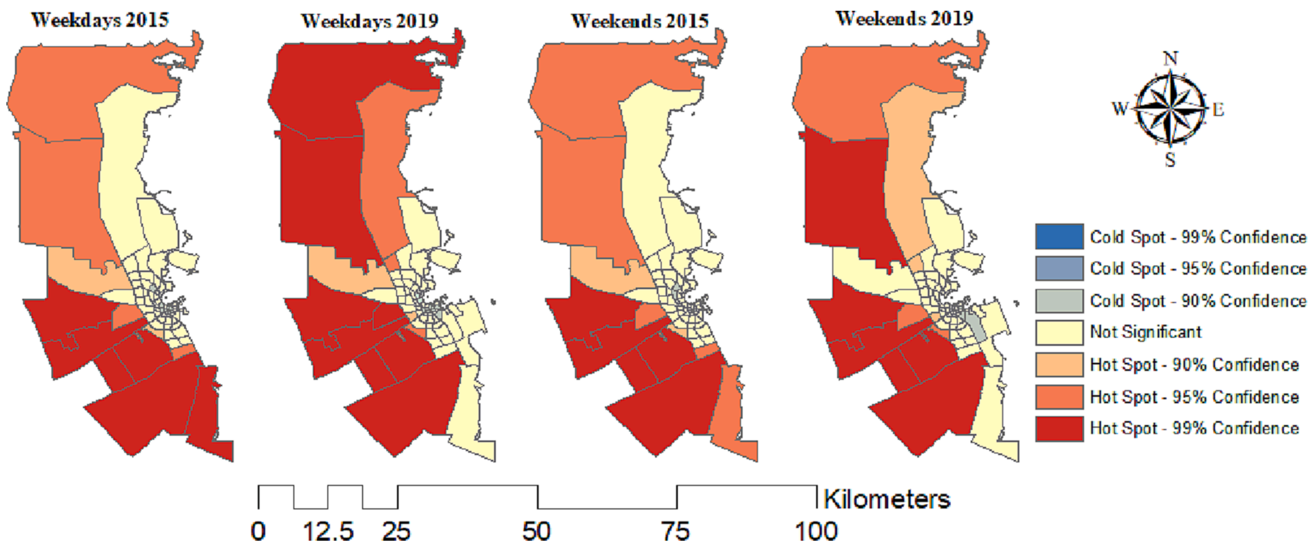


Fig. 13. The Getis-Ord G* of traffic crashes on weekdays and weekends of 2015 and 2019.

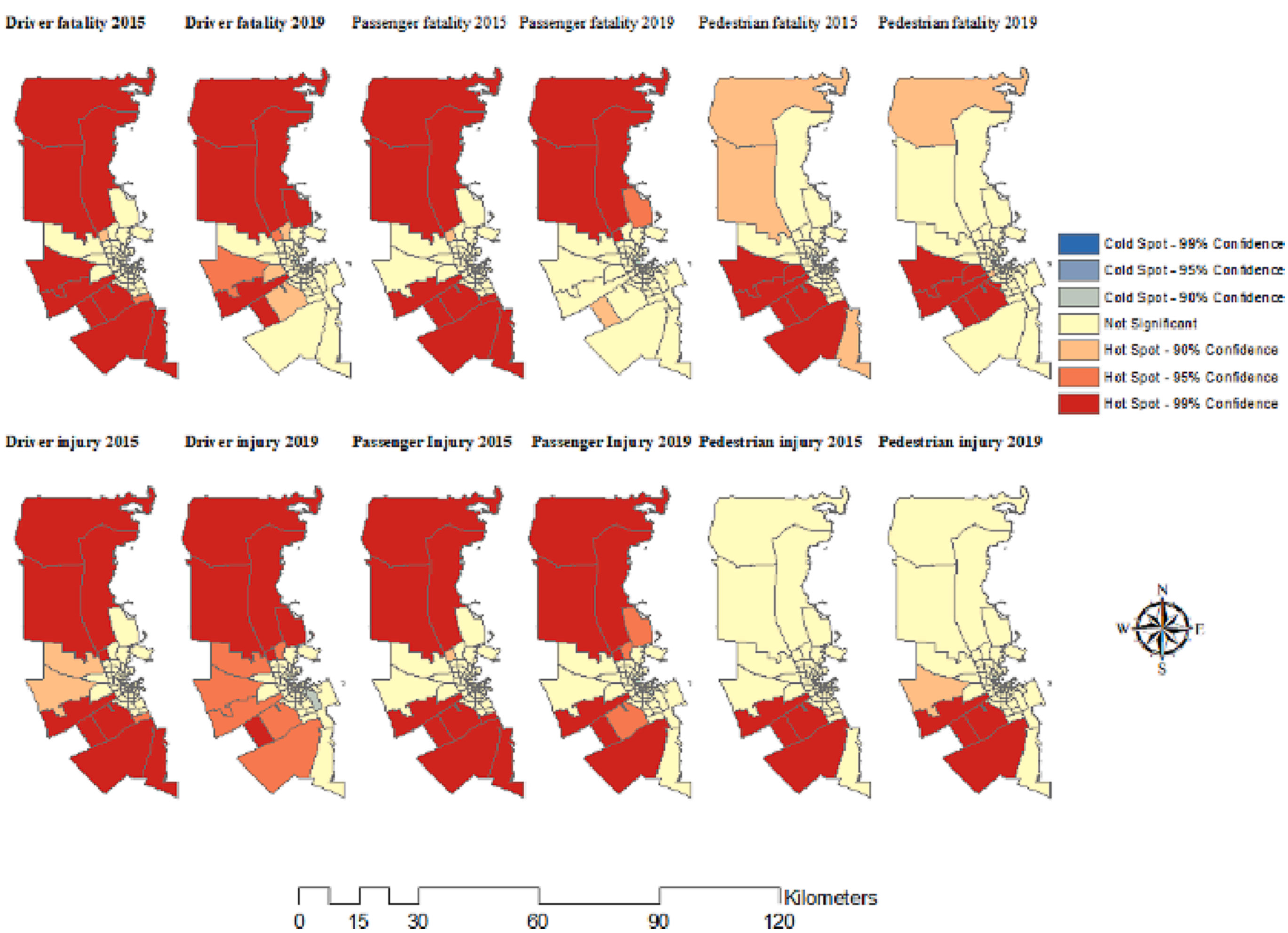


Fig. 14. The Getis-Ord G* of crash causality between 2015 and 2019.

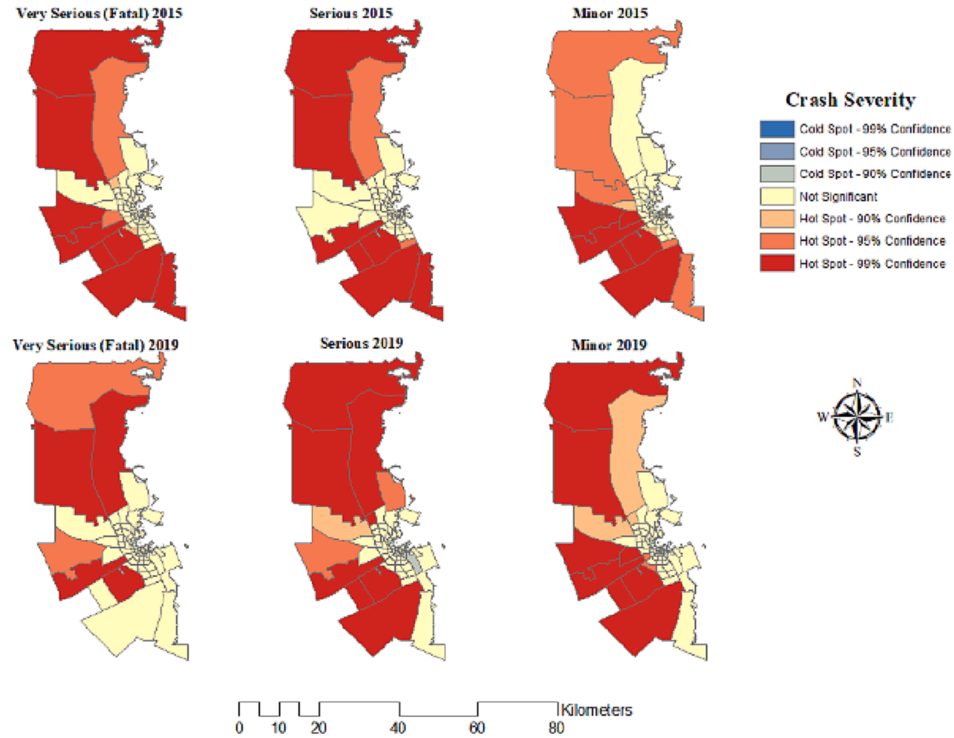


Fig. 15. The Getis-Ord G* of crash severity between 2015 and 2019.

The occurance of road traffic crashes is generally higher on weekdays as the number of days is more than double of weekends. Weekday trips are mostly related to commuting between home and workplace/schools. As shown in Fig. 9 in 2015, the crashes were mainly to the southwest of Doha city but expanded to include the newly developed areas to the north. A similar pattern is shown in 2019 except it has intensified. On weekends, however, trips are fewer and mainly made for shopping and recreational purposes. The distribution of crashes remains similar to that of the weekdays but less intense.

The most common causes of crashes in Qatar, as reported by the traffic police, are related to the failure of drivers to make an appropriate judgment on the road or practice risky behaviors. They make up more than half of all road traffic crashes. Due to the difficulty in addressing such a behavioral problem, the pattern in 2015 remained the same in 2019 except with the addition of areas that saw major developments in the later years. In 2016, Qatar increased its traffic violations fine for all categories in order to deter unsafe maneuvers on the road. This may have had a greater impact on the low-income areas in the south more than anywhere else in the country as shown in Fig. 10.

4.2. Spatiotemporal distribution of traffic crashes

Fig. 11 displays the spatial and temporal distributions of road traffic crashes in Qatar's zones, utilizing the time–space cube model in ArcGIS with a time step value of one month. In 2015, the eastern strip of zones displayed potential persistent hot spots (high crash frequency) as shown in Fig. 11a, while the extreme northern, western, and southern areas were potential cold spots (low crash frequency) (Fig. 11a). The areas surrounding the capital city, however, showed no particular pattern of crashes. Considering the crash spatiotemporal distribution and their significance, only a small zone in central Doha (Fig. 11c) requires further investigation.

In contrast, the crash pattern distribution in 2019 showed significant changes compared to 2015. Those same areas that showed no crash pattern in 2015 now indicate emerging patterns varying from sporadic to persistent crash frequency distribution (Fig. 11b and Fig. 11d). It should be noted that zones with high crash frequency do not necessarily indicate crash hot spots. Further analysis of the spatiotemporal features, and trends of the crash frequency in the area and its neighboring zones is necessary to establish statistically backed crash hotspots.

4.3. Spatial autocorrelation and clustering of crashes

The Time-Cube analysis provided an overview of the spatiotemporal characteristics of the crashes but did not consider other factors, such as the nature of crashes in the proximity of the zones that could affect the selection of the zones as true crash hotspots. Therefore, further analysis was conducted to address this issue. The spatial autocorrelation (Local Moran's *I*) tool is a powerful tool for spatial analysis that measures spatial autocorrelation based on both feature locations and feature values simultaneously. The tool evaluates whether the pattern expressed is clustered, dispersed, or random. It calculates Moran's *I* Index value and both a z-score and p-value to evaluate the significance of that Index. Its value ranges from -1 to 1 with a value greater than 0 denoting a positive correlation at spatial distribution, i.e, clustered distribution, and a value less than 0 indicating an area with dispersed distribution of attributes (crash frequency in this case). A value that approaches 0 (from either side, positive or negative) represents a random distribution. Fig. 12 shows that all the attributes included in our study have a Moran's *I* value greater than 0 and Z value above 2.58 suggesting that all of them have a statistically significant positive correlation spatial distribution (clustered).

In 2015, the spatial distribution of crashes that occurred on weekdays showed random distribution but tend to be more clustered in 2019. The reverse is observed during weekends, where in 2019 the crashes have increasingly shown random distribution. While fatal and serious crashes showed more clustered distribution in 2019 compared to 2015, the distribution of the victims of these crashes tends to be more randomly distributed in 2019 than in 2015, especially for pedestrian fatalities. Crashes caused to failure to maintain safe distance showed

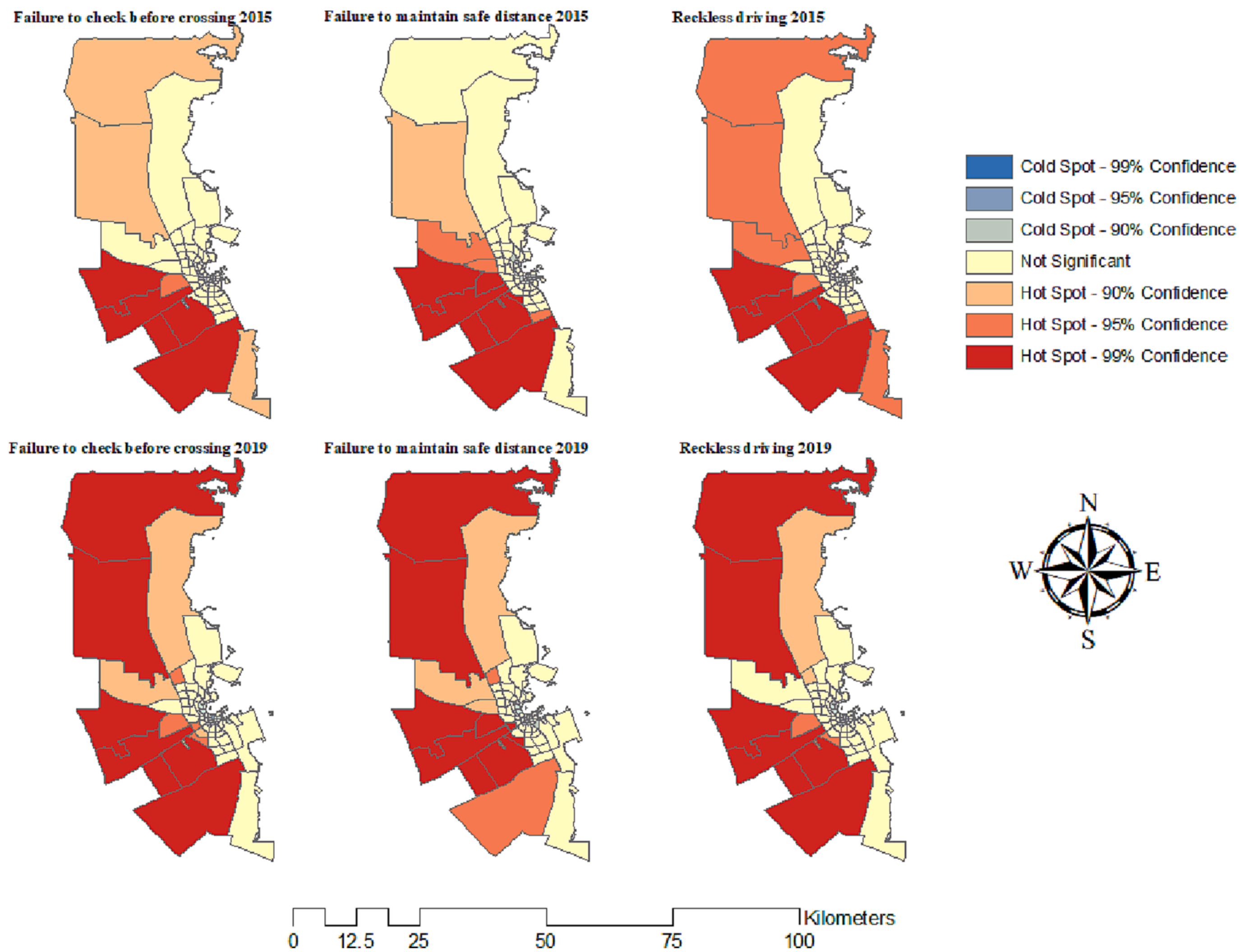


Fig. 16. The Getis-Ord G*of traffic crashes causalities between 2015 and 2019.

more clustered distribution in both 2015 and 2019. Crashes due to failure to check while crossing has shown *an* increased tendency to be randomly distributed in 2019 compared to 2015.

4.4. Traffic crash pattern recognition

Moran's Index analysis above showed that the traffic crashes in the study area are aggregated from the spatial aspect with statistical significance and that this aggregation changed between 2015 and 2019. However, Moran's Index analysis does not indicate exactly where the crashes gathered (i.e., the specific aggregated locations). The Getis-Ord G* analysis method can provide the specific aggregation ranges of the crashes and preliminarily identify the hotspots. Regarding the days of the week, the results of Getis-Ord G* analysis (Fig. 13) show that the northwest to the southwest zones of the area of interest remains to exhibit clustered distribution of crashes but are more pronounced during weekdays than weekends.

Similarly, the same analysis of the distribution of crashes by crash severity and victim type Fig. 14 and Fig. 15 show the aggregation of minor crashes is clustered northwest to the southwest of the area of interest. The statistically significant clustered distribution of crashes with driver and passenger injury is in the northern zones with those in the southern zones tending to be more randomized and less significant in 2019 compared to 2015. However, crashes that result in pedestrian fatality and injury remain clearly clustered in the southwestern zones in both years.

Crashes that were caused due to failure to maintain safe distance showed statistically significant clustered distribution in both 2015 and 2019 (Fig. 16). In the latter year, however, the aggregation of this type of crash expanded to include those zones in the north as well as those in the southwest. A similar distribution is shown to those due to reckless driving and failure to check before crossing although the latter is approaching a more random distribution.

4.5. Emerging hot spot analysis

The above Getis-Ord G* analysis has identified the crash hot spots. Turning to the emerging hot spot analysis, a more detailed interpretation and classification of the crash hot spots and how they change can be made using the emerging spatiotemporal hotspot analysis toolbox in ArcGIS 10.7. It classifies the hot and cold spot areas as shown in a snapshot in Fig. 17. The visualization results snapshot of crash hot spots over time for the year 2019 (from January to December) is shown inFigure 17. The area of interest in our study is the intensifying hot spot which presents an increasing trend of crashes over time. The opposite of such a trend is the diminishing cold spot whose crash frequency is

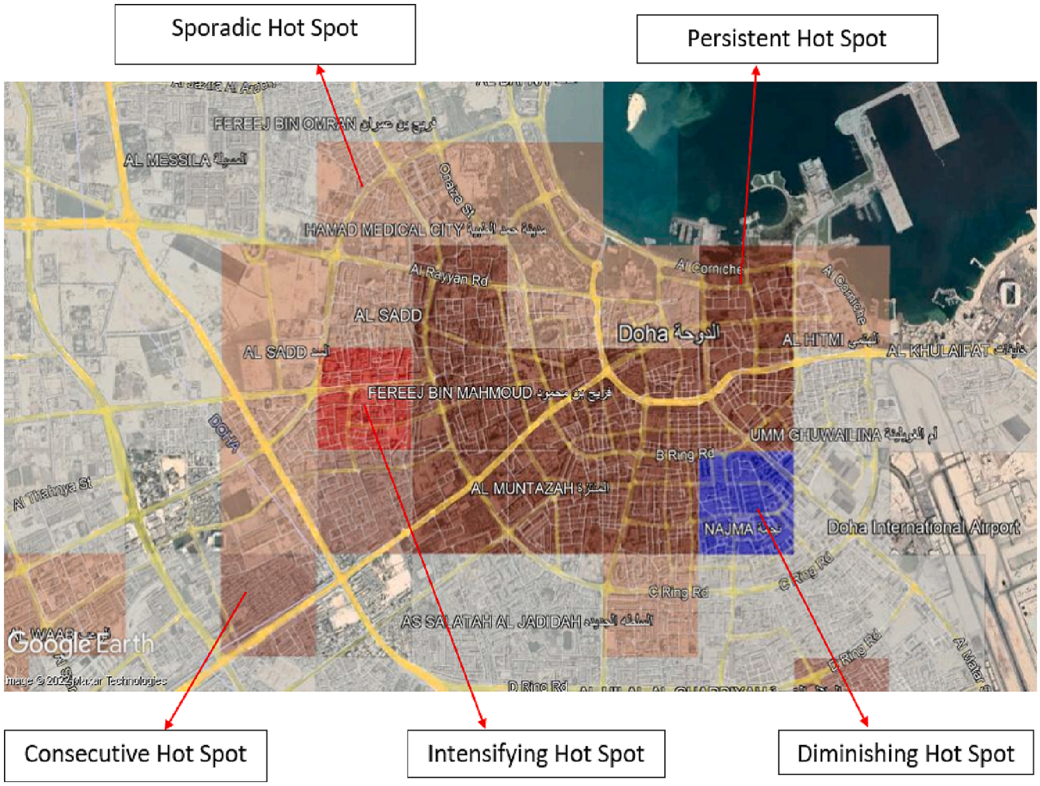


Fig. 17. Snapshot of Emerging Hot Spot Analysis.

decreasing over time.

By zooming into the intensifying hot spot area, we can conduct a more in-depth investigation to better understand the increasing trend in crash frequency in the area. Looking at the satellite images from 2015 and 2019, an overview of any dramatic changes to the land use or road design that may influence road crashes can be carried out.

As shown in Fig. 18 in the case of intensifying hot spots, the area in Doha that shows intensifying hot spots for crashes is a highly mixed commercial and residential area with a major arterial road. It accommodates a significant volume of traffic generated from such land use. On the other hand, as Fig. 19 depicts the area with diminishing hot spots is a mainly residential area with also a major arterial road that passes through on one edge. Interestingly, both areas accommodate metro stations. The metro stations were however operational from mid-2019 which could have influenced the crash frequency in that year.

4.6. Spatial association between crashes and analysis variables

The GWR was employed to investigate the local spatial variation of traffic crash attributes. The spatial differences are shown in Fig. 20-24. The maps show variations in crashes amongst Qatar Municipalities. For example, as appeared in Fig. 20 during weekdays the northern and middle municipalities have a lower deviation in crash frequency than on weekends, while in the southern municipality Al Rayyan Municipality has a big deviation between weekdays and weekends in 2015. Yet, the situation improved a little bit in 2019.

5. Discussions and policy implications

The goal of this study was to provide policymakers with an approach to incorporate spatial and temporal variation in road traffic crashes. The study used Time-Space Cube Analysis, Moran's *I*, and Getis-Ord Gi* to analyze crash data from 2015 and 2019, including crash frequency by severity, victim type, weekday/weekend, month, and causes. By comparing changes in these factors at the zonal level, the study identified which factors significantly influenced crash frequency in specific areas and how the trend changed over time. This information can be used to formulate customized interventions that are supported by stakeholders. By using these tools over time, policymakers can also evaluate the effectiveness of interventions in resolving local problems.

The results of this study show that road traffic crashes are mainly in the central-eastern section of the country which is where the majority of the population resides. While in 2015 the area with higher crash frequency was closer to the center of the capital city Doha, in 2019, this area expanded to include major zones in the north and west of the city. This can be attributed to the significant infrastructure network expansion that Qatar underwent between 2015 and 2019, particularly in the north and west of Doha, as part of the country's economic development plan - the Qatar National Vision 2030. As a society that heavily relies on cars, such expansion of the road network increased exposure to risk and subsequently, led to an increase in the number of crashes as found in (Timmermans et al., 2019).

Moran's Index analysis of the crashes near the identified zones revealed a stronger clustered distribution during weekdays in 2019 compared to 2015, indicating a probable systematic cause for the crashes. Additionally, crashes reported by police as resulting from a failure to maintain safe driving distance showed a clustered distribution in both 2015 and 2019. The results of the Getis-Ord Gi* analysis were statistically significant and pointed towards the north and west zones of Doha as the areas requiring greater attention. This approach of considering the spatial and temporal variations of road crash frequency facilitates the unification of efforts by road safety stakeholders and enables the development of an effective road safety plan at a zone level.

The emerging hot spot analysis is a useful tool for monitoring and

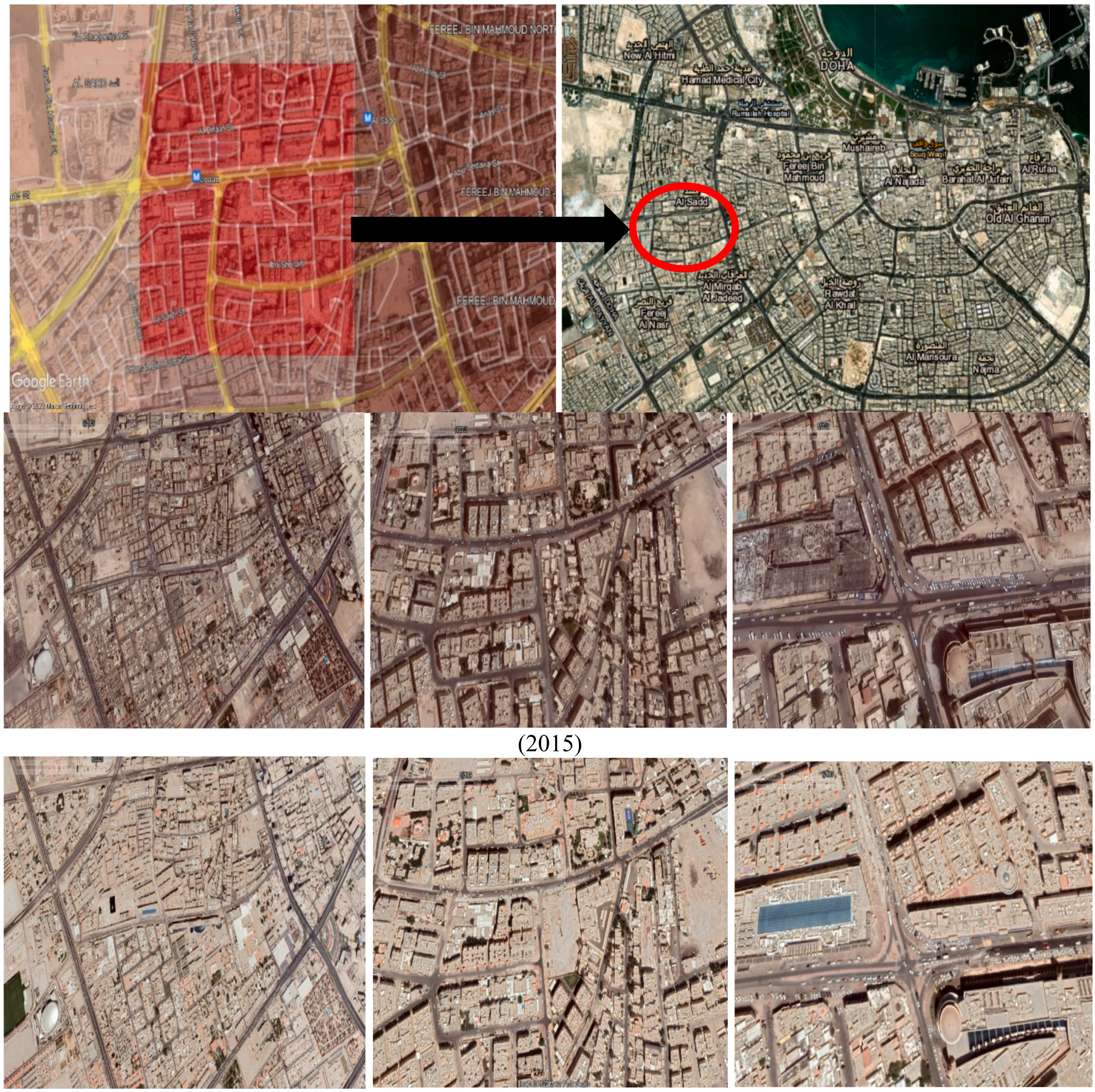


Fig. 18. Intensifying Hot Spot.

evaluating the effectiveness of interventions implemented according to a road safety plan. Policymakers can use this analysis to identify and target persistent and intensifying hot spot areas with specific measures. By adopting the established Safe Systems framework at the zonal level, policymakers can readily identify strategies that target significant predictors of crash frequency in a particular zone. Using this approach, policymakers can implement the Safe Systems framework to prevent all fatalities and severe injuries through Road Safety Management, Safe Roads, Safe Vehicles, Safe Road Users, and Post-Crash Response. This approach can thus effectively target the most easily achievable measures that have the potential to reduce the frequency of crashes in specific locations.

The proposed approach of implementing the Safe Systems framework at the zonal level and targeting the low-hanging fruits aligns with previous studies on road safety management. For instance, a study by Elvik (Elvik, 2021) found that a multi-faceted approach focusing on a combination of road safety measures is the most effective way to reduce the number of traffic fatalities and severe injuries. Therefore, the approach of utilizing emerging hot spot analysis and the Safe Systems framework at the zonal level can effectively address the specific factors contributing to crashes in identified hot spot areas and reduce their occurrence.

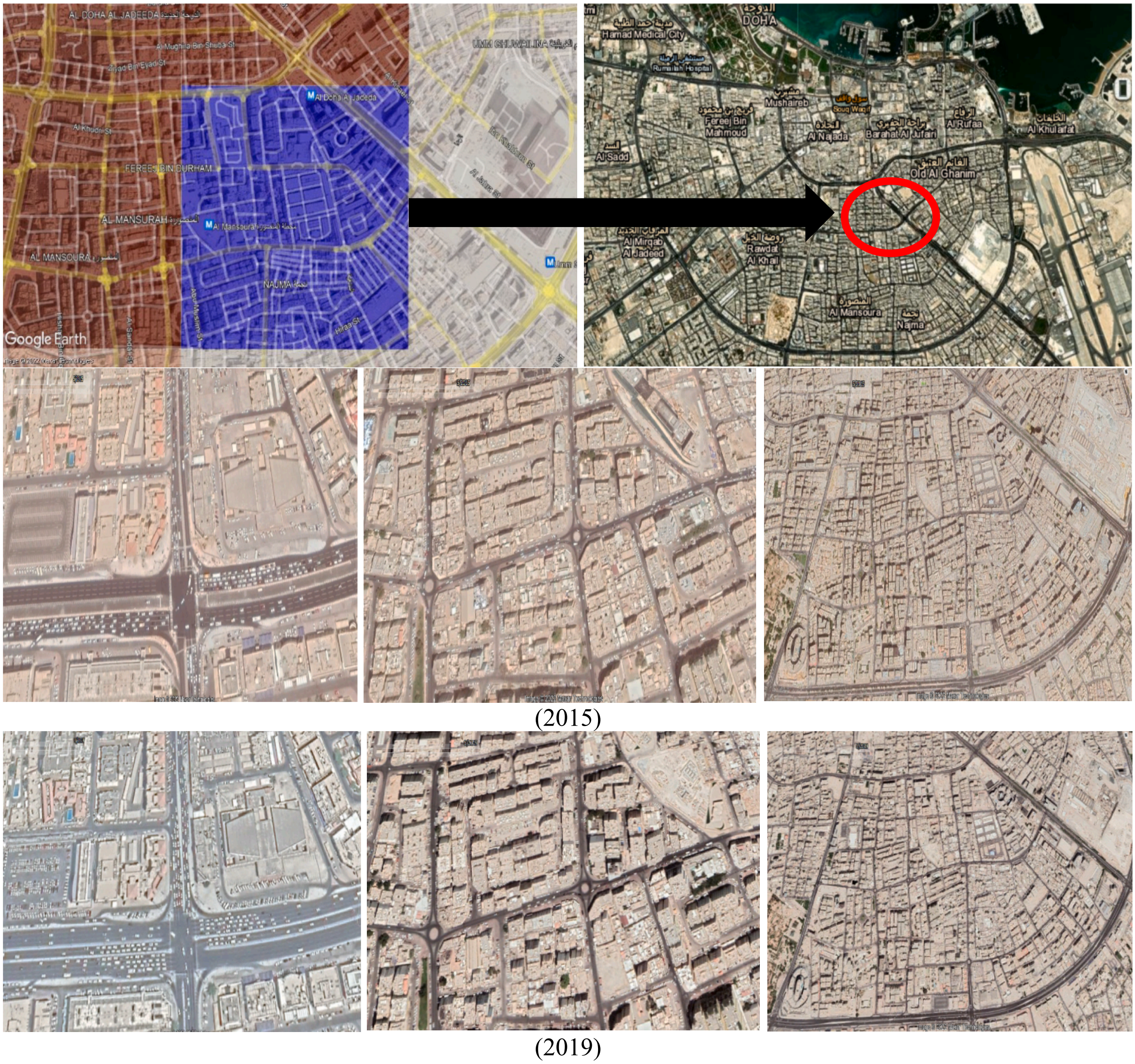


Fig. 19. Diminishing Hot Spot.

6. Conclusion

The current study utilized Time-Space Cube Analysis, Moran's Index, and Getis-Ord Gi* to identify and compare crash hotspots in 2015 and 2019, providing policymakers with a comprehensive understanding of the road crash situation and enabling them to develop timely solutions at the zonal level. The results indicate that road traffic crashes are most prevalent in the central-eastern section of the country, which has the highest population density, suggesting that current traffic management approaches in urban areas are inadequate in preventing or mitigating the negative effects of crashes. Furthermore, the severity of injuries sustained by different types of road users has been increasing over time. The study's findings point to several areas for further research and ways to improve existing systems for transportation safety and sustainability while avoiding negative environmental impacts such as increased air pollution levels due to longer travel times caused by increased traffic congestion.

The study highlights several areas where further research could be conducted to improve transportation safety and sustainability in Qatar, and the findings of this study provide valuable insights that can guide this future research. Specifically, the study identified the areas of the country with the highest density of population as the locations with the most frequent crashes, suggesting that current traffic management approaches in urban areas need improvement. The study also found that different types of road users experienced varying degrees of severity of injuries sustained in crashes and that these differences had been increasing over time. To improve safety for all road users, future research could analyze data on crash rates, causes, and consequences, as

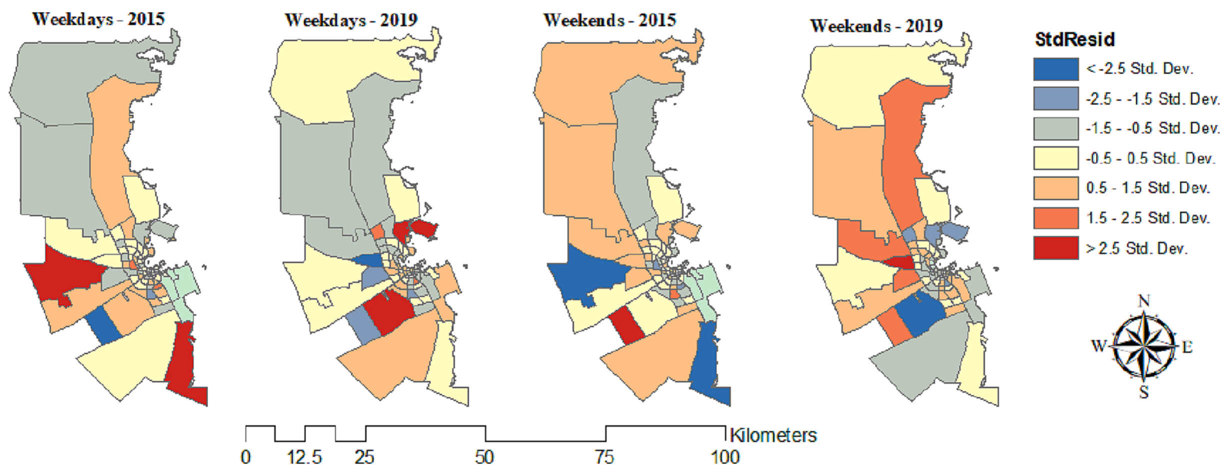


Fig. 20. Impact of the time of the week on traffic crashes on a zonal level during 2019.

Fig. 21. Impact of the time of the year on traffic crashes on a zonal level during 2015 and 2019.

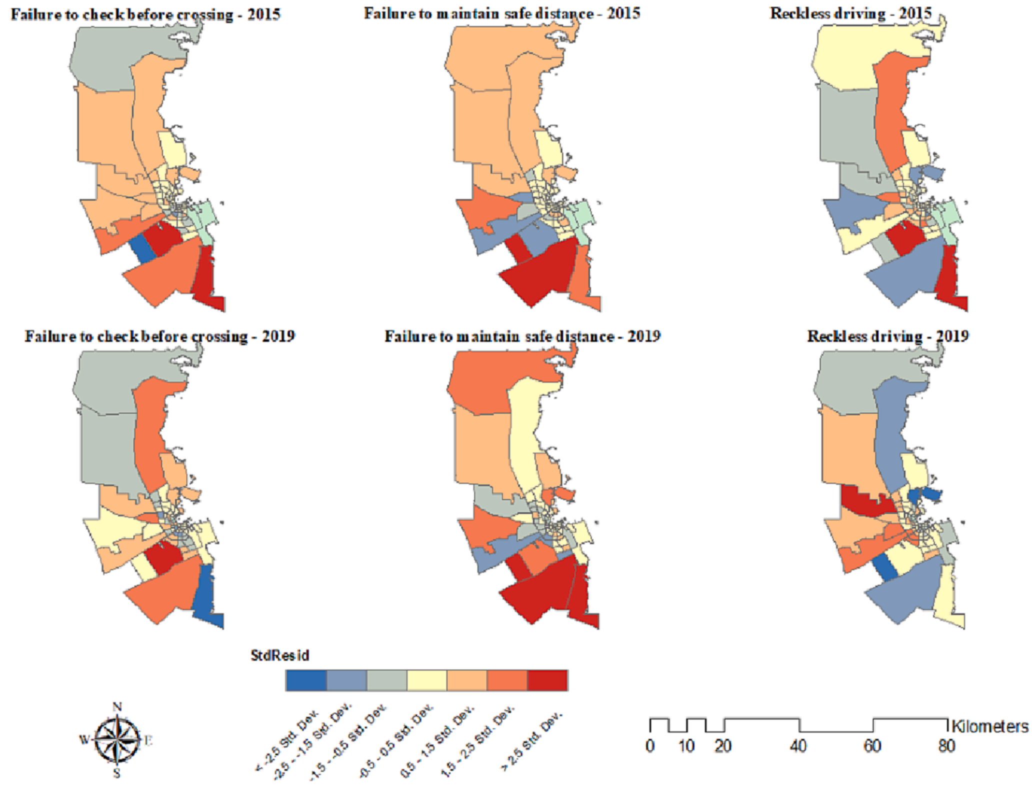


Fig. 22. Impact of the causality on traffic crashes on a zonal level during 2015 and 2019.

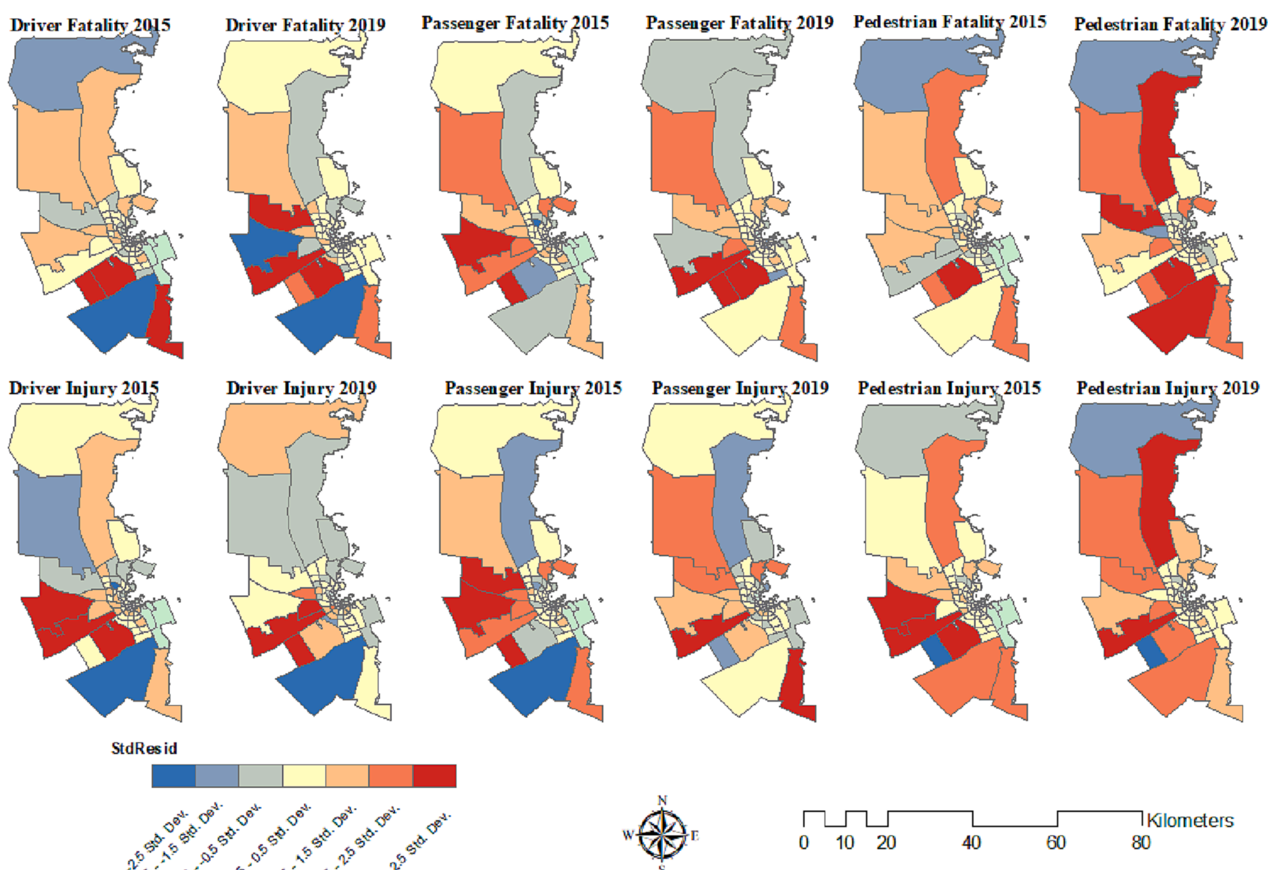


Fig. 23. Impact of fatalities and injuries on traffic crashes on a zonal level during 2015 and 2019.

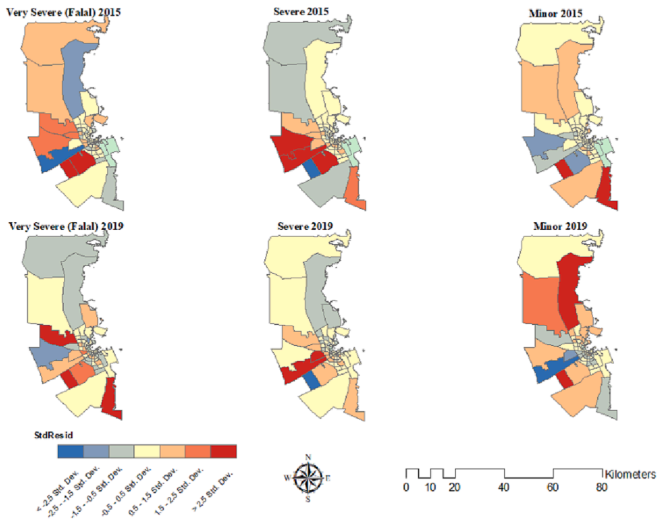


Fig. 24. Impact of crash severity on traffic crashes on a zonal level during 2015 and 2019.

well as vehicle speeds and other factors that contribute to the severity of injuries sustained by different road users. Overall, the findings of this study can inform the development of more effective methods for preventing crashes and improving safety on Qatar's roads while also ensuring that these methods do not cause negative environmental impacts.

CRediT authorship contribution statement

Semira Mohammed: Conceptualization, Methodology, Formal analysis, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Aya Hasan Alkhereibi:** Conceptualization, Formal analysis, Methodology, Data curation, Writing – original draft. **Ammar Abulibdeh:** Conceptualization, Formal analysis, Data curation, Methodology, Writing – original draft, Funding acquisition. **Rana N. Jawarneh:** Conceptualization, Resources, Formal analysis, Methodology, Validation, Writing – original draft. **Perumal Balakrishnan:** Conceptualization, Resources, Formal analysis, Methodology, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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