Identifying Spatial Patterns of Road Accidents in Madaba City by Applying Getis-Ord Gi* Spatial Statistic

Rana Ibrahim Abid

Abstract: Road safety has become a subject of great interest among policymakers worldwide as they seek effective strategies to mitigate traffic accidents. There exist various approaches to examine the occurrences of road traffic accidents in terms of their spatial information and consequences. Geographical information systems (GIS) have been widely employed to analyse the spatial patterns of road traffic accidents; they offer various statistical analysis tools to reveal the hotspot locations of road accidents. Reducing the number of traffic accidents and mitigating their negative impact by identifying hotspot locations has gained serious attention from the Public Security Directorate (PSD) in Jordan. This study analyses road traffic accidents in Madaba City using spatial statistics to determine the hotspot locations. The GTIS-Ord (Gi) spatial statistics method was applied to 5730 reported traffic accidents between 2017 and 2019. The results accurately located the groups of chosen accidents and identified 37 hotspots, accounting for 1.89% of the reported cases. The Maximum Z score was 30.99, and 691 reported cases led to the identification of 13 high-priority hotspots. These hotspots occur at significant thoroughfares, busy roundabouts, and uncontrolled intersections. Driving errors and excessive speeding were the most common causes of fatal and non-fatal accidents in Madaba City. Efficient countermeasures to mitigate the number of accidents in Madaba City include deploying more police inspectors to the city centre, installing speed cameras, and erecting traffic signs at uncontrolled intersections. The outcomes of this work may encourage the PSD to adopt GIS statistical tools in analysing the spatial patterns of road traffic accidents, thereby achieving more accurate results.*

Keywords: Getis-Ord Gi, GIS, Madaba, RTAs.

I. INTRODUCTION

Road traffic safety is a branch of transportation engineering that aims to find solutions and measures to overcome road accident problems that threaten the community's economy and health. Road traffic accidents (RTAs) are on the rise globally, especially in low-resource countries, and they are causing significant social and economic problems. In these nations, both the population and vehicle ownership rates are rising rapidly.

The occurrence of RTA has significantly increased as a result of the rising population and vehicle count. Jordan's population has increased from 1508200 inhabitants in 1970 to 11057000 in 2021, and the number of registered vehicles has increased from 21970 in 1970 to 1795215 in 2021 (DOS,2021, [1]).

Additionally, over the past five years, there have been more RTAs, with 28.6 accidents per day in 2017 and 30.8 accidents per day in 2021(PSD, 2021, [2]). RTAs are the leading cause of rising fatality rates in Jordan, affecting the social and economic development of Jordanian cities with limited resources (S. Al Jazzazi, et al, 2018, [3]). Because of this negative impact, effective countermeasures must be implemented. Identifying areas of the city's road network where safety is lacking is a strategy for enhancing road network safety (N. Manap et al., 2019). The implementation of the selected countermeasures necessitates identifying the most hazardous locations based on RTA location analysis, a process known as Hotspot Analysis. Geographical Information System (GIS) spatial techniques have been widely used to specify the locations of RTAs geographically and to visualise the distribution of evaluated patterns by providing a variety of statistical and spatial analysis tools. GIS offers a Spatial Statistics toolbox to determine hotspot locations, which includes several statistical tools for analysing spatial patterns from different sources. These statistical tools utilise geographic data, unlike mathematical statistical methods, which rely on the number of accidents and descriptive data. The Getis-Ord-Gi* spatial statistic and Kernel Density Estimation (KDE) are examples of spatial statistical tools which are widely used in the literature. This study aimed to determine the hotspot locations of RTAs in Madaba City over three consecutive years using Getis-Ord Gi* statistical analysis in conjunction with Moran's I (MI) statistical analysis. To achieve the research objectives, the article is divided into the following sections: Section Two presents a detailed literature review, Section Three outlines the research methodology, analysis, and results presented in Chapter Four, and finally, Section Five provides the research conclusion.

II. LITERATURE REVIEW

The Getis-Ord-Gi* spatial statistic and Kernel Density Estimation (KDE) are widely used in the literature. Gi* Statistics are a type of statistic that assesses the dependence of spatially distributed patterns, particularly when combined with Moran's I (MI) statistical tool.

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MI determines whether the patterns expressed by feature locations and values are clustered or dispersed by measuring the spatial dependence of the RTA locations and analyzing the spatial pattern. For each feature in the dataset, Gi* Statistics were used to identify hotspots of RTAs. A high value of the Gi* statistic represents a cluster of high index values (hot spots), whereas a low value represents a cluster of low index values (cold spots) (R. Satria, and R. Castro, 2016, [5]). KDE calculates the risk distribution of RTAs, which can be identified as the area around the cluster where such risk may increase as a result of RTA. The result of this analysis was the raster output.

(Z. Xie, and J. Yan, 2008, [6]) studied and investigated the kernel density estimation approach through tested traffic accident data for the year 2005 and a road network in the Bowling Green, Kentucky area. The study found that the analysis results may vary according to several factors, such as pixel lengths and search bandwidths. The search bandwidth *dictates* the highest influence by controlling the smoothness of the spatial pattern and revealing the hotspots. (J.K. Krisp, and O.Špatenková, 2010, [7]) used the kernel density estimation method to study the relationships between the accident distribution and accident density. They concluded that the results of this method depend on various parameters that facilitate the data visualisation process, and these parameters are contingent upon user requirements. (A. Soltani, and S. Askari, 2014, [8]) used the Kernel Estimation Density (KED) method to determine the hotspot locations of traffic accidents during the period 2011-2012 in Shiraz, Iran. The results showed that the majority of accidents occur on the main road, during peak traffic congestion hours, and in Areas with higher traffic speeds and volumes.

(L. Thakali, et al, 2015, [9]) used the Kriging method and kernel density estimation (KDE) method to determine the hotspot locations of traffic accident data for years between 2003 and 2007 in Hennepin County, Minnesota, U.S. The study found that the kriging method surpassed the KDE method in detecting hotspot locations. Additionally, the locations of hotspots determined by the two methods were found to be moderately different, highlighting the importance of selecting the appropriate spatial analysis method for hotspot identification. (R. Satria, and R. Castro, 2016, [5]) conducted an extensive review of GIS tools that are used in analysing traffic accidents. They found that Getis-Ord Gi* statistics are the most popular and powerful tool for studying traffic accident occurrence using spatial methods. (S. Hashimoto, et al, 2016, [10]) used the Kernel density estimation (KDE) method to study the relation between traffic accidents and city characteristics such as population, road factors, and spatial factors. They found a correlation between the occurrence of accidents and the studied factors. The study recommended using traffic calming to reduce the number of traffic accidents, even if the traffic accident data are not available. (A. Abdulhafedh, 2017, [11]) used Moran's I and Getis-Ord Gi* statistics to determine the spatial patterns of 2013 traffic accidents and identify the hotspot locations, and utilised Density Estimation (KDE) to produce concentration maps showing the density of accidents for the selected road network in Indiana. He found that the adopted approach is influential in determining the location of hotspots. (S. Kumar, et al, 2017, [12]) determined the hotspot locations of traffic accidents in Madurai city for the year (2007-2011) using the kernel density estimation method. The results showed that the extracted locations would be crucial for traffic managers and police departments to take the necessary actions to help reduce traffic accidents. (B. Romano, and Z. Jiang, 2017, [13]) suggested a new method called Spatial-Temporal Network Kernel Density Estimation (STNKDE) for the kernel density estimation method to analyse the traffic accidents for a selected location in New York City. (M. A. Aghajani, et al, 2017, [14]) identified accident distribution and analysed hotspots using Moran's I and Getis-Ord Gi* statistics for Ilam Province in Iran. Nine hundred forty-four accidents from 2013 were examined, and maps of accident density, topography, and rainfall were generated to identify a relationship between hotspot locations and these factors. Results showed a significant positive correlation between the hotspot locations and both the rainfall amount and the type of accidents at those locations. (U. Ahmad, et al, 2019, [15]) used Moran's I and Getis-Ord Gi* statistics and Kernel Density Estimation (KDE) spatial analysis tools to study the spatial patterns of traffic accidents in Dhaka city in Bangladesh. The analysis revealed 22 hotspots in the study area for the years 2010-2012. (G. LE, et al, 2019, [16]) used the kernel density estimation method to determine the hotspot locations for traffic accidents for the years 2015-2017 in Hanoi, Vietnam. The results showed that the adopted method was successful in identifying the hotspots of traffic accidents. (N.Manap, et al, 2019, [4]) used Moran's I and Getis-Ord Gi* statistics tools to determine hot spots on the 772 km length of the controlled-access expressway in Malaysia. The study analysed 47,359 accidents from 2016 to 2019. Results identified 25 hotspot locations, which had a total length of 87.1 km and involved 12,698 accidents. (S. Lakshmi, et al,2019) studied different statistical and spatial methods used in determining the hotspot locations of the years 2008 to 2012 traffic accidents in Des Moines city, Iowa, USA. The study concluded that a 500m bandwidth is ideal for locating hotspots, as demonstrated in the selected case study. However, when using bandwidths of 250 m, 750m, and 1000m, hotspots were not identified. (M. S. Yahya, et al, 2021, [17]) studied the development of the Selangor public transport network by analysing the spatial pattern and hotspots using Moran's I and Getis-Ord Gi* statistics. The study results indicated the GIS mapping capabilities in generating maps and spatial interpretations. (Q. Ma et al, 2021, [19]) used density analysis and cluster analysis methods to study the spatial distribution of traffic accidents in Wales for the year 2017. The results concluded that density analysis is more understandable compared to cluster analysis. The design method can help in understanding the spatial distribution of traffic accidents directly, whereas cluster analysis depends on the accident points. (K. Hazaymeh, et al, 2022, [17]) used Moran's I and Getis-Ord Gi* statistics to study the traffic accident pattern for Irbid City in Jordan for the years 2015 to 2019. The study results indicated the clustering patterns of traffic accidents.

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Irbid city roads and encouraged the traffic managers and decision-makers to use the results of their study to apply measures and actions to improve the hotspot locations and enhance traffic safety situations. (A. Afolayan, et al, 2022, [4]) used Moran's I and Getis-Ord Gi* statistics to determine the hotspots for selected highways in Nigeria. The study analysed accident data from 2013 to 2017. The results showed a random distribution of traffic accidents for the case study.

III. RESEARCH METHODOLOGY

The primary goal of this study was to identify RTA hotspot locations in Madaba City, Jordan. Madaba City has a total population of 214,100 inhabitants and an area of 940 km^2 (DOS, 2021, [1]). Madaba is located in the following geographical area: longitude 35 ° 47'38.11″ E, latitude 31 ° 42'57.56″ N. To determine the hotspot locations of the case study RTAs, the proposed research methodology employs Getis-Ord Gi* from the Mapping Clusters toolset in ArcMap 10.7. According to previous studies, the Getis-Ord Gi* method is commonly used to identify RTA hotspot locations. For three years, the RTA data were collected from the Traffic Police Department in the PSD (2017, 2018, and 2019). The location of RTAs (X, Y coordination), causes or types (crash, loss of control, collision), and severity (injuries (high, medium, slight), fatal, and property damage only PDO) were recorded. The RTA locations were mapped using ArcMap 10.7 by converting the X and Y coordinates into point features. To obtain the weighted point data, the data were processed using the Integrate Tool from the Data Management Toolset with X- and Y-tolerance distances of 10 m. The significance of this step is to maintain the integrity of shared RTA boundaries, or the identity of RTAs, by ensuring that the RTAs fall within specified X and Y tolerances. The MI method from the Spatial Statistics toolset was then used to measure the spatial autocorrelation of RTAs with a distance threshold of 100 m. (Changing the distance threshold from zero to 1000 did not affect the results.) This tool determines whether the expressed pattern is clustered, dispersed, or random and returns five values: Moran's I Index, Expected Index, Variance, z-score, and p-value. When the z-score or p-value indicates statistical significance, a positive Moran's I index value indicates proclivity toward clustering. In contrast, a negative Moran's I index value indicates proclivity toward dispersion.

MI's p-value and Z score of MI indicate whether there is a statistically significant relationship between the features in the dataset, which is also known as the null hypothesis. If the p-value is not statistically significant, the null hypothesis cannot be rejected, and the relationship between the features in the dataset is not substantial. Suppose the p-value is statistically significant and the z-score is positive. In that case, the spatial distribution of high and/or low values in the dataset is more spatially clustered (the null hypothesis cannot be rejected). If the p-value is statistically significant and the z-score is positive, the spatial distribution is high and/or the null hypothesis may be rejected. Finally, the Hotspot locations of the RTAs were investigated using the Getis-Ord Gi* method from the hotspot analysis mapping cluster toolset. For the weighted point data from the previous steps, this method identified statistically significant spatial clusters of high values (hotspots) and low values (cold spots). The Z-scores and p-values are statistically substantial measures indicating whether the null hypothesis should be rejected. They indicate whether the observed spatial clustering of high or low values is more pronounced than expected in a random distribution of the same values. When the p-value is very small, the observed spatial pattern is unlikely (low probability) to be the result of random processes, and the null hypothesis can be rejected. While Z-scores are standard deviations, extremely high or extremely low (negative) Z-scores associated with extremely small p-values were found in the tails of the normal distribution. The Gi Bin field, which identified statistically significant hot and cold spots, was the result of this analysis. Features in the +/-3 bins had statistical significance with a 95% confidence level, features in the +/-2 bins had a 95% confidence level, features in the +/-1 bins had a 90% confidence level, and clustering for features in bin 0 was not statistically significant (N. Manap, et al, 2019, [4]). The flowchart in Fig. 1 summarises the methodology used to identify RTA hotspot locations in Madaba City. The method of this research begins with collecting RTA data and culminates in creating a map of hotspot locations.

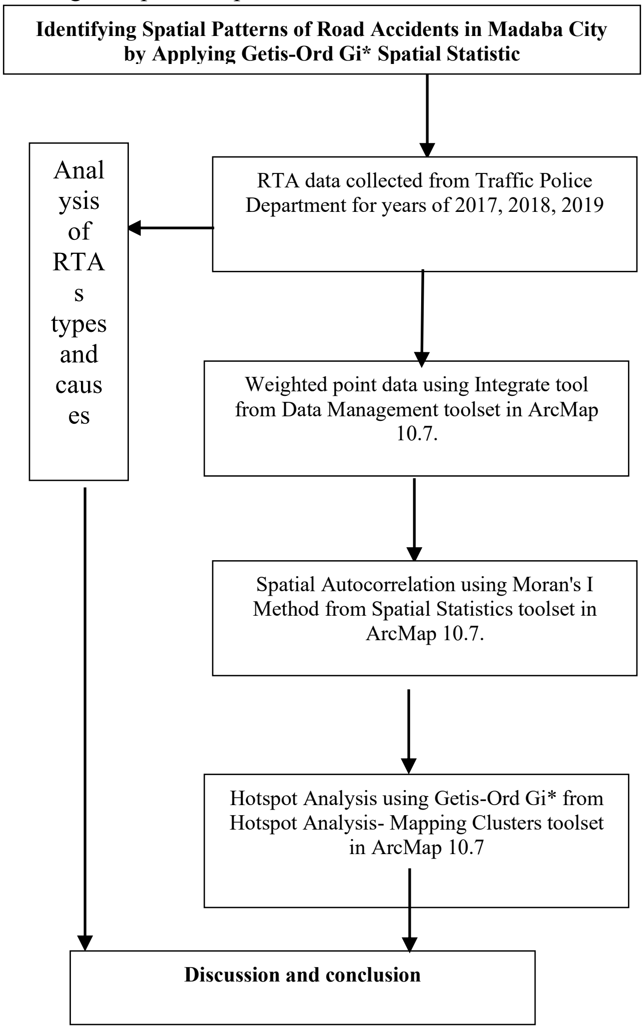

Fig. 1. Flowchart of the Research Methodology

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IV. ANALYSIS AND RESULTS

A. Accident Data

The Madaba City RTAs' data for three consecutive years (2017-2019) were analysed and summarised, as shown in the Table. 1. In Madaba, 5,730 accident locations were recorded over three years. The distribution of the 5,857 accidents was as follows: 8.23% minor injuries, 4.20% medium injuries, 1.74% severe injuries, 0.87% fatal injuries, and 84.96%. Over the three years, 5,399 accidents were recorded based on accident type, as summarised in the table. 2; 2.76% of accidents were loss of control, 5.33% were crashes, and 91.91% were collisions. The following are the causes of the three types of accidents recorded in the dataset: driving in the wrong lane, turning the vehicle in a way that obstructs traffic, wrong overtaking in cases and places where overtaking is prohibited, U-turning in controlled intersections, turning in the middle of the road, reversing the vehicle, changing the lane suddenly and wrongly, not respecting your speed, stop, and road marking signs, not securing the stability of cars while parking, drivers following too closely, opening the vehicle door from the sides or the back while the car is in motion, loss of control resulting from vehicle skidding or tire explosion, driving a car without taking the necessary traffic safety precautions, violations of traffic rules and priorities, and over speeding.

Table-1. Total Recorded RTAs in Madaba City

Total Accidents	Total accidents Locations	Total Slight Injuries	Total Medium Injuries	Total Severe Injuries	Total Fatal	Total PDO
5857	5730	482	246	102	51	4976

Table-2. Total Recorded RTAs in Madaba City

Accident type	Total Number of Accidents
Loss of Control	149
Crash	288
Collision	4962
Total	5399

The reasons for the differences in the total number of accidents, the total number of accidents by location, and the total number of accidents by type are that some accidents share more than one result, such as property damage accidents, which are also associated with injuries, and null accident causes, which reduce the total number of accidents. Fig. 2 shows the locations of Madaba's RTAs. According to the previously mentioned figure, a large number of accidents occur in the city centre of Madaba, where the majority of Madaba's population resides. Additionally, along the main highway connecting Madaba with southern cities, there are frequent occurrences of RTAs.

Fig. 2. RTA Locations for Madaba City

B. Weighted Point Data

The weighted point data were a collection of identical points that held the sum of all incidents at each unique location using a tolerance distance of 10 m X, Y. Fig. 3 shows that the largest weighted point dataset was (223). Because a hotspot location is identified based on the values of the surrounding locations, locations with high-weight values may not statistically indicate a hotspot location.

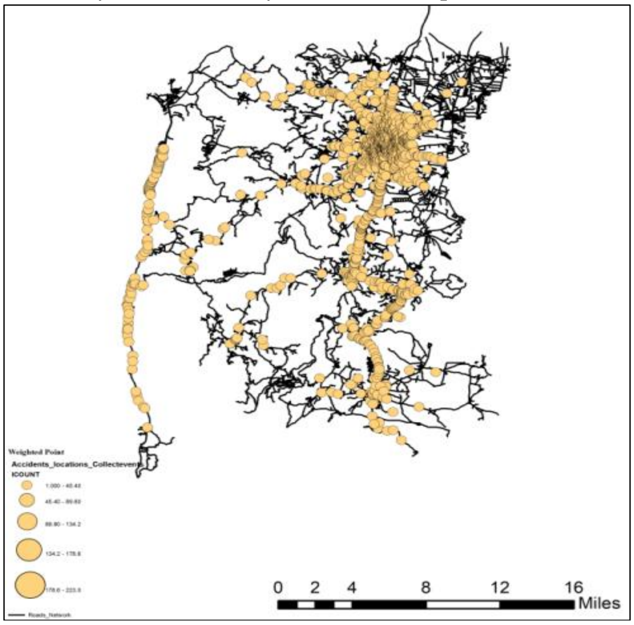

Fig. 3. Weighted Point Data of RTAs

C. Spatial Autocorrelation (Moran's I Method)

Moran's I statistic calculates the z-score and p-value to determine whether the dataset's pattern is clustered, dispersed, or random, based on feature locations and attribute values. Fig.4 shows that the Moran Index, Z score, and p-value were calculated as (0.075752, 57.247114, and 0.000000, respectively), The calculated values indicate that the spatial distribution of high and/or low values in the dataset is more spatially clustered and that a statistically significant relationship exists between the dataset features.

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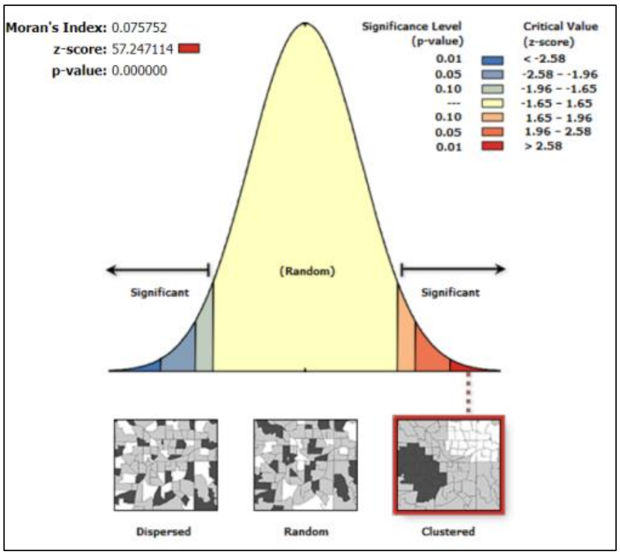


Fig. 4. Spatial Autocorrelation Report

D. Hotspot Analysis

The Getis-Ord Gi* spatial statistical method was used to locate the hotspots. This method defines a statistically significant hotspot as a location with a high value surrounded by equally valuable neighbours. Gi* was run with the following inputs: the weighted point feature (ICOUNT) as the input field, inverse distance as the input to the spatial relationship conceptualization, and zero as the input to the threshold distance, indicating that all accident locations were considered neighbors of one another. The RTA locations were classified into three categories based on their statistical significance level (Z-score) and output Gi Bin. Z-scores of 1.65, 1.96, and 2.58 (as the category's lower limit) and Gi Bin values between 1 and -1, 2 and -2, and 3 and -3 indicate 90%, 95%, and 99% confidence levels, respectively. RTAs with Gi Bin values of 1, 2, or 3 were classified as low-, medium-, or high-priority locations, respectively. In contrast, RTAs with Gi Bin values of zero were classified as non-significant locations. Gi* statistics analysis of 5730 RTAs yielded 1958 locations:37 significant locations with 1017 RTAs and 1921 non-significant locations with 4713 RTAs, representing 1.89% 98.11% of reported locations, and 17.75%, and 82.25% of reported RTAs, respectively. Fig. 5 illustrates the locations of hotspots and cold spots within the city of Madaba. The hotspot locations are concentrated in the city centre of Madaba, while the cold spot locations are concentrated outside the city. Fig. 6 provides a closer view of high-priority, medium-priority, and low-priority

Hotspot locations at the Madaba city centre. Table 3 displays the results of the analysis for low-, medium-, and high-priority hotspot locations. The mean Z scores for high-, medium-, and low-priority hotspots were 7.58006498, 2.19622241, and 1.80397077, respectively, according to the hotspot locations. The greater the z-score, the more intense the clustering in the area and the rejection of the null hypothesis, which is evident in high-priority hotspots with a maximum Z-score of 30.99033608 and a total of 691 accidents. Including too many objects in the output can draw attention away from the most critical analytical results. As a result, only hotspots were selected for the display. The hotspots were located in the Madaba City Centre, the busiest part of the city. The city centre of Madaba has dense commercial activities that attract personal trips by private vehicles, on-street parking that reduces road capacity and disrupts traffic flow, narrow and undivided roads that affect traffic flow, numerous signalised intersections, non-signalised intersections, and roundabouts that are responsible for continuously interrupted flow.

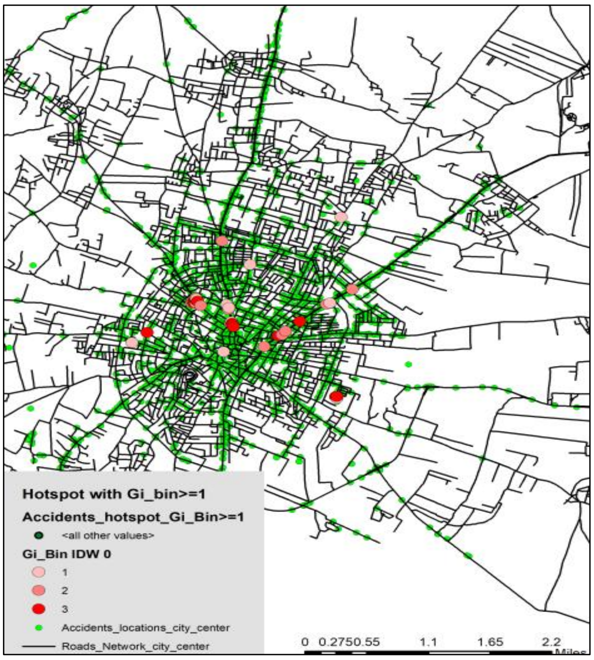


Fig. 5. Hotspot Analysis (Getis-Ord Gi*) Decade Analysis 2017–2019.

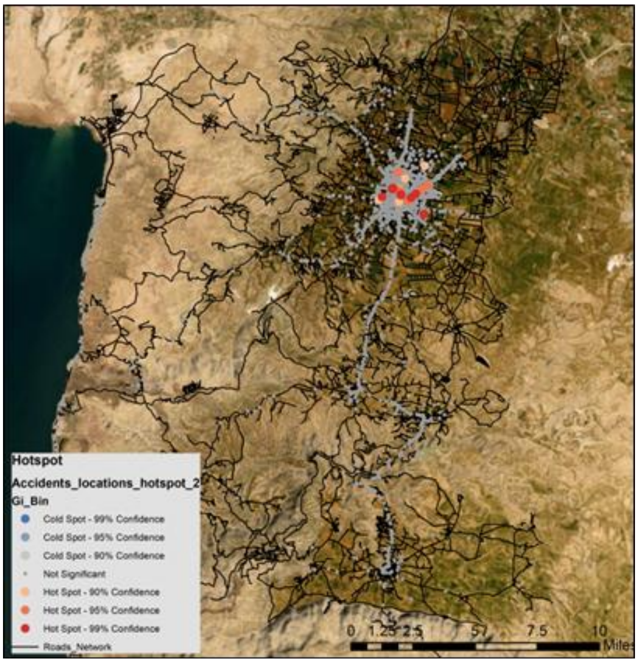


Fig. 6. High Priority, Medium Priority, and Low Priority Hotspot Locations

Table-3. Analysis Results for Low, Medium, and High-Priority Hotspot Locations

Number of Locations	Priority	Total RTAs	% of Hotspot locations	% of RTAs	Mean Z score	Max Z score
13	High	691	35.14%	67.94%	7.58006498	30.99033608
14	Medium	188	37.84%	18.49%	2.19622241	2.524385451
10	Low	138	27.03%	13.57%	1.80397077	1.943693414

Fig. 7-1 shows that the high-priority hotspot locations (13 locations with 691 RTAs) were divided into five groups, as listed in the Table. 4. Group (A), as depicted in Fig. 7-2, consists of five hotspots and 469 RTAs on Palestine Street near its intersection with Al-Quds Street. The main arteries of the city are Palestine Street and Al-Quds Street. Group (A) contained locations with high Z scores (location 1 had a Z score of 30.99, and location 2 had a Z score of 28.519) and the highest number of RTA accidents (223 RTAs for location 1 and 204 RTAs for location 2). Group (B), as depicted in Fig. 7-3, contains two hotspots and 75 RTAs at an uncontrolled intersection of two local roads. Group (C), as depicted in Fig. 7-4, includes three hotspots and 78 RTAs along King Talal Street near the Al-Mohafaza Roundabout. One of the busiest intersections in the city centre is the Al-Mohafaza roundabout. Group (D), as depicted in Fig. 7-5, consists of one hotspot and 25 RTAs at an uncontrolled intersection near the Madaba Engineering Association. Group (E), as depicted in Fig. 7-6, consists of two hotspots and 44 RTAs on Madaba Street near its intersection with King Hussein Street. Madaba Street has three traffic signals and is plagued by high speeds. In terms of fatalities, the study area has 51 deaths, with nine fatalities in Group E, seven fatalities in Group A, one fatality in Group D, and 34 fatalities on rural roads.

Table-4. High Priority Hotspot Locations

Group	Location Number	Total RTAs	Z score	Location Description
A	1	223	30.990336	Palestine Street near its intersection with Al-Quds Street
	2	204	28.519228	
	3	19	3.6821386	
	4	15	3.3278911	
	5	8	2.8023855	
B	6	51	6.7549645	Uncontrolled intersection of two local roads.
	7	24	3.328021	
C	8	27	3.678513	King Talal Street near Al-Mohafaza Roundabout
	9	26	3.5433064	
	10	25	3.3244823	
D	11	25	3.0384164	Uncontrolled intersection near Madaba Engineering Association.
E	12	23	2.9641691	Madaba Street
	13	21	2.5869924	Intersection of Madaba Street and King Hussein Street

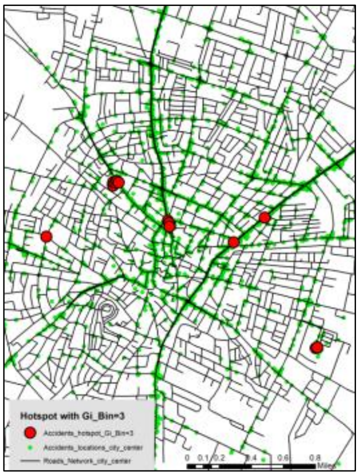
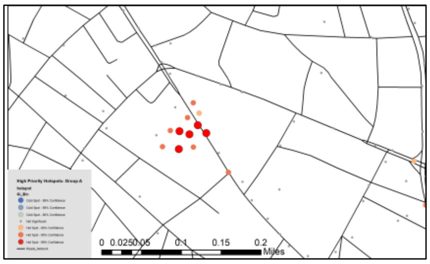


Fig7-1



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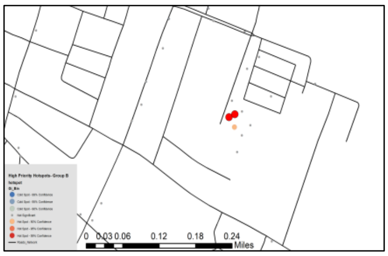

Fig7-3

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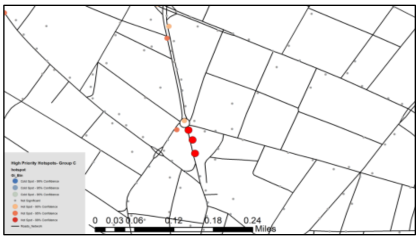
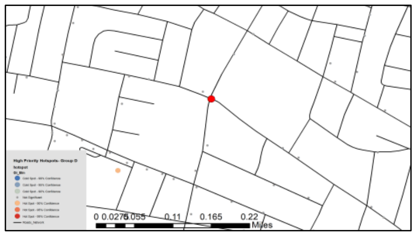


Fig7-4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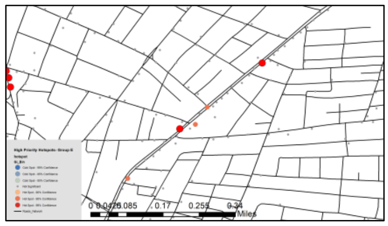
Fig7-6

Fig. 7. High Priority Hotspot Locations: 1) High priority Hotspot Locations, 2) Group A, 3) Group B, 4) Group C, 5) Group D, 6) Group E

V. CONCLUSIONS

Using statistical and spatial analysis tools in GIS, this study identified the RTA hotspot locations for Madaba city. Moran's I statistics revealed a clustered pattern of RTAs for 2017, 2018, and 2019. In contrast, hotspot analysis using Getis-Ord Gi* Spatial Statistics identified 37 hotspots, encompassing a total of 1017 RTAs. The hotspot locations were categorised into three priority levels: high, medium, and low. Each group had 13, 14, and 10 hotspots and RTAs and 691, 188, and 138, respectively. High-priority hotspots were identified and classified into five groups based on their proximity to one another: Groups A, B, C, D, and E. The most significant hotspots are in Group A, with maximum and minimum Z scores of 30.99 and 2.8, respectively. High-priority hotspots were found near the major thoroughfares, busy roundabouts, and uncontrolled intersections. Moran's I statistic and Getis-Ord Gi* Spatial Statistic were successful in identifying RTA hotspots in Madaba. However, hotspot locations with the most RTAs did not have the highest number of fatalities or deaths. According to fatal RTAs, 84.31% of fatalities have occurred on rural roads over the last three years (highways). Installing speed cameras at these locations is an effective way to prevent such accidents. The leading cause of non-fatal RTAs, according to non-fatal RTAs, is the drivers. Increasing police inspectors and monitoring in the city center, applying serious violations, particularly for drivers who do not follow traffic rules, and improving uncontrolled intersections, particularly in residential areas, with appropriate traffic signs, such as stop and priority signs, are some suggested countermeasures to reduce the number of non-fatal RTAs in Madaba.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	I am the sole author of the article.

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