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Safety on Jordan's highways: A GIS-Based approach to identifying road accident hotspots

Safa Sababhi · Shatha Aldala'in · Aymen Al Taani · Shatha Al Rawashdeh · Thahab Al Barari · Zubeida Aladwan · Teh Sabariah Binti Abd Manan

Abstract High numbers of road accidents at Jordan's major highways pose a substantial threat to public safety, necessitating strategic road safety interventions. This study presents hotspot spatial analysis based on severity indices for three prominent highways in Jordan via geographic information system (GIS) software. A comprehensive road accident network was constructed based on Jordanian road accident data (locations: Highways 30, 35, and 10) from year 2016 to 2019. Each incident's severity index was taken into consideration. Hotspot patterns were identified using GIS tools namely (a) Getis-Ord Gi* statistic and (b) Global Moran I index for spatial autocorrelation analysis, as they provide detailed information about the spatial distribution as well as statistical significance measures for road accident hotspots. The results revealed critical insights into the distribution of accident hotspots along the selected highways. In ascending order, the statistically significant hotspots observed were 14, 17, and 78 hotspots from Highways 10, 30, and 35. Hotspot patterns can be classified as random (Highway 30), dense (Highway 10), and dense clusters (Highway 35). Highway 35 demands targeted interventions to mitigate accidents along this route. This research takes away the hotspots along the highways that can be a good reference for stakeholders (e.g., transportation planners, policymakers, and relevant authorities) to implement best practices and road safety measures on Jordan's major highways.

Keywords Road accidents · Getis-Ord Gi* · Global Maron's I · Severity index · Spatial analysis · Geographic information system (GIS)

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Introduction

Roadway accidents remain a pressing concern worldwide, posing substantial threats to public safety, economic stability, and societal well-being (Heydari et al., 2019). In Jordan, as with many other countries, the occurrence of roadway accidents necessitates effective strategies to mitigate their impact and enhance road safety (Aldala'in et al., 2023). In Jordan, road accidents stand as the second primary cause of fatalities, underscoring their significant impact on public safety (Alomari, 2019). In the year 2022, there were 169,409 documented road accidents, leading to 562 fatalities and 17,097 injuries (Jordan Traffic Department, 2022).

Road accident hotspots refer to specific geographic locations or segments within a road network that exhibit a concentrated and consistently high occurrence of traffic accidents (Afolayan et al., 2022; Khatun et al., 2024; Sajed et al., 2019). These hotspots are characterized by a clustering of accidents, indicating the presence of contributing factors that elevate the risk of collisions. Recognizing and analyzing these hotspots is critical for developing effective road safety strategies and interventions targeted at reducing accidents in these problematic areas (Alam & Tabassum, 2023).

Road accident hotspots are an important aspect of any targeted intervention or strategies to minimize the number and severity of accidents (Alkaabi, 2023). These hotspots act as a center for several contributing factors which together can increase the risk of collision and associated injuries or deaths (Tamakloe, 2023).

Identifying the road accident hotspots in these locations enables transport authorities and safety agencies to maximize their efforts and make a larger impact with road safety programs (Rahman et al., 2020). Additionally, identification and mitigation of accident hotspots also serve global goals like sustainable urban development or transportation planning. By creating safer environments for their roads, cities, and communities can promote active transportation modes like walking or cycling, lower emissions from vehicular traffic, as well as enhance citizens' overall well-being (Wilches-Mogollon et al., 2024).

Jordan's highways have consistently witnessed a significant number of accidents, signifying a persistent road safety concern that requires immediate attention. Despite ongoing efforts to enhance safety measures and regulations, the necessity to pinpoint road accident hotspots remains of utmost importance. These hotspots correspond to specific locations along the highways where accidents happen more frequently and tend to be more severe. Through a systematic analysis aimed at identifying these hotspots, we can gain deeper insights into the underlying factors and patterns contributing to these accidents (Al-Rousan et al., 2021).

Geographic Information Systems (GIS) have emerged as powerful tools for spatial analysis, enabling the identification and understanding of accident patterns and hotspots (Atumo et al., 2022; Bisht & Tiwari, 2023; dos Santos et al., 2022; Jima & Sipos, 2023; Masron et al., 2019; Pusuluri et al., 2023a). GIS enables the integration of road-related, demographic, and geographical data, thereby facilitating the investigation of spatial relationships and the detection of accident-prone areas(Azari et al., 2023; Sae-ngow & Kulpanich, 2023).

Despite the increasing utilization of GIS for identifying road accident hotspots for identifying road accident hotspots (Munasinghe, 2023), there remains a notable gap in the research literature pertaining to the specific context of Jordan (Hazaymeh et al., 2022). While studies from various regions have demonstrated the efficacy of GIS in pinpointing accident-prone areas, the unique geographic, demographic, and infrastructural characteristics of Jordan necessitate a tailored approach (Maaiah et al., 2021). Existing research predominantly focuses on developed countries and metropolitan areas, often leaving regions like Jordan underrepresented in the analysis of road safety patterns. Furthermore, many studies primarily concentrate on accident frequency without delving into the severity of accidents (Aldala'in et al., 2023), hindering the formulation of precise and effective mitigation strategies.

In this study, we conducted a comprehensive spatial analysis of road accidents along three major highways in Jordan (Highways 10, 30, and 35), utilizing two key spatial statistical measures: the Global Moran I index and the Getis-Ord Gi statistic. Our analysis focused on evaluating the spatial distribution and arrangement of these accidents, taking into account their severity index. To ensure robust results, our dataset encompassed all reported traffic accidents that transpired during the period spanning from 2016 to 2019. This approach allowed us to gain deeper insights into the spatial patterns of road accidents on these critical roadways, aiding in the identification of accident hotspots and the assessment of their significance.

Literature review

Hotspot analysis is a spatial analysis and mapping technique focused on identifying spatial clusters (Al-Aamri et al., 2021; Zahran et al., 2019). These clusters refer to the specific locations of events or objects, represented as points on a map (Mohammed, 2023). Notably, widely used techniques in this field include Moran I (Babaei & Kunt, 2023; Pusuluri et al., 2023b), Kernel Density Estimation (KDE) (Bayiga Zziwa et al., 2023; Khan et al., 2023), and Getis–Ord Gi* (Bindajam et al., 2023; Samani & Amador-Jimenez, 2023; Zhang & Wang, 2023), chosen for their ability to unveil the statistical significance of road accident hotspots. Among them, the Getis-Ord Gi* and Moran I methods are prominent global statistics frequently utilized to convert non-spatial correlation into a spatial context, enabling spatial autocorrelation analysis (Erdogan et al., 2015).

Getis –Ord GI* is a method for locating hotspots in a dataset for each characteristic (Colak et al., 2018; Tang et al., 2019). The generated p-values and z-scores reveal the spatial distribution of characteristics with low or high values. This instrument analyses each feature in relation to its neighbour(s). While a feature with a high value might be intriguing, it attains statistical significance when surrounded by neighboring features with similarly high values (Baldík et al., 2020).

Moran's I and Getis-Ord outperform kernel density estimation in identifying road accident hotspots (Hovenden & Liu, 2020). Moran's I detects clustering patterns based on the similarity of values in nearby areas. This aids in identifying areas where accidents are not randomly distributed but rather clustered, indicating potential hotspots. Kernel density estimation, on the other hand, focuses solely on event concentration without regard for spatial relationships or clustering patterns (Abdulhafedh & Abdulhafedh, 2017). Furthermore, Getis-Ord Gi* calculates statistical significance for identifying hotspots of road accidents. It distinguishes between random fluctuations and true spatial patterns, allowing authorities to prioritize interventions in areas of high clustering (Alkaabi, 2023). Kernel density estimation does not automatically provide statistical significance measures for hotspot detection (Srikanth & Srikanth, 2020). Also, Moran's I and Getis-Ord statistics provide flexibility in analyzing various types of spatial data and are relatively simple to understand. They provide detailed information about the spatial distribution of road accidents as well as the significance of identified hotspots (Behanova et al., 2022). Kernel density estimation is useful for visualizing density gradients, but it may not provide as clear or actionable insights into event clustering (Sarker, 2021).

Wee et al., (2021) conducted a study with the aim of identifying areas in Singapore with notably higher occurrences of road accidents resulting in severe injuries, defined by an Injury Severity Score exceeding 15, and to develop a spatiotemporal model. The study utilized data from the National Trauma Registry, and the geographical locations of road accidents were mapped onto a Singapore map. Spatial statistical techniques, particularly the Getis-Ord Gi* algorithm, were applied for analysis, revealing the presence of nine significant hotspots (p < 0.01). The study's conclusion highlights the importance of information gained from studying these hotspots, especially for road accident causing severe injuries, as it can be a valuable resource for various agencies to optimize resource allocation.

Alam and Tabassum (2023) conducted a study focusing on accident hotspot locations and crash severity in Ohio. In the field of safety research, advanced GIS-based hotspot analysis has been utilized to analyze road accident data over time. This study utilized four years of Ohio crash data (2017–2020) and spatial autocorrelation analysis via GIS to identify high-risk accident areas. The approach assessed crash severity levels and revealed both high and low crash severity cluster zones. The study utilized tools like, crash severity index, Getis Ord Gi*, and Moran's I spatial autocorrelation. Notably, identified hotspot locations in significant Ohio cities, including Cincinnati, Cleveland, Columbus and Toledo, underscore the need for proactive traffic management efforts to mitigate the socio-economic impact of road accidents and necessitate thorough investigations.

Mesquitela et al., (2022) introduced a method for pinpointing accident-prone areas based on geographic references. Employing ArcGIS Pro, they utilized Kernel Density and Getis-Ord Gi* tools to detect potential high-risk zones by considering both their geographical location and surrounding conditions. Additionally, they assessed various factors, including environmental factors, human behavior and situational circumstances, which could contribute to the severity of accidents. The findings underwent validation through evaluation by an expert panel.

Qalb et al., (2023) created a partially automated system for examining and forecasting road accident trends in Kasur, an intermediate city in Pakistan, using five years of accident data (from year 2014 to 2018). They employed Python-based software tools and the Jupyter Notebook platform to implement various methodologies such as the Getis-Ord Gi* statistic, radar charts, analysis time series indices, and Moran's I spatial autocorrelation. The findings revealed that October had the highest number of accidents, while April had the fewest. Accidents peaked at 7 am, and weekends had notably more accidents compared to weekdays. The central city area was identified as a major hotspot with a significant cluster of accidents. The team also created a real-time, zoomable spatiotemporal visualization interface using GitHub and Tableau.

Hisam et al., (2022) investigated how road geometry relates to road accidents in Kajang, Selangor. They harnessed GIS for its statistical analysis capabilities and its role in identifying accident-prone areas on maps. The study employed Moran's I technique to gauge spatial autocorrelation and Getis Ord Gi* tools from GIS to uncover the connection between road layouts and accidents. Pinpointing hotspot locations through spatial analysis offers a valuable approach to enhance safety at accident-prone sites. The study effectively analyzed the map of accident hotspots and the link between road geometries, revealing that T-intersections experienced the most accidents, making them the riskiest intersection type.

Mhetre and Thube, (2023) directed their research towards road safety, specifically the identification of areas prone to high and low accident rates along a rural National Highway in Maharashtra, India. They based their analysis on accident data collected from 2016 to 2020, considering three distinct time frames: 2016–2018, 2017–2019, and 2018–2020. The objective was to compare these time frames in order to discern the primary hotspots and coldspots for road accidents. Interestingly, throughout all scenarios, the highway sections between chainage 592.24 km–611.5 km and 712 km–725 km consistently exhibited low accident rates, classified as coldspots, with no hotspots in between. Conversely, the sections spanning from 611.5 km–629 km and 679.5 km–707 km showed no coldspots in scenario 2 and scenario 3. Notably, there was a 49.68% reduction in the number of accident hotspots in scenario 2 and a 20.25% reduction in scenario 3, while the number of accident coldspots increased by 46.42% in scenario 2 and 48.78% in scenario 3 each year.

Mekonnen et al., (2023) adopted the criteria outlined in the Hungarian road planning guideline to enhance road safety by reducing the frequency of accidents over a three years period. This approach aimed to improve the accuracy and simplicity of their analysis. They conducted a comparison between the K-means and hierarchical clustering algorithms for data segmentation, with K-means demonstrating superior performance based on metrics like the, Davies–Bouldin, Calinski–Harabasz indexes and Silhouette. For the final hotspot identification, they employed the Empirical Bayes (EB) method. Utilizing a dataset spanning three years (2016–2018), the study identified three distinct hotspots in Budapest. To assess these hotspots further, an optimized hotspot analysis was conducted using GIS techniques, specifically the Getis-Ord Gi* spatial autocorrelation analysis. This analysis categorized areas into hotspots, coldspots, or areas with no significant patterns, considering both 95% and 90% confidence levels.

Prasad et al., (2023) conducted an analysis to enhance the safety of accident-prone areas. The data used for this analysis was gathered from police station records spanning from 2013 to 2019. They employed the Weighted Severity Index (WSI) method, which involves assigning scores based on the number and severity of accidents occurring in specific locations over the past few years. The primary objective of the project was to identify significant hotspots within the Narasaraopet mandal and propose measures for reducing road accidents and enhancing overall road safety. To achieve this, they selected six out of the 44 identified hotspots for in-depth study and recommended improvements based on detailed road assessments and observations of road features.

Methodology

Locations

This study examined three prominent Jordanian highways. The first one, known as Highway 30 or the Al Azraq—Zarqa highway, holds strategic importance within the country. This road establishes a crucial connection between Al Azraq, situated in the eastern region, and Zarqa, positioned northwest of the capital, Amman. The length of the stretch is 72 km. Serving as a pivotal transport conduit, the

highway plays a fundamental role in linking local commuters and long-distance travelers in the area.

The second highway, Highway 35 (Amman-Irbid highway), acts as a vital link between the capital city of Amman and Irbid in the northern part of Jordan. The length of the stretch is 118 km. This roadway serves as a pivotal route, facilitating the seamless movement of people, goods, and services between these two significant urban centers.

The third highway, namely Highway 10 (Almafraq-Irbid highway), forms a vital connection between the cities of Almafraq and Irbid in the northern sector of Jordan. The length of the stretch is 26km. This route plays a substantial role in enhancing transportation by linking these two cities, enabling the efficient movement of people, goods, and services within the northern region of the country. Figure 1 shows the 10,30,35 Highways map.

Data preprocessing

Figure 2 illustrates the procedural steps followed in this study. The data regarding road accidents was obtained from the Jordan Traffic Department, covering the three-year period from 2016 to 2019. This dataset includes accident attributes and the corresponding coordinates of the locations, encompassing both latitude and longitude information.

In Fig. 3a, the data displays the frequency of accidents along with the corresponding fatality rates (calculated as the number of fatal accidents divided by the total number of accidents). Among the highways, highway 30 had the most fatal accidents, totaling 42, followed by highway 35 with 30 fatal accidents, and highway 10 with 9 fatal accidents. In terms of fatality rates, highway 30 exhibited the highest rate at 2.55%, followed by highway 10 at 1.54%, and highway 35 at 0.58%. Figure 3b reveals that highway 30 accounted for the highest number of major injuries (126), trailed by highway 10 with 73 major injuries, and highway 35 with 7 major injuries. Notably, highway 10 exhibited the greatest rate of major injuries (12.46%), followed by highway 30 at 7.66%, and highway 35 at 1.38%. In Fig. 3c, it is evident that highway 35 recorded the highest number of minor injuries, totaling 714 cases, followed by highway 30 with 445 minor injuries, and highway 10 with 240 minor injuries. When considering rates of minor injuries, highway 10 exhibited the highest proportion at 40.96%, followed by highway 30 at

27.07%, and highway 35 at 13.86%. In Fig. 3d, the data indicates that highway 35 experienced the most significant amount of property damage, totaling 4685 cases. This was followed by highway 30 with 1350 cases and highway 10 with 439 cases. Highway 35 also had the highest proportion of property damage at 90.95%, with highway 30 at 82.12% and highway 10 at 74.91%.

The spatial analysis process began with the integration of road accident data into ArcGIS. Within ArcGIS 10.7, the base map tool was employed to visually represent this dataset. To ensure consistency and precision, the entire dataset was transformed into 30 UTM-ED50 coordinate units. Through the utilization of latitude and longitude coordinates, the specific geographic locations of road accidents were accurately marked.

To facilitate spatial analysis, the data underwent a conversion process, transforming it into a spatial representation. This conversion was achieved utilizing ArcCatalog's Data Management tools. Subsequently, the shapefiles that include the accident data were structured and modified to seamlessly integrate with various ArcGIS applications. These shapefiles underwent necessary adjustments to meet the specified requirements for spatial analysis and visualization.

Severity index

The severity index (SI) is a value with no dimensions, indicating the danger of a spot on the road (Cao et al., 2020). The severity index method is used to locate the hotspots. Using this method, a severity value can be assigned to each accident's location based on the number of fatalities, injuries, and property damage (Mohammed Fayaz et al., 2018). SI aids in evaluating the repercussions of road accidents by quantifying their seriousness. It offers a consistent metric that enables comparisons among various accidents, locations, or timeframes. This evaluation holds significant importance in comprehending the human casualties, property loss, and broader implications resulting from road accidents (Ahmed et al., 2023).

The SI was computed based on the severity weights at accident sites along Highways 35, 30, and 10 between 2016 and 2019. The criteria employed in this research to identify high-risk locations align with the findings of studies conducted by the Jordan Traffic Institute (2009–2011). These
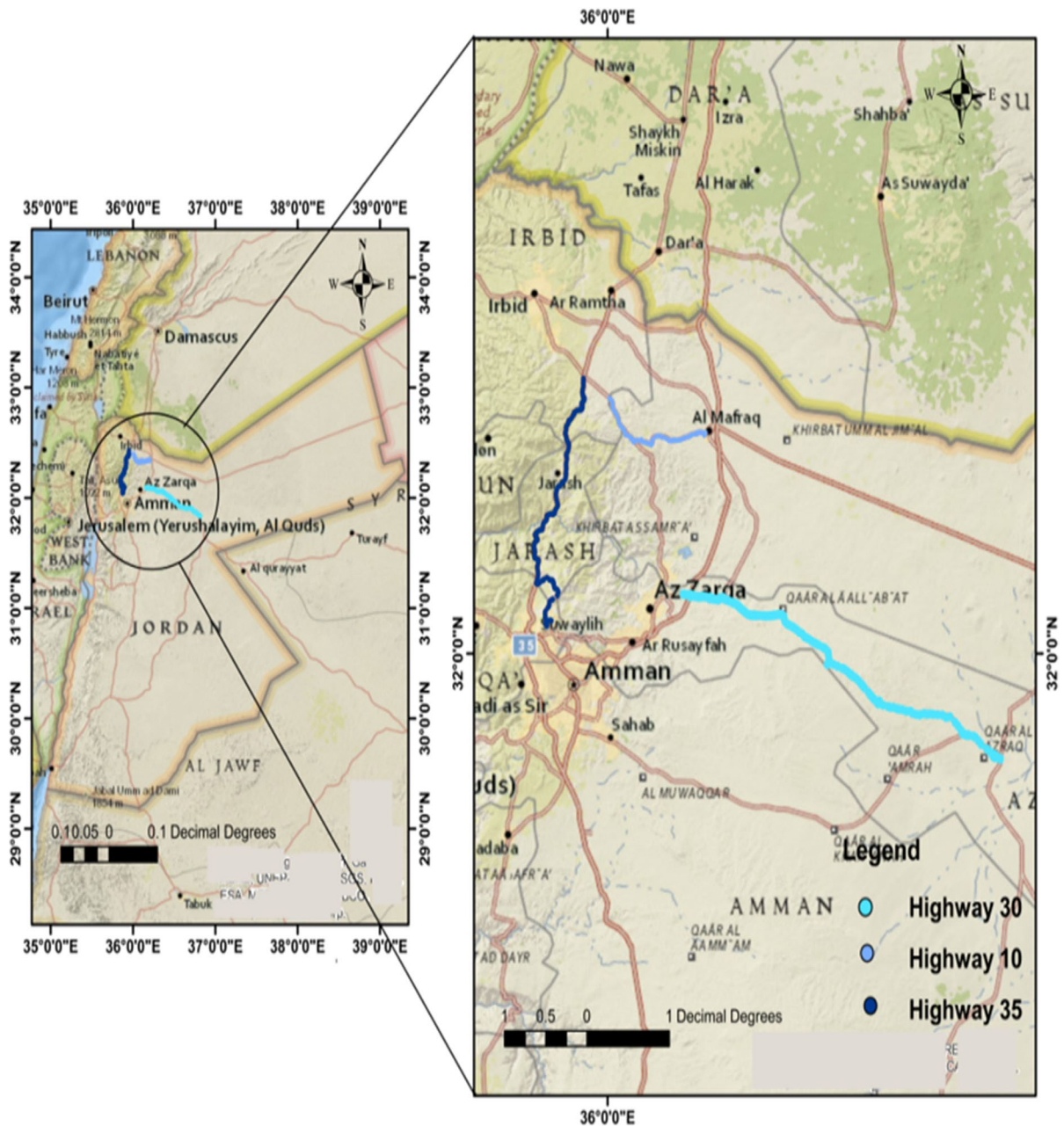
Fig. 1 Study area

studies explored various techniques that could be utilized, and the selection criteria in this current study encompass the severity index as outlined in Eq. 1(Abuaddous et al., 2022):

$$SI = (Number\ of\ Fatalities \times 3) + (Number\ of\ Injuries \times 1)$$
$$+ (Number\ of\ Property\ Damage \times 0.33) \tag{1}$$

Global moran's I

The Spatial Autocorrelation tool, also known as Global Moran's I, was used to assess spatial autocorrelation by considering both the geographical positions of features and their attribute values concurrently (Le et al., 2020). When applied to a set of features and their associated

Fig. 2 Flowchart of the study
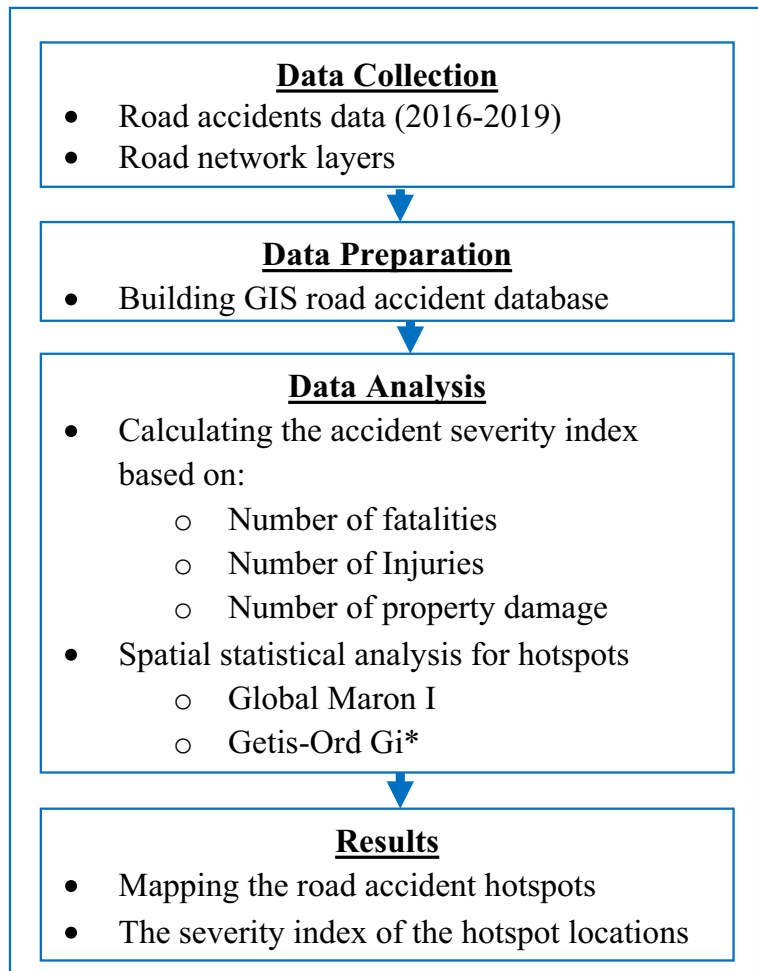
attributes, it determines whether the observed pattern is clustered, dispersed, or random. This tool computes the Moran's I Index value and provides both a z-score and p-value to gauge the statistical significance of this Index. The p-values are numeric approximations of the area under a known distribution curve, bounded by the test statistic. The Moran's I, along with its associated p-value and z-score, were calculated using the Spatial Autocorrelation tool as defined by Eq. (2) (Wang et al., 2023). This process involved selecting the fix distance band method to establish a cutoff distance, serving as the approach for conceptualization of spatial relationships. This choice allowed for the analysis of each feature (road accidents) within the context of neighboring features. Specifically, neighboring features falling within this specified distance were given a weight of one and factored into the calculations for the target feature. Conversely, other features outside this specified distance were assigned a weight of zero and did not impact the computations for the target feature.

$$I = \frac{N \sum_I \sum_J W_{I.J}(X_I - \overline{X})(X_J - \overline{X})}{(\sum_I \sum_J W_{I.J}) \sum_I (X_I - \overline{X})(X_J - \overline{X})^2} \qquad (2)$$

In this equation, where N represents the number of cases, Xi denotes the variable value at a specific location, Xj represents the variable value at another location, $\overline{X}$ stands for the mean of the variable, and W signifies a weight applied to the comparison between location i and location j. Wij represents a weight matrix based on distance, specifically, it's the inverse of the distance between locations i and j, denoted as 1/dij.

To calculate distances from each feature to its neighboring features, the Euclidean Distance method,

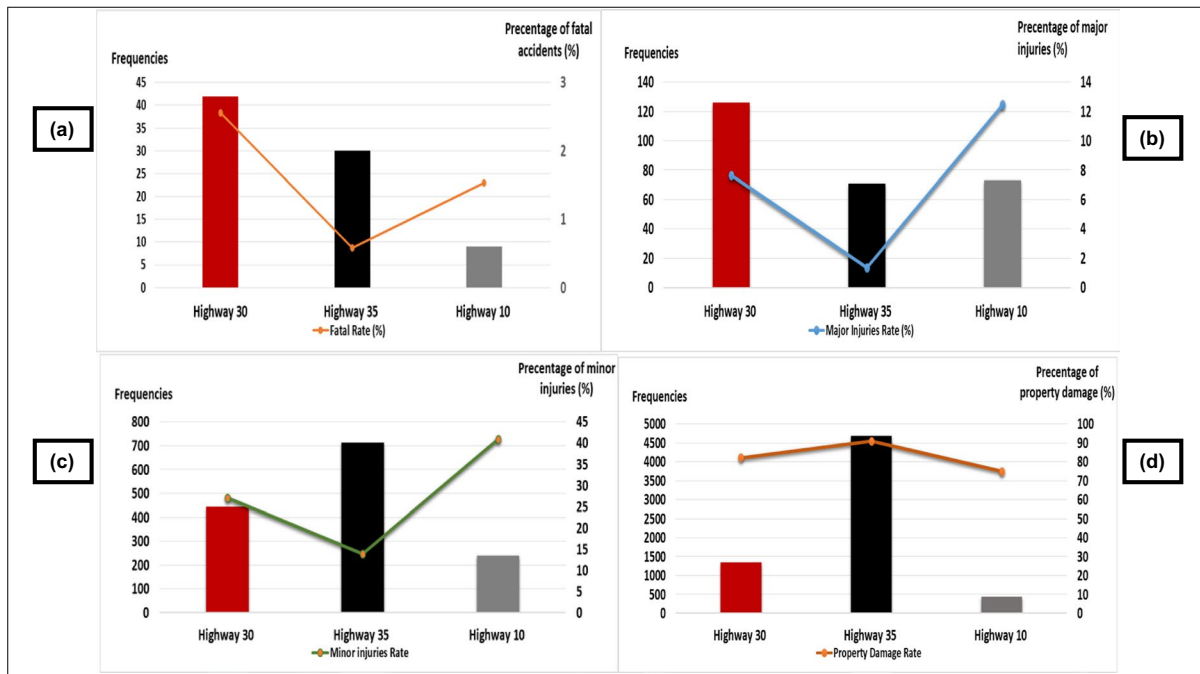**Fig. 3** Road accidents of highways 30, 35, and 10 between 2016 and 2019 in four categories: (**a**) Fatal accidents, (**b**) Major injuries, (**c**) Minor injuries, and (**d**) Property damage

represented by Eq. (3), was employed. Furthermore, the Distance Band or Threshold Distance, which defines the scale of analysis, was determined using the Incremental Spatial Autocorrelation function in ArcGIS Pro. This function computed the "Distance Band from Neighbor Count," assisting in pinpointing the initial distance at which to commence the spatial autocorrelation analysis and the interval at which to increase this distance.

$$d = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2} \qquad (3)$$

Here, $(X2, Y2)$ represents the coordinates for point a, $(X1, Y1)$ signifies the coordinates for point b, and 'd' corresponds to the direct, straight-line distance between points a and b.

The getis-ord g_i^*

The Getis-Ord G_i^* method was employed to statistically examine the spatial distribution pattern of traffic accidents at the zonal level. This approach is utilized to pinpoint both hotspots (areas with clustered high values) and coldspots (areas with clustered low attribute values) of these accidents. This helps determine whether the crashes exhibit spatial clustering (dependency) or occur randomly. The Getis-Ord G_i^* technique operates on the premise that if a particular geographical area is identified as a hotspot for traffic crashes, then neighboring areas should also display elevated traffic accident occurrences. Hence, this method serves as a measure for local spatial autocorrelation analysis. Each geographical zone is associated with a z-score and a p-value via Getis-Ord G_i^*. Larger Z-score values indicate a more concentrated clustering of traffic accident values in that zone (hotspot). These values provide insights into whether zones with either low or high accident rates tend to cluster together in space. Mathematically, the calculation of the Getis-Ord G_i^* is conducted using the formula provided below (Alkhatni et al., 2023).

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_{j} - \overline{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{i,j}^2 (\sum_{j=1}^{n} w_{i,j})}{n-1}}} \qquad (4)$$

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{5}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \overline{X}^2} \tag{6}$$

In this context, $w_{i,j}$ represents the weight associated with accident features i (the first location) and j (the second location), $'x_j'$ denotes the attribute value of feature j (specifically, the accident severity index), $'G_{i*}'$ stands for a z-score statistical measure, $'\overline{X}'$ represents the mean value, $'S'$ signifies the standard deviation, and $'n'$ corresponds to the total number of features.

Results

Global moran's I

Figure 4 provides a comprehensive visual representation of autocorrelation analysis, which focuses on distance metrics, particularly highlighting key findings for three prominent highways in Jordan. This analysis is crucial for understanding the spatial patterns and correlations related to accident occurrences along these highways. For Highway 35 (Fig. 4(a)), we initially employed the Distance Band from Neighbor Count Method, revealing an average distance of 210 m between accident locations. This initial distance served as our reference point for investigating spatial autocorrelation and was used as the increment distance. When this distance was applied in the incremental spatial autocorrelation function calculation, we identified a significant peak at 250 m. This specific distance was associated with the highest z-score value in the analysis. The z-score is a statistical measure that helps us determine the significance of spatial clustering. In this case, the elevated z-score at 250 m suggests a noteworthy spatial correlation in accident occurrences along Highway 35 within that range.

Moving on to Fig. 4(b) and Highway 10, our analysis started with an initial distance of 488 m for examining spatial autocorrelation, also serving as the increment distance. Notably, we observed a maximum peak distance at 496.98 m, accompanied by a corresponding z-score of 7.07. This indicates a strong spatial autocorrelation pattern in accident locations along Highway 10, specifically within that nearly 497-m distance range. In Fig. 4(c), focusing on Highway 30, we began our spatial autocorrelation examination with an initial distance of 1492 m, which was also the increment distance. The results revealed a maximum peak distance at 1712.47 m, along with a corresponding z-score of 5.51. This finding suggests that accident occurrences along Highway 30 exhibit a significant spatial autocorrelation pattern within that distance range.

These spatial autocorrelation analyses are crucial for identifying areas of concern and understanding how accident incidents cluster along these highways. The z-scores provide statistical evidence of these patterns, helping us pinpoint specific locations where further investigation and intervention may be necessary to improve road safety. Table 1 shows a comprehensive and insightful exploration of the global Moran's I values. These values were computed at different distances using the incremental spatial autocorrelation function, and they serve as a fundamental tool for gaining a deeper understanding of the spatial distribution patterns of road accidents that transpired between 2016 and 2019 along three significant highways: Highway 35, Highway 30, and Highway 10.

Figure 5 complements these Moran's I values by presenting a spatial autocorrelation graph that visually represents the associated z-scores and p-values, shedding further light on the significance and characteristics of the spatial clustering patterns. In Fig. 5(a), the analysis for Highway 35 reveals a Moran's I value of 0.050, a z-score of 13.994, and a corresponding p-value of 0.000. These results collectively convey a highly significant spatial clustering pattern. The positive Moran's I value signifies a positive spatial autocorrelation, indicating that road accidents along Highway 35 are not randomly distributed but tend to cluster together. The substantially high z-score emphasizes the intensity of this clustering, while the minuscule p-value is crucial as it indicates that the observed clustering pattern is highly improbable to occur by random chance, with a probability of less than 1%. This implies that the spatial distribution of traffic accidents on Highway 35 is not random but exhibits a significant and concentrated clustering pattern. Figure 5(b) presents a similar scenario for Highway 10, with a Moran's I value of 0.127, a z-score of 7.864, and a p-value of 0.000. These results also suggest a statistically significant status characterized by dense clustering. Similar to Highway 35, the positive Moran's I value, high z-score, and small p-value
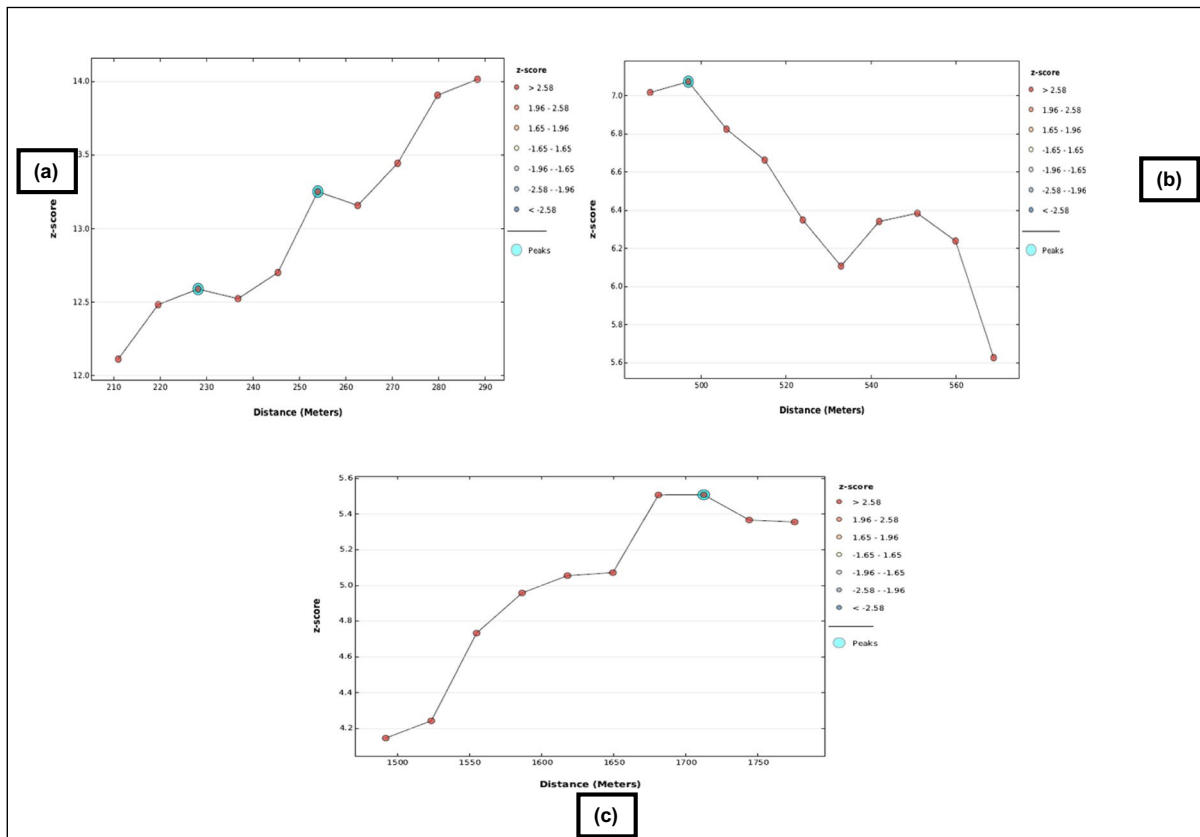
Fig. 4 Incremental Spatial Autocorrelation Analysis Based on Distance and Peak Values (**a**) For Highway 35, (**b**) for Highway 10, and (**c**) for Highway 30

collectively underscore the presence of pronounced spatial clustering among traffic accidents along Highway 10. This indicates that road accidents on Highway 10 also exhibit a significant spatial clustering pattern, albeit with somewhat different intensity compared to Highway 35.

Figure 5(c) offers a contrasting perspective for Highway 30, where Moran's I is calculated as 0.002, accompanied by z-score of 0.284 and a p-value of 0.776. These findings suggest a lack of statistical significance in terms of spatial clustering. It appears to be distributed in a relatively random manner.

Hotspot analysis

The analysis of road accident hotspots, conducted using the Getis Ord Gi* method, was based on the severity index associated with each accident location.

This approach aimed to identify statistically significant spatial clusters characterized by high severities, which are referred to as "hotspots" in this context. The outcomes of the hotspot analysis were subsequently utilized to create maps depicting the locations of these road accident hotspots. The Getis-Ord Gi* method generated new output feature classes for each accident severity index. These feature classes include essential attributes such as a z-score, a p-value, and a field indicating the confidence level, denoted as "Gi Bin," specific to the respective highways.

The comprehensive analysis unveiled a noteworthy distribution of hotspots for road accidents along the three highways studied. Along Highway 35, a substantial total of 78 hotspots were identified, characterized by severity indices that ranged from 4 to 24. This suggests that these locations experienced a wide spectrum of accident severity levels, with some incidents being relatively less severe (severity index of 4) while others

Table 1 Summarizing the global Moran's I value over varying distances, as computed through the incremental spatial autocorrelation

Highway	Moran's Index	Distance	Expected Index	p_value	Variance	z_score
Highway 35	0.046	211.00	-0.00024	0.000	0.00001	12.113
	0.047	219.60	-0.00024	0.000	0.00001	12.484
	0.046	228.20	-0.00024	0.000	0.00001	12.591
	0.045	236.79	-0.00024	0.000	0.00001	12.524
	0.045	245.39	-0.00024	0.000	0.00001	12.703
	0.046	253.99	-0.00024	0.000	0.00001	13.254
	0.045	262.59	-0.00024	0.000	0.00001	13.160
	0.045	271.19	-0.00024	0.000	0.00001	13.445
	0.046	279.79	-0.00024	0.000	0.00001	13.908
	0.045	288.38	-0.00024	0.000	0.00001	14.016
Highway 10	0.089	488.00	-0.00162	0.000	0.00017	7.019
	0.089	496.98	-0.00162	0.000	0.00016	7.075
	0.085	505.96	-0.00162	0.000	0.00016	6.826
	0.083	514.95	-0.00162	0.000	0.00016	6.664
	0.078	523.93	-0.00162	0.000	0.00016	6.350
	0.074	532.91	-0.00162	0.000	0.00015	6.108
	0.077	541.89	-0.00162	0.000	0.00015	6.343
	0.077	550.88	-0.00162	0.000	0.00015	6.386
	0.074	559.86	-0.00162	0.000	0.00015	6.240
	0.064	568.84	-0.00162	0.000	0.00014	5.627
Highway 30	0.023	1492.00	-0.00082	0.000	0.00003	4.145
	0.023	1523.50	-0.00082	0.000	0.00003	4.242
	0.025	1554.99	-0.00082	0.000	0.00003	4.733
	0.027	1586.49	-0.00082	0.000	0.00003	4.958
	0.027	1617.98	-0.00082	0.000	0.00003	5.055
	0.026	1649.48	-0.00082	0.000	0.00003	5.072
	0.029	1680.98	-0.00082	0.000	0.00003	5.508
	0.028	1712.47	-0.00082	0.000	0.00003	5.509
	0.027	1743.97	-0.00082	0.000	0.00003	5.367
	0.027	1775.47	-0.00082	0.000	0.00003	5.356

were considerably more severe (severity index of 24). In contrast, Highway 10 exhibited a lower count of hotspots, totaling 14. The severity indices associated with these hotspots ranged from 2 to 16. This indicates that while Highway 10 had fewer hotspots, the accidents within these areas also displayed varying degrees of severity, with the lowest being a severity index of 2 and the highest reaching 16. Furthermore, the analysis identified 17 hotspots along Highway 30, with severity indices spanning from 13 to 1. This implies that the accident hotspots on Highway 30 encompassed a range of severity levels, from relatively high (severity index of 13) to less severe (severity index of 1).

Table 2 provides details on the Getis-Ord Gi* results, locations, and severity indices for the most severe road accident hotspots on the highways. The results underscored the significant impact of these accident hotspots on accident occurrences, as evidenced by p-values of less than 0.001, p-values greater than 0.05, and p-values equal to 0.10 for each hotspot. Furthermore, the z-values were less than 2.58, less than 1.96, and less than 1.65, corresponding to confidence levels of 90%, 95%, and 99% (designated as G-bin values 1, 2, and 3, respectively). This implies that all points within these ranges were statistically significant in contributing to road accidents, with confidence levels ranging from 90 to 99%.

Figure 6 shows a spatial map that effectively illustrates road accident hotspots as identified using the Getis Ord Gi method. This analysis has yielded

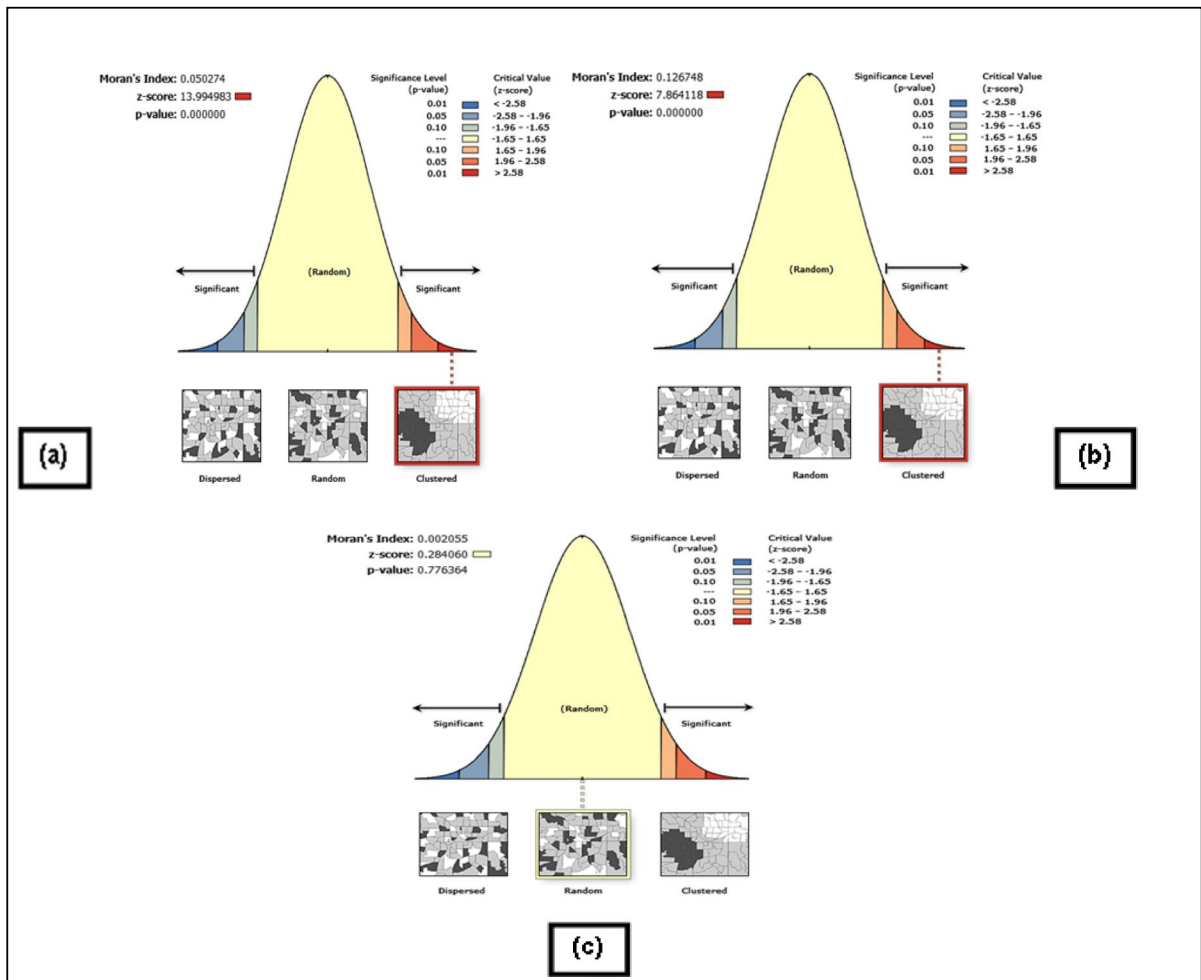**Fig. 5** Spatial autocorrelation report for road accidents in Highway 35, Highway 30, and Highway 10 using the data from 2016–2019. (**a**) Highway 35, (**b**) Highway 10, (**c**) Highway 30

a notable discrepancy in hotspot counts among the three highways under examination. Along Highway 35, a substantial total of 78 hotspots for road accidents have been identified. In contrast, Highway 10 displays a considerably lower count with 14 recorded hotspots, and Highway 30 falls in between with 17 hotspots. This variance in hotspot distribution among the highways underscores the importance of pinpointing areas with higher accident occurrences. It suggests that Highway 35, with its significantly higher hotspot count, may require more focused road safety measures and interventions compared to the other two highways. These hotspots, essentially areas of concentrated accident incidents, serve as critical indicators for allocating resources and implementing

targeted strategies to enhance road safety in specific regions.

On the map, these specific points are distinctly marked and considered statistically significant in terms of their association with accident occurrences. These significant points, referred to as hotspots, are categorized into confidence levels of 99% (Gi-bin = 3), 95% (Gi-bin = 2), and 90% (Gi-bin = 1). This categorization aids in understanding the robustness of these hotspots. For instance, those classified under the 99% confidence level (Gi-bin = 3) are particularly noteworthy, as they represent areas where the clustering of accidents is highly unlikely to occur by random chance. On the other hand, the 90% confidence level (Gi-bin = 1) includes areas with a somewhat lower

Table 2 The output from the Getis-Ord Gi* analysis, along with severity indices and the precise locations of the most critical road accident hotspots on the highways

Highway	P-value	Gi-Bin	Z-score	Location	SI
Highway 35	0.0024	3	3.04	35°53′4.905″E 32°12′59.036″N	24
	0.0000	3	7.227	35°56′56.745″E 32°24′0.345″N	14
	0.0001	3	4.043	35°52′57.919″E 32°6′50.972″N	11
	0.0091	3	3.133	35°51′15.416″E 32°8′10.19″N	10
	0.0017	3	5.981	35°57′5.367″E 32°23′37.292″N	9
	0.0000	3	6.721	35°55′48.702″E 32°22′23.876″N	7
	0.0560	3	6.726	35°55′47.26″E 32°22′24.235″N	7
	0.0000	3	5.53	35°57′6.456″E 32°23′40.188″N	7
	0.0000	3	4.043	35°52′56.538″E 32°6′50.711″N	7
	0.0000	3	6.851	35°55′47.275″E 32°22′23.52″N	6
	0.0001	3	7.227	35°56′49.492″E 32°23′57.168″N	6
	0.0192	3	5.947	35°57′4.288″E 32°23′35.857″N	5
	0.0000	3	3.971	35°55′6.584″E 32°21′34.9″N	5
	0.0000	3	6.851	35°55′47.619″E 32°22′23.512″N	5
	0.0134	3	3.825	35°50′53.86″E 32°10′20.975″N	5
	0.0000	3	6.726	35°55′47.249″E 32°22′23.878″N	5
	0.0001	3	4.085	35°53′47.379″E 32°13′44.026″N	4
	0.0000	3	6.726	35°55′47.627″E 32°22′24.94″N	4
	0.0001	3	3.685	35°56′59.265″E 32°25′35.387″N	4
	0.0000	3	3.971	35°55′6.22″E 32°21′33.091″N	4
Highway 10	0.0000	3	4.421	35°53′4.905″E 32°12′59.036″N	9
	0.0000	3	4.694	36°2′43.439″E 32°20′12.457″N	16
	0.0000	3	4.445	36°1′18.038″E 32°21′55.102″N	6
	0.0001	3	4.042	36°6′37.764″E 32°20′11.733″N	12
	0.0011	3	3.258	36°0′33.067″E 32°23′5.772″N	4
	0.0000	3	4.267	36°0′32.388″E 32°23′28.661″N	4
	0.0000	3	4.267	36°0′27.438″E 32°23′33.972″N	4
	0.0201	1	2.324	36°8′2.398″E 32°19′49.416″N	8
	0.0000	3	4.267	36°0′33.022″E 32°23′27.023″N	3
	0.0080	2	2.652	36°5′57.642″E 32°20′11.163″N	6
	0.0080	2	2.652	36°1′20.997″E 32°21′32.371″N	3
	0.0080	2	2.652	36°8′42.701″E 32°19′50.879″N	9
	0.0000	3	4.385	36°0′33.164″E 32°23′25.559″N	2
	0.0004	3	3.535	36°2′48.336″E 32°20′9.157″N	4
Highway 30	0.0011	1	3.264	36°20′50.494″E 32°3′33.884″N	13
	0.0001	2	3.911	36°32′57.803″E 31°55′58.418″N	8
	0.0002	2	3.758	36°21′55.077″E 32°3′26.265″N	6
	0.0004	2	3.555	36°21′50.368″E 32°3′28.792″N	6
	0.0004	2	3.555	36°21′49.103″E 32°3′29.637″N	6
	0.0005	2	3.456	36°21′49.098″E 32°3′29.507″N	4
	0.0005	2	3.456	36°21′43.332″E 32°3′33.36″N	4
	0.0001	2	3.911	36°32′55.291″E 31°55′58.423″N	3

Table 2 (continued)

0.0004	2	3.555	36°21′49.098″E 32°3′29.507″N	3
0.0002	2	3.703	36°21′47.907″E 32°3′31.324″N	3
0.0004	2	3.555	36°21′53.292″E 32°3′26.442″N	2
0.0001	2	3.911	36°32′57.834″E 31°55′56.275″N	1
0.0002	2	3.703	36°21′49.317″E 32°3′31.319″N	1
0.0002	2	3.69	36°25′48.704″E 32°0′59.021″N	1
0.0004	2	3.555	36°21′50.909″E 32°3′26.928″N	1
0.0004	2	3.555	36°21′52.882″E 32°3′25.642″N	1

level of statistical significance but still indicative of accident clustering trends.

Figure 7 provides illustrative examples of road accident hotspots occurring along highways with a high severity index. These hotspots are prominently concentrated at key locations, such as intersections and interchanges. The visual representation in Fig. 7 offers a vivid depiction of these critical points along the highways where accidents with significant severity levels tend to cluster. This clustering is a matter of concern, as it suggests areas of heightened risk for road users and underscores the need for targeted safety measures and interventions at these specific junctions and transition points.

Discussion

This study delved into the spatial distribution of road accidents along three major highways in Jordan; Highway 35, Highway 10, and Highway 30. The analysis employed spatial autocorrelation techniques to identify accident hotspots and clustering patterns, offering valuable insights for road safety planning and resource allocation.

The incremental spatial autocorrelation analysis, as depicted in Fig. 4, illuminated distinct patterns for each highway. Highway 35 exhibited a peak distance of 250 m, signifying significant clustering of accidents within this range. This finding aligns with Moran's I value of 0.050, a high z-score of 13.994, and a p-value of 0.000 (Fig. 5a). These results indicate statistically significant dense clustering. A noteworthy parallel can be drawn to the study conducted by (Wee et al., 2021) in Singapore,

where they identified areas with notably higher occurrences of severe road accidents. Although their methods and locations differed, both studies recognized the importance of spatial analysis in pinpointing accident hotspots. Similarly, Highway 10 displayed a peak distance of 496.98 m, with a Moran's I value of 0.127, a z-score of 7.864, and a p-value of 0.000 (Fig. 4b). These values also suggest statistically significant dense clustering. This outcome reinforces the significance of addressing specific accident-prone areas, aligning with the findings of (Mhetre & Thube, 2023) in Maharashtra, India, where they focused on road safety and identified accident hotspots on a national highway. Conversely, Highway 30 presented a unique scenario with a peak distance of 1712.47 m (Fig. 4c). The Moran's I value of 0.002, a z-score of 284, and a p-value of 0.776 (Fig. 5c) indicate a lack of statistical significance in terms of spatial clustering. This suggests that accidents along Highway 30 appear to occur in a relatively random fashion, distinguishing it from the clustering patterns observed on the other two highways.

Comparing severity index results with other relevant studies provides valuable context. Similar studies conducted in various regions have shown variations in accident severity patterns, influenced by factors such as road design, traffic flow, vehicle types, and driver behavior. For instance, (Alam & Tabassum, 2023) conducted a study in Ohio, focusing on accident hotspot locations and accident severity. Their findings, similar to ours, highlighted the presence of both high and low accident severity clusters. This suggests that the coexistence of different severity levels in accident-prone areas is a common phenomenon.
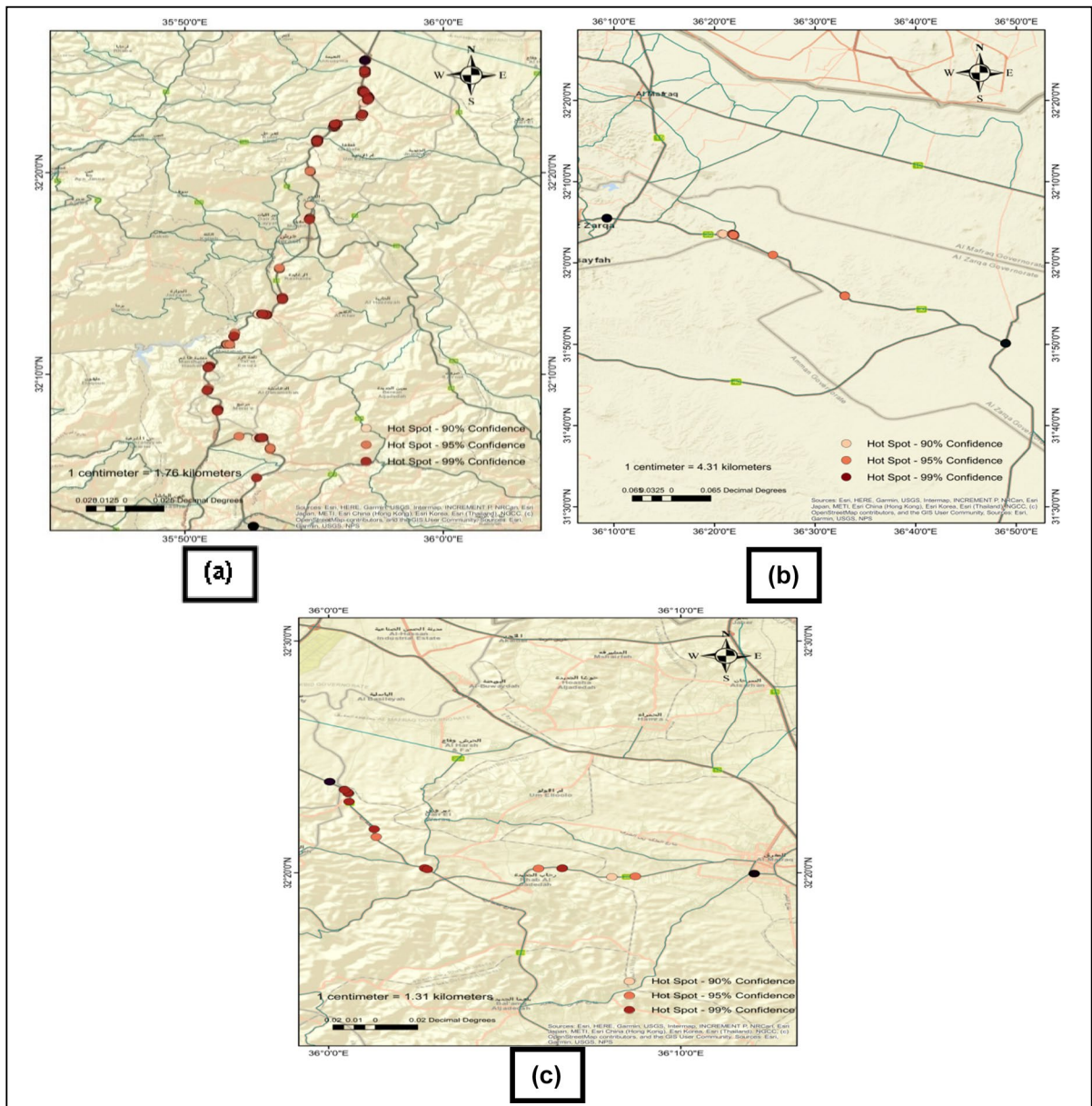
Fig. 6 The spatial map of road accident hotspots: (**a**) For Highway 35, (**b**) for Highway 10, (**c**) for Highway 30

Comparing Getis-Ord Gi findings with other studies underscores the importance of tailored road safety measures. Highway 35's dense clustering pattern necessitates focused interventions within the identified hotspots, which resonate with the recommendations made by (Mekonnen et al., 2023) in Budapest, Hungary, where they applied clustering algorithms for road safety improvements. Highway 10, although displaying fewer hotspots compared to Highway 35, still

requires targeted safety measures within the identified clusters. The findings aligned with the approach taken by (Wee et al., 2021) in Singapore, where they utilized various statistical techniques to pinpoint severe accident locations. Highway 30's relatively random accident distribution implies a broader approach to road safety improvement may be necessary. Similar findings were observed by (Mhetre & Thube, 2023)on a rural national highway in Maharashtra, India, where
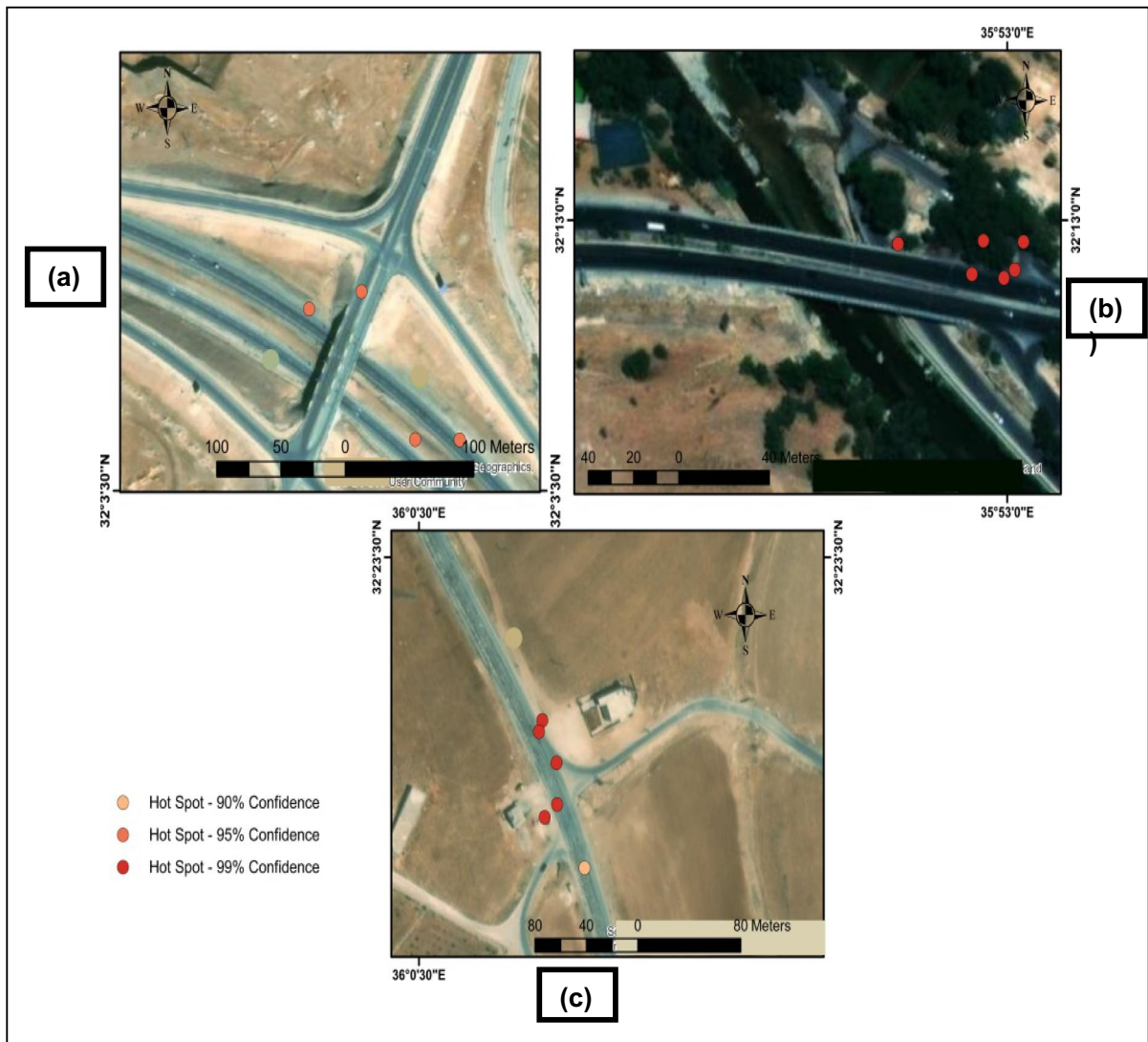
Fig. 7 Examples of the road accident hotspots that have the highest severity index: (**a**) Highway 30, (**b**) Highway 35, Highway 10

they noted a transition from hotspots to cold-spots over time. Understanding the dynamics of such transitions can inform proactive safety measures.

Limitations of the study

This study had some limitations. Road accident data before 2016 and after 2019 were excluded from the study because the Jordanian traffic department began using GPS to pinpoint the locations of accidents in 2016. Furthermore, this study excluded the effect of

COVID-19 on traffic volume after 2019 because vehicle movement was restricted during the pandemic.

Conclusion

Road accidents continue to present significant challenges worldwide, and Jordan is no exception, with a substantial number of accidents recorded annually. The objective of this research was to identify and analyze road accident hotspots and severity patterns along Highways 35, 10, and 30 using GIS techniques.

The findings have several key implications for road safety in Jordan.

- Firstly, the identification of road accident hotspots along these highways is a crucial step in developing targeted interventions to reduce accidents and enhance safety. The variation in hotspot counts among the highways underscores the need for tailored strategies, as each highway exhibits unique accident clustering patterns.
- Highway 35, with its significantly higher hotspot count and dense clustering, requires focused attention and strategic interventions to mitigate accident risks. Highway 10, although exhibiting fewer hotspots, also displays significant clustering. Therefore, measures to enhance road safety should be implemented in these specific areas. In contrast, Highway 30, with its random distribution of accidents, may benefit from broader safety initiatives rather than hotspot-specific interventions.
- The incremental spatial autocorrelation analysis based on distance provided valuable information about the peak clustering distances. For Highway 35, the peak clustering distance was 250 m, indicating that accidents tend to cluster within this range. Highway 10 exhibited a peak distance of 496.98 m, while Highway 30 had a peak distance of 1712.47 m. These distances are crucial for understanding the spatial extent of accident clustering.
- The severity index played a significant role in identifying the hotspots. For Highway 35 and Highway 10, the presence of statistically significant hotspots indicated dense clustering, emphasizing the severity of accidents within these areas. However, Highway 30 showed a lack of statistical significance, suggesting a more random distribution of accident severity.
- The hotspot analysis using the Getis Ord Gi* method further reinforced the clustering patterns observed in the spatial autocorrelation analysis. Highway 35 exhibited the highest number of hotspots (78), followed by Highway 10 (14) and Highway 30 (17). These hotspots represent areas where accidents occur more frequently and are statistically significant in terms of their contribution to accidents.
- This study establishes a foundation for future research and ongoing monitoring of road safety in Jordan. Long-term monitoring of these hotspots and the effectiveness of implemented safety measures is essential to assess progress and make necessary adjustments.

Declarations

Ethical approval The study is based on secondary sources of data. We have followed all ethnical terms and conditions to prepare the manuscript. The sources are declared with references. Therefore, this study did not require ethics review.

Conflicts of interest The authors declare no conflict of interest.

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