SRSD
Spatial Review for Sustainable Development
SRSD 3(1): 17–35
ISSN 3062-8229

Institute for Advanced Science, Social and Sustainable Future
MORALITY BEFORE KNOWLEDGE

Examining the influence of early rainfall on road traffic accidents: A spatial approach

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Received Date: December 20, 2025 Revised Date: February 4, 2026 Accepted Date: February 27, 2026

ABSTRACT

Background: Road Traffic Accidents (RTAs) pose a significant hindrance to efficient road transportation and a substantial risk to public safety. This research provides a stepwise analysis of RTA frequency and spatial distribution in the Special Region of Yogyakarta Province, using self-reported accident data from a prominent local social media platform. While RTA research is extensive globally, a paucity of localized studies specifically focusing on Yogyakarta using advanced spatial techniques necessitated this investigation to address the existing literature gap. The study's objective was to determine the frequency of RTA incidents across temporal and incident categories, identify spatial clustering patterns, and precisely locate high-frequency red zones (hotspots). **Methods:** The methodology employed a multi-method approach, integrating IBM SPSS Statistics for descriptive analysis and ArcGIS for spatial analysis, explicitly using the Nearest Neighbour Analysis (NNA) and Kernel Density Estimation (KDE). The study focused on RTA data from the early onset of the rainy season (October 1st to late October 2025), using this temporal constraint as a control for seasonal risk. The ultimate goal is to generate actionable insights and provide practical solutions to reduce accident occurrences. Insights were derived through statistical analysis, spatial mapping of accident-prone areas, and detailed categorization of incidents. **Findings:** The analysis revealed that traffic accidents were most frequent during weekdays preceding the weekend. Two-wheel vehicle collisions accounted for the majority of incidents, particularly at night and in the early morning (18:30–06:30). Spatially, accidents were not randomly distributed but clustered along major arterial roads within Yogyakarta City's urban core. These hotspots align strongly with areas of high traffic density, emphasizing the vulnerability of two-wheeler users during the early rainy season. This align with previous studies suggesting that reduced visibility, driver fatigue, and slippery road conditions during early rainfall events amplify accident risks especially among vulnerable two-wheeler users. **Conclusion:** The study highlights that the early rainy season significantly intensifies accident risks in high-traffic urban corridors. Strengthening targeted traffic management in high-risk areas and during these times is essential to mitigating future accidents. **Novelty/Originality of this article:** This study isolates the early rainy season as a temporal window for assessing accident vulnerability, offering new insights into the transitional weather phase. It also introduces the use of social media–based incident data integrated with spatial–temporal analysis (NNA and KDE) as a quick, low-cost approach to mapping road safety risks.

KEYWORDS: geographic information system; road traffic accidents; spatial analysis; rain season.

1. Introduction

Road transportation is the lifeblood of a country's development. In nations grappling with increasing urbanization, population density, and high vehicle use, road safety is a pressing concern (Novikov et al., 2021). Within the context of road safety, traffic congestion and the high incidence of traffic accidents have made street safety and security a global challenge (Nayak & Goyal, 2024). Fatalities resulting from road traffic crashes affect

Cite This Article:
Nugraheni, D. R. (2026). Examining the influence of early rainfall on road traffic accidents: A spatial approach. *Spatial Review for Sustainable Development*, *3*(1), 17-35. https://doi.org/10.61511/srsd.v3i1.2026.3181

individuals during their most productive years. Among the productive age bracket of 5–29 years, such traffic accidents inflict devastating physical, mental, and economic impacts on individuals and communities (Ashraf et al., 2025).

Given the multitude of negative impacts of road traffic accidents, an analysis of the contributing factors to these incidents is necessary for effective traffic management (Nayak & Goyal, 2024). A traffic management approach is required to prevent and mitigate the adverse effects of crashes in urban areas (Mohammed et al., 2023). Geographic Information Systems (GIS) have proven to be an effective tool for analyzing the diverse characteristics of accidents (Nayak & Goyal, 2024) and for understanding the spatial and temporal variation in road traffic crashes (Ziakopoulos & Yannis, 2020; Ashraf et al., 2025). GIS provides a robust platform for understanding, analyzing, and addressing the complexities of road traffic accidents (Ashraf et al., 2025). With the aid of GIS, spatial analysis to identify accident-prone areas is made possible, thereby assisting transportation authorities, particularly in these traffic accident hotspots (Aati et al., 2024). The locations where accidents occur most frequently, or the hotspots, are often areas with high density (Mohammed et al., 2023), which typically correspond to urban settings.

The Special Region of Yogyakarta is recognized as one of Indonesia's major urban areas. As an urban region experiencing significant urbanization, which has increased the number of vehicle users, and as a significant domestic and international tourist destination, the population and vehicle density in the Province of the Special Region of Yogyakarta are considerably high. According to data from the Yogyakarta Regional Police, 193 road traffic accidents were recorded from April 4th to April 16th. These road traffic accidents are attributed to various factors, including rain (Nugroho et al., 2022). Previous research conducted in Sleman, one of Yogyakarta's regencies, indicates that rainy weather conditions significantly increase the incidence of accidents (Nugroho et al., 2022)

Rain is a significant contributing factor to the high accident rate worldwide. Similar to Yogyakarta, Singapore, which shares comparable weather conditions, experiences daily variations in temperature and rainfall that elevate traffic injuries and increase the likelihood of road traffic accidents (Chua et al., 2025). In the United States, precipitation causes over 28,000 crashes, 12,000 injuries, and an annual economic loss of 381 million dollars in the surveyed states (Black et al., 2017). The risk of road accidents escalates on days with high rainfall accumulation, with the risk increasing by 51%; notably, this significant increase occurs primarily in urban areas, especially on roads heavily traveled by commuters when they are exposed to rain (Black et al., 2017). Consequently, urban population growth coupled with the projected increase in extreme weather events due to climate change is likely to position weather as a significant hazard for road traffic accidents (Jaroszweski & McNamara, 2014; Zou et al., 2024).

Using Geographic Information Systems (GIS), this study aims to identify areas within the Yogyakarta Special Region with high concentrations of road traffic accidents. This study addresses the research gap concerning the limited localized spatial analysis of traffic accident vulnerability during the early rainy season in Yogyakarta, a tropical urban area making it essential to examine how seasonal rainfall patterns influence road traffic accidents to support mitigation strategies. The integration of spatial statistical methods in GIS has proven effective in identifying accident-prone points and high-risk road sections (Iamtrakul & Chayphong, 2025). Beyond identifying accident hotspots, the study also applies statistical analysis to examine the frequency, temporal distribution, and common types of accidents during the observation period. The accident data were obtained from citizen-reported incidents shared on the Instagram account @merapi_uncover from October 1st (start of the rainy season) until October 22nd, 2025, one of Yogyakarta's largest social media platforms for reporting local traffic accidents. The collected data were subsequently processed using SPSS and GIS-based spatial analyses, primarily the Nearest Neighbour Analysis (NNA) and Kernel Density Estimation (KDE) methods.

2. Methods

A stepwise approach was followed to implement our research objectives effectively. The acquired data was verified and sorted in Microsoft Excel to identify outliers prior to initiating our analysis. Extensive use of ArcGIS software was made, including creating sample point coordinate plots and performing mapping and spatial analysis. The data collection, processing, and analysis were conducted according to the methodology shown in Figure 1.

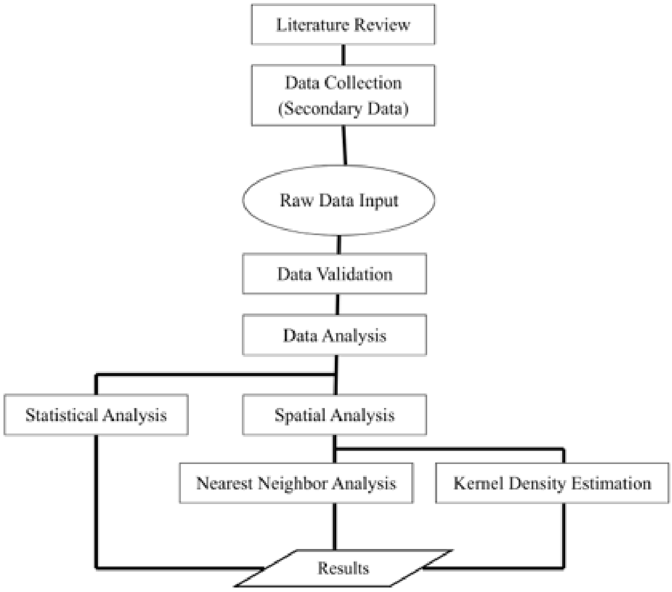

Fig. 1. Research methodology flowchart

2.1 Data collection

Data collection for this study was conducted using citizen reports submitted directly to the official social media account @merapi_uncover on Instagram. This approach utilized an alternative, publicly accessible data stream due to the inherent difficulty in acquiring comprehensive, real-time government archives in the region. The @merapi_uncover account serves as a dynamic, widely followed social media platform that actively reports on a diverse range of incidents across the Special Region of Yogyakarta Province. Operating across multiple social media channels, including Instagram, X (formerly Twitter), and Threads, the account serves as a central hub. It systematically monitors, verifies, and uploads reports submitted spontaneously by Yogyakarta residents, detailing events such as structural fires, flash floods, seismic activity (earthquakes), public events, and, most frequently, Road Traffic Accidents (RTAs).

RTA data were collected by systematically mining public posts from the @merapi_uncover Instagram account. To ensure the data captured the intended environmental variable, accident records were meticulously compiled from October 1, 2025, until October 22, 2025. This specific temporal window was deliberately chosen because it marks the official start of the rainy season in Yogyakarta, serving as a critical control factor for assessing early-season risk. A total of 71 distinct accident incidents were identified and extracted for this period, constituting the primary dataset for the subsequent analysis. Following the acquisition, a rigorous data pre-processing phase was initiated. The geographic locations for all 71 road traffic accident incidents required precise spatial definition. The longitude and latitude of each accident site were systematically geocoded as (x and y) coordinates. This geocoding process, crucial for enabling spatial analysis, was meticulously conducted with the indispensable aid of Google Maps. The resulting complete set of coordinates is held and available for full verification. Each of these 71 accident sites was marked and logged with a suite of specific informational attributes. These included the exact location (street name or landmark), the precise time of the incident, the specific type of vehicle involved, and the categorization of the road traffic accident type (e.g., single-vehicle, 2W vs. 4W collision, etc.). These facts, including the date and location of each accident and the classifications of the vehicles involved, formed the foundational database used in all statistical and spatial calculations, providing a robust, albeit non-official, snapshot of the RTA landscape during the vulnerable early rainfall period. The careful classification and geocoding of this primary data set were prerequisite steps before initiating the statistical verification and comprehensive spatial mapping using ArcGIS.

Fig. 2. Map of research area

2.2 Data analysis and validation

The initial phase of data acquisition, while yielding critical incident reports, concurrently presented several inherent challenges that required extensive pre-processing and validation before any meaningful analysis could commence. A review of the raw data revealed common issues typical of crowdsourced information, including duplicate entries, internal inconsistencies, and minor spelling errors. Furthermore, a significant constraint was the inconsistent recording of specific temporal details for certain accident types; data fields such as the precise time and date of occurrence were found to be occasionally incomplete or ambiguously documented. Addressing these inconsistencies was a crucial methodological prerequisite. Microsoft Excel was systematically used during the data verification stage to meticulously scrutinize the dataset, enabling the identification and flagging of several outliers and duplicate data points. The presence of these initial data flaws necessitated further cross-validation and rigorous checking against the source reports to ensure the fidelity and reliability of the data used for final analysis. Accident records were considered valid only if they contained clearly identifiable location information and occurred within the predefined temporal window of the early rainy season. Entries were excluded if they merely reported the occurrence of a road traffic accident without sufficient contextual details. Since most self-reported social media entries did not include geographic coordinates, location identification was conducted through textual analysis of the incident chronology. Each report was manually examined to extract explicit spatial descriptors. Coordinates were then determined through manual geocoding by matching these descriptions with corresponding road segments and reference points on digital maps. Reports lacking adequate spatial descriptors that could not be reliably geolocated were excluded from the final dataset. But there are potential underreporting bias inherent in crowdsourced data, which is acknowledged as a limitation of the study.

Consequently, after this extensive and meticulous cleaning and verification process was concluded, the final, validated total number of accidents utilized for the study was precisely determined to be 71 distinct incidents. This final, confirmed dataset became the foundation for all subsequent statistical and geospatial modeling. The methodology then transitioned to the spatial analysis phase, commencing with plotting incident locations. The cleaned accident locations were subsequently plotted onto a dedicated base map, the visual representation of which is formally presented in Figure 3. This foundational step in geospatial mapping of the accident locations was then carried out using the powerful ArcGIS software. This comprehensive toolset was employed not merely for visualization but to gain a more profound, empirical understanding of the underlying road traffic crash behavior and its geographical manifestation within the study area.

The analytical pathway was designed in a stepwise manner to unlock insights from the data sequentially. The subsequent spatial processing began with the Nearest Neighbor Analysis (NNA). This fundamental statistical technique was conducted to objectively determine the overall spatial pattern of the total accident locations, specifically testing the hypothesis of randomness versus clustering. Following this, for each specific type of accident identified (as determined during the frequency analysis), a Kernel Density Estimation (KDE) analysis was carefully conducted. This robust technique, using the specialized Spatial Statistics program in ArcGIS, visually and quantitatively defined the most concentrated hotspots of risk across the province.

In parallel with the geospatial modeling, the accident data were simultaneously subjected to detailed statistical analysis using IBM SPSS Statistics. This parallel processing was performed to ascertain the essential descriptive characteristics of the incidents, focusing specifically on quantifying the frequency of the date of occurrence, the critical time (hour) of the incident, and the specific type of event that transpired. This multi-faceted approach, combining statistical and geospatial techniques, ensures a comprehensive interpretation of the RTA patterns. The final methodological step involves synthesizing these diverse findings. The subsequent discussion section is designed to encompass a thorough review of the analytical findings derived from both SPSS and ArcGIS, followed directly by the conclusions drawn from the entirety of the data analysis results, and concluding with managerial recommendations specifically aimed at enhancing road safety and accident reduction within the Province of the Special Region of Yogyakarta.

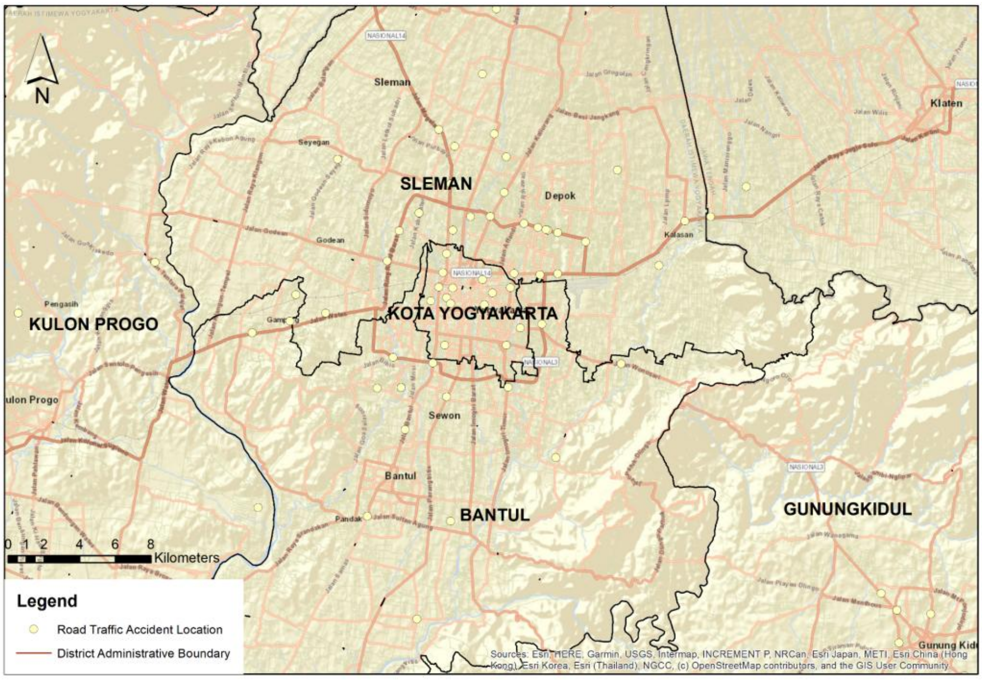

Fig. 3. Map of sample point locations for road traffic accidents

3. Results and Discussion

3.1 Descriptive characteristics of accident data

The frequency of traffic accidents during the selected time period is presented in Tables 1, 2, and 3. As shown in Table 1 and Figure 4, the highest frequency of traffic accidents happened on October 2, 2025 (Thursday), followed by October 19, 2025 (Sunday), October 10, 2025 (Friday), October 16, 2025 (Thursday), and October 17, 2025 (Friday). Contrarily, the lowest incident frequency occurred on October 1, 2025 (Wednesday), October 6, 2025 (Monday), October 8, 2025 (Wednesday), and October 20, 2025 (Monday). Shown in Table 1, the incident was particularly high on 2nd October 2025 making it have a huge gap with other days.

Table 1. Incidents frequency by date

Date	Number of incidents	Percentage (%)
02-10-2025	13	18.31
19-10-2025	8	11.27
10-10-2025	5	7.04
16-10-2025	5	7.04
17-10-2025	5	7.04
13-10-2025	4	5.63
14-10-2025	4	5.63
21-10-2025	4	5.63
03-10-2025	3	4.23
05-10-2025	3	4.23
11-10-2025	3	4.23
04-10-2025	2	2.82
07-10-2025	2	2.82
09-10-2025	2	2.82
12-10-2025	2	2.82
15-10-2025	2	2.82
01-10-2025	1	1.41
06-10-2025	1	1.41
08-10-2025	1	1.41
20-10-2025	1	1.41

Overall, the frequency of accidents was high at the beginning of the month, then decreased and later increased again, albeit not significantly, toward the end of the period (Figure 4). The highest accident incidence happened on the last weekday of the week (Thursday and Friday), while traffic accidents also decreased on Monday and Wednesday. For further details, the specific types of accidents that occurred are presented in Table 2. Table 2 provides a detailed overview of the frequency of road traffic accidents by incident type. Specifically, the incidents were categorized into fourteen distinct classifications. These fourteen categories encompass: Two-Wheel Vehicle (2W) vs. 2W Collision, Single-Vehicle Accident (2W), Single-Vehicle Accident (Four-Wheel+), Four-Wheel Vehicle (4W) vs. 4W Collision, 2W vs. 4W Collision, 2W vs. Pedestrian Collision, Other Single-Vehicle Accidents (such as bicycle, *becak*, or *delman*), 2W Multi-Vehicle Pile-up, Mixed Multi-Vehicle Pile-up (2W with 4W and other vehicles), Other Multi-Vehicle Pile-up (involving pedestrian interference), Other Non-Collision Accidents (due to external factors, e.g., fallen tree), 4W vs. Pedestrian Collision, Other 2W Collisions (2W vs. *delman* or *becak*), and Single Pedestrian Accident. For clarification, the Two-Wheel Vehicle (2W) classification in Table 2 includes motorcycles, electric motorcycles, bicycles, and electric bicycles. In contrast, the Four-Wheel Vehicle (4W) classification encompasses trucks, buses, cars, and public transport vehicles. This specific categorization was based on the diverse range of incident types encountered during the data collection period.

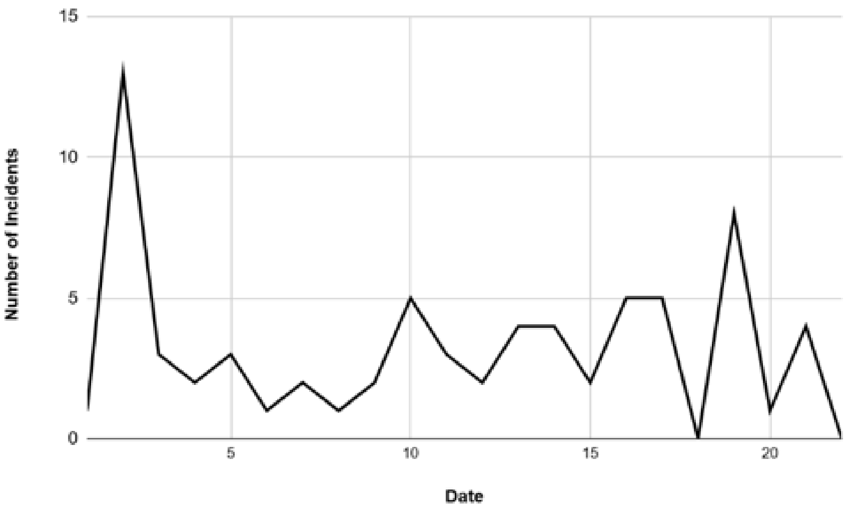

Fig. 4. Daily frequency of road traffic accidents in Yogyakarta, October 1–22, 2025

Based on the data presented in Table 2, the highest frequency of accidents is overwhelmingly associated with two-wheel vehicles. The predominant types of 2W accidents observed are collisions between two-wheel vehicles and single-vehicle 2W accidents. In stark contrast, the frequency of accidents involving four-wheel vehicles is notably infrequent, with the highest 4W-related incidents being single-vehicle accidents. Intriguingly, there is a significant disparity between the frequency of incidents involving two-wheelers compared to four-wheelers. Road traffic accidents involving four-wheel vehicles are substantially fewer than those involving two-wheelers. This observation strongly underscores the vulnerability of two-wheel vehicle users, particularly during the early rainfall season.

Table 2. Incidents frequency by accident type

Accident type	Number of incidents	Percentage (%)
Two-Wheel Vehicle vs. Two-Wheel Vehicle Collision	20	28.17
Single-Vehicle Accident (Two-Wheel)	14	19.72
Single-Vehicle Accident (Four-Wheel+)	9	12.68
Four-Wheel Vehicle vs. Four-Wheel Vehicle Collision	6	8.45
Two-Wheel Vehicle vs. Four-Wheel Vehicle Collision	6	8.45
Two-Wheel Vehicle vs. Pedestrian Collision	4	5.63
Other Single-Vehicle Accidents	3	4.23
Multi-Vehicle Pile-up (Two-Wheel)	3	4.23
Mixed Multi-Vehicle Pile-up	1	1.41
Other Multi-Vehicle Pile-up Accidents	1	1.41
Other Non-Collision Accidents (External Factors)	1	1.41
Four-Wheel Vehicle vs. Pedestrian Collision	1	1.41
Other Two-Wheel Vehicle Collisions	1	1.41
Pedestrian Collision (Other)	1	1.41

A significant number of road traffic accidents happen between 11:30 PM and 6:30 AM, a period characterized by low traffic volume and officially classified as the Early Morning/Evening period, as shown in Table 3 and Figure 5. The RTAs are particularly high at those period, making it the most vulnerable time to drive. The next most vulnerable time period is from 6:30 PM to 11:30 PM, categorized as the Night period, as shown in Table 3. All-time observations are meticulously monitored based on Western Indonesian Time (WIB). As shown in Figure 5, accidents increase progressively as nighttime approaches. Specifically, as the sun sets, the number of accidents substantially increases, then subsequently decreases as the sun begins to rise. These two periods represent the most common times for road traffic accidents within the Special Region of Yogyakarta Province.

Interestingly, roads tend to be relatively quiet during these two time slots, as they fall outside the region's typical morning and evening rush hours.

Table 3. Incident frequency by time category

Time category	Number of incidents	Percentage (%)
23:30-06:30 (Early Morning/Night)	22	30.99
18:30-23:30 (Evening/Night)	16	22.54
06:30-08:30 (Morning Rush Hour)	12	16.9
15:30-18:30 (Afternoon Rush Hour)	8	11.27
11:30-15:30 (Daytime)	7	9.86
08:30-11:30 (Morning)	6	8.45

Table 3 further illustrates the frequency of accidents by daily time category. The highest crash frequencies are observed during the Early Morning (23:30–06:30) and Night (18:30–23:30) periods. This result is unique because it happened during quiet traffic times, unlike the morning or evening, when traffic accidents often happen, as identified in other studies (Ma et al., 2021). This finding is consistent with prior research in Hanoi by Le et al. (2020), which also identified a high occurrence of accidents from noon (12:00) until late Night (23:59). During these hours, factors such as poor lighting conditions and driver fatigue contribute to accidents at these specific hotspots, particularly when two-wheel vehicle users are involved. These points exhibit a high intensity during the critical accident hours (23:30–06:30 Western Indonesia Time), while their intensity is not high during other daily intervals, mirroring the results from Le et al. (2020) study in Hanoi.

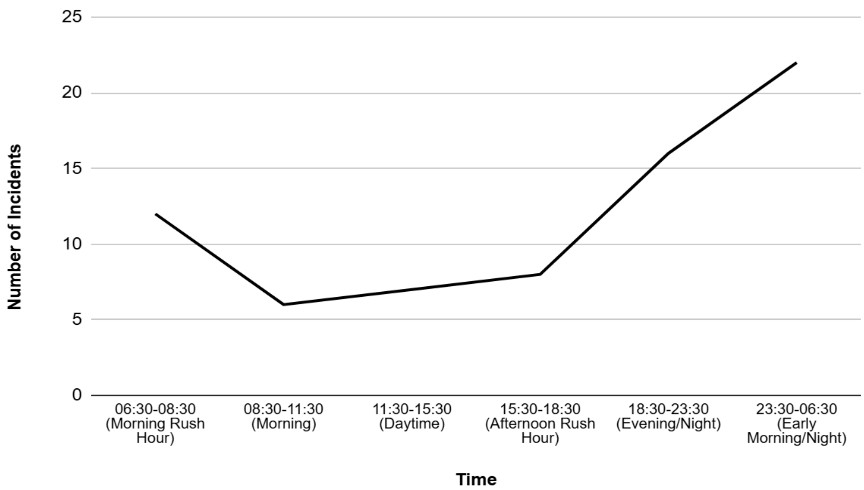

Fig. 5. Distribution of road traffic accidents by time of day

3.2 Spatial pattern of accidents: Nearest neighbor analysis

To gain a profound understanding of the risk landscape, spatial pattern analysis was conducted using the Nearest Neighbor Analysis (NNA) method. The primary objective of this specific analytical step was to objectively determine the inherent distributional tendency of all recorded Road Traffic Accident (RTA) incidents across the entire geographical expanse of the Special Region of Yogyakarta Province. This analysis was performed exclusively on the data collected during the vulnerable period of the early rainfall season (October 1st to October 22nd, 2025). This constraint ensured that the identified patterns reflected risks heightened by the onset of adverse weather conditions. The rigorous computational analysis of this dataset yielded a decisive result: the overall spatial distribution of RTAs exhibits a clear, definitive clustering tendency. This critical finding is not based merely on visual observation but is strongly supported by robust statistical metrics. The NNA calculation produced a statistically significant z-score of -2.954866, coupled with a corresponding p-value of 0.003128.

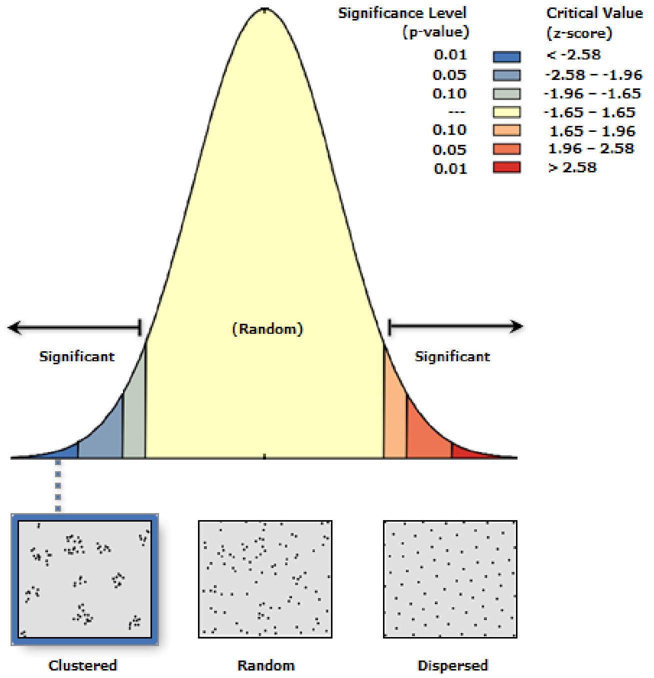

Fig. 6. Results of the nearest neighbor analysis (NNA)

This result warrants scrutiny. Because the obtained z-score falls decisively outside the acceptable range of expected standard deviations for a random distribution, and the calculated p-value is significantly smaller than the conventional 0.05 threshold. This powerful statistical confirmation mandates a shift in perspective: the finding firmly confirms that accident locations are not haphazardly dispersed throughout the province, but are, in fact, systematically concentrated in well-defined geographical areas. The revelation of this clustered pattern carries significant implications for traffic safety policy and research. It directly suggests the omnipresence of underlying risk factors, whether related to road geometry, traffic management flaws, or behavioral issues, that are consistently sufficient to trigger a high concentration of RTAs in proximate locations. In simpler terms, the data indicate that accidents are highly prone to recurring in proximity due to persistent environmental or structural deficiencies. This localized phenomenon clearly identifies accident-prone areas, or hotspots, that demand immediate and focused attention. This crucial clustering pattern, objectively identified and statistically verified through the Nearest Neighbor Analysis, therefore provides the essential foundation for the subsequent mapping phase. The clustering will be visually reinforced and further verified through the high-resolution density map generated by the Kernel Density Estimation method, the results of which are formally presented in the following sub-section.

3.3 Accident density identification: Kernel density estimation

The Kernel Density hotspots were generated utilizing the Spatial Analyst tool in ArcGIS. This kernel density function produces a raster file that visually shows the distribution of accidents within the defined study area. Figure 7 illustrates the resulting kernel density, effectively highlighting areas with high and low accident concentrations. From Figure 7, we know the findings clearly indicate that Yogyakarta City has the most vulnerable road segments, with the highest accident rates. The specific geographic locations identified as accident hotspots are consistently situated along the North Ring Road, Magelang Road, Kaliurang Road, and the area surrounding Malioboro Road, all of which fall within the

Kapanewon (districts) of Gedongtengen, Gondomanan, Condongcatur, and Depok, as shown in Figure 7.

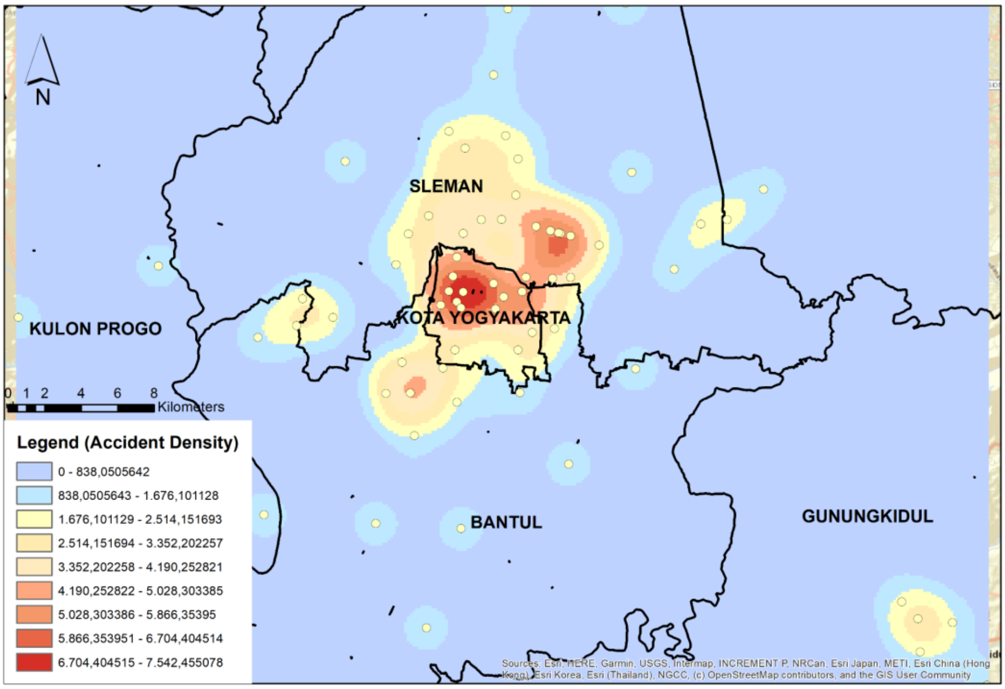

Fig. 7. Kernel density map of road traffic accidents in Special Region of Yogyakarta

Crucially, these accident hotspots fluctuate over time. Figure 8 accurately illustrates the derived hotspots corresponding to the four most frequent accident periods observed. During the morning rush hour, accidents are most frequently concentrated on Magelang Road, Gito Gati Road, and the South Ring Road (Kasihan). Contrarily, during the afternoon rush hour, the most frequent hotspots are established on Magelang Road, Godean Road, and Kaliurang Road, between km 1 and km 6 of Pangeran Mangkubumi Road. Following the afternoon rush hour, significant hotspots during the evening period are found within the Gowok, Sorowajan, Laksda Adisucipto Street, and Kusumanegara Street areas. Finally, during the midnight/early morning period, Affandi Street, the North Ring Road (District Police Headquarters), and Anggajaya Street at the Condongcatur intersection are identified as the primary risk zones, underscoring the dynamic nature of accident vulnerability. In the KDE time series in Figure 8, the density of RTA can be seen to change per period dynamically. However, they tend to be located in relatively close areas, with some even intersecting. This aligns with previous studies that found RTAs tend to cluster at specific locations (Al-Aamri et al., 2020).

A hotspot is formally defined as an area where the probability of a road crash is higher than the average, meaning road users are significantly at risk of becoming accident victims. Simply put, an area with a higher accident rate is commonly referred to as a hotspot or black spot. Based on the statistical significance of the frequency, higher- and lower-clustering of incidents is initiated, and a pattern of hotspots and cold spots is developed. High and low spatial data values are grouped. A high value indicates a hotspot, whereas a low value indicates a cold spot. Within the study area, as shown in Figure 7, the accident hotspot areas in the Special Region of Yogyakarta Province are concentrated in Yogyakarta City, specifically in the Kapanewon of Gedongtengen, Gondomanan, Condongcatur, and Depok. The roads experiencing frequent accidents include the Ring Road Utara (near the Special Region of Yogyakarta Regional Police Office), Jalan Kaliurang, Jalan Magelang, and the vicinity of Jalan Malioboro. The use of these hotspot results can be highly beneficial for traffic police in identifying high-accident areas and formulating practical approaches to accident management and reduction in these areas.

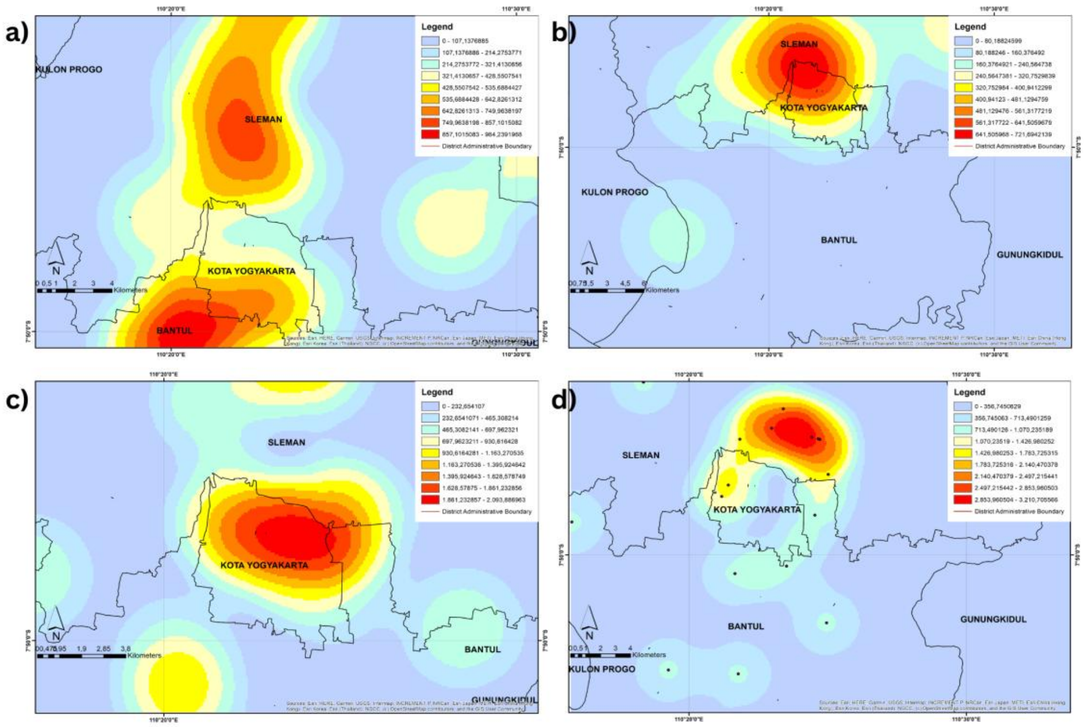

Fig. 8. Spatial distribution of road traffic accidents based on kernel density estimation (KDE) by time period (a) Morning rush hour (06:30–08:30); (b) Afternoon Rush Hour (15:30–18:30); (c) Evening/Night (18:30–23:30), (d) Early Morning/Night (23:30–06:30)

3.4 Interpretation of accident frequency and type

Accident frequency analysis was conducted to precisely determine accident rates rather than merely accounting for the overall collision count (Alam & Tabassum, 2023). A simple analysis focusing on accident frequency by date of event (Table 1) clearly reveals a clustering pattern, with accidents tending to aggregate on specific days, most notably on weekdays leading up to the weekend. These pre-weekend days account for a significant share of the total traffic incidents, reflecting the likely psychological state of drivers during that time. As the weekend approaches, there is an associated increase in mobility driven by heightened desire for travel and leisure (Saladié et al., 2020). These results are consistent with previous studies that found that traffic accidents are generally higher on weekdays because the number of days is more than double the number of weekends (Mohammed et al., 2023). On weekdays, most trips are made commuting to work or school, so almost everyone does it. In contrast, on weekends, trips are fewer and mostly made for shopping and recreation, which not everyone does (Mohammed et al., 2023). The distribution of accidents remains similar to weekdays, but the intensity is lower (Mohammed et al., 2023).

The heightened frequency of these accidents is likely exacerbated by the onset of the rainy season. Accidents associated with high severity indices are frequently reported during the cold/winter season (Le et al., 2020). Yogyakarta is a central urban area in Indonesia. As a tropical nation, Indonesia experiences significantly higher rainfall during the rainy season compared to other countries. These relatively severe weather conditions have been shown by prior research to influence the number of road traffic accidents (Le et al., 2020). Seasonal variations, characterized by a high concentration of accidents, often coincide with the cold season (Alsahfi, 2024), which corresponds to Indonesia's wet (rainy) season. Accidents tend to surge during extreme weather conditions, such as the cold season (Alsahfi, 2024; Gu et al., 2025). The rainy season, under such extreme conditions, results in a substantially higher number of accidents than other seasons (Le et al., 2020). As happened in Singapore where time is cool or rainfall is heavy, the number of RTAs is high (Chua, et al., 2025). Rain does affect accidents, but its effect on severity varies, depending on several other parameters such as fog, smoke, and dark conditions (Sadeghi & Goli, 2024). This seasonal trend indicates a correlation between human activity and environmental factors such as prevailing weather conditions (Alsahfi, 2024). Temperature has consistently been the most significant predictor of road traffic accidents in previous studies, with the majority of crashes occurring during the cold season (Mirzahossein et al., 2025). Given this seasonal pattern, it is crucial to prevent and mitigate road traffic accidents during this period by employing seasonal traffic management strategies (Alsahfi, 2024).

3.5 Significance of spatial clustering

The spatial pattern of Road Traffic Accidents (RTAs) across the Special Region of Yogyakarta Province was meticulously analyzed, revealing distinct clustering. This crucial finding, initially validated through the statistical rigor of the Nearest Neighbor Analysis (NNA) and subsequently visualized in Figure 4 (Nearest Neighbor Analysis Map), immediately shifts the focus from a province-wide uniform risk to one characterized by specific, highly vulnerable zones. This distinct clustering pattern was most profoundly and visibly confirmed in Figure 5 (Kernel Density Map). Here, an intense and localized concentration of accident incidents is graphically evident, centered on the dense urban core of Yogyakarta City and extending along its primary northern vehicular thoroughfare, Jalan Ring Road Utara. KDE RTAs generally happen on highways and locations within city blocks. RTAs at city-block locations are primarily caused by high turning movements and poor obedience with traffic regulations (Alkaabi, 2023). The central city area is the most affected area by RTAs. More than half of RTAs occur in the city's red zone, characterized by densely populated business districts (Alkaabi, 2023).

The concentration of RTAs within this narrow geographic band is not merely noticeable, it is striking. However, it also substantially surpasses the cumulative total of crashes recorded across all other areas of the province combined. The four specific Kapanewon (sub-districts) identified as exhibiting this high incident concentration, namely Gondomanan, Gedongtengen, Condongcatur, and Depok, represent the province's true accident hotspots. This high-risk clustering stands in stark contrast to the remaining geographical areas, which function as low-accident zones, or 'cold spots.' In these cold-spot areas, the crash prevalence remained remarkably low, with fewer than two incidents recorded during the entire three-week data collection period. In fact, a careful examination reveals that the majority of surrounding areas registered significantly lower incident rates, with most districts reporting minimal incidents. This disparity is critically important, as these regions with low RTA incidence underscore areas with inherently higher baseline traffic safety within the provincial system.

The identification of this pronounced clustering pattern of road traffic accidents exclusively within Yogyakarta City and its immediate urban fringes is notably analogous to findings in the global urban safety literature, such as Alsahfi's (2024) research. Similar patterns found in other significant cities consistently indicate the formation of severely traffic-vulnerable zones in densely populated areas. This correlation underscores the urgent need for enhanced safety measures and targeted policy interventions focused on these population-dense, localized areas. Mechanistically, these road traffic accident hotspots are typically concentrated in locations defined by a challenging confluence of factors: complex road conditions (including narrow streets, multiple intersections, and irregular geometry) and excessively high vehicular traffic density (Jayasinghe et al., 2025). The intense and intricate relationship between a high frequency of accidents and localized traffic density is a primary mechanism driving the RTA risk.

3.6 Characterization of accident hotspots

Figure 7 and figure 8 presents the Kernel Density Estimation (KDE) hotspot map, which effectively visualizes the spatial distribution of road traffic accident density across the Special Region of Yogyakarta Province. A map of this nature is significant for driver and passenger safety, as it directly addresses the critical question: "Where are the most dangerous road areas?" (Alam & Tabassum, 2023), which this visualization effectively answers. The map utilizes color intensity to represent accident density quantitatively. Consistent with the methodology described by Kamh et al. (2024), darker colors on the road traffic accident density map indicate higher crash concentrations, while lighter colors indicate lower crash concentrations. This categorization of intensity, from low to high, is instrumental for pinpointing both prominent accident hotspots and areas less affected (Kamh et al., 2024). Figure 7 thus reinforces the findings of the Nearest Neighbor Analysis (NNA), which demonstrated that road traffic accidents in the region exhibit clustering. This multi-methodological approach facilitates crucial cross-validation, whereby insights derived from one technique (NNA) are verified and elaborated upon by another (KDE) (Alsahfi, 2024). Such a combination allows for a layered analysis of traffic crash data, clearly illustrating hotspot locations, frequency by type, and the underlying clustering patterns.

Table 4. Top 10 Most accident-prone roads in Yogyakarta (October 2025)

Rank	Prior level	Location	Dominant time period of accidents	Spatial characteristic
1	Extremely High	Jalan Magelang	18:30-23:30 (Evening/Night) and 06:30-08:30 (Morning Rush Hour)	Major northern arterial corridor connecting city center to Sleman and Magelang, high mixed-traffic volume.
2	Extremely High	Jalan Ringroad Utara	18:30-23:30 (Evening/Night)	Outer arterial belt with frequent high speed vehicle (especially near police HQ)
3	Extremely High	Jalan Affandi (Gejayan)	18:30-23:30 (Evening/Night)	Dense commercial–residential corridor, high night-time activity and cross traffic.
4	Extremely High	Jalan Bantul	18:30-23:30 (Evening/Night)	Southern arterial with heavy two-wheeler traffic (heavy commuter flow), limited street lighting in several sections.
5	Extremely High	Jalan Godean	15:30-18:30 (Afternoon Rush Hour)	Western commuter corridor, high traffic.
6	Extremely High	Jalan Laksda Adisucipto	18:30-23:30 (Evening/Night)	Eastern arterial linked to airport access, frequent high-speed accidents.
7	High	Jalan Kusumanegara (north of Gembira Loka Zoo)	18:30-23:30 (Evening/Night)	Urban collector road near educational and tourism zones, moderate lighting condition when night.
8	High	Jalan Kyai Mojo	15:30-18:30 (Afternoon Rush Hour)	Central arterial connecting to major intersections and congestion-prone during peak hours.
9	High	Jalan Tentara Pelajar-Pangeran Diponegoro Corridor	All the time (no specific time)	North–south corridor with complex intersections and mixed traffic modes.
10	High	Jalan Ringroad Selatan (Kasihan Section)	06:30-08:30 (Morning Rush Hour)	Peri-urban highway segment, commuter flow from Bantul toward Yogyakarta core.

Based on the overall hotspot results (Figure 7) and the temporal analysis findings (Figure 8), the roads showing the most frequent accidents were identified and later grouped into the 10 most dangerous roads presented in Table 4. Main arterial roads, such as Magelang Road, North Ring Road, Affandi Road, Bantul Road, and other similar corridors, account for the majority of traffic incidents, accurately reflecting their role as primary corridors for vehicular movement and the inherent risk of road traffic accidents (RTAs) due to their significantly higher traffic volumes. This observation aligns deeply with previous findings (Ma et al., 2021; Sunset et al., 2021; Kamh et al., 2024), which showed that highways and arterial roads account for a significant proportion of accidents owing to their high usage, in contrast to local roads, which record minimal crashes due to lower traffic flows. High levels of traffic interaction describe these roads. Hotspots are more prominent on roads with the highest levels of traffic interaction (Al-Aamri et al., 2020). These arterial roads also feature numerous intersections. Intersections are areas with the highest risk of RTA occurrence (Al-Aamri et al., 2020). Indeed, traffic segments with relatively low flow do not significantly influence accident hotspots.

Conversely, the arterial roads identified as hotspots serve as vital thoroughfares connecting the city center with surrounding districts. The majority of commuters utilizing these principal connecting roads are workers traveling from the suburbs (Le et al., 2020). Due to their high traffic volumes and complex design configurations, such main roads are inherently hazardous (Kamh et al., 2024). They pose a risk comparable to major intersections and pedestrian centers, thereby contributing significantly to the identified crash hotspots (Jayasinghe et al., 2025). Consequently, the proper design and construction of these key arterial roads are paramount, as well-designed and executed road construction can substantially mitigate the number of road accidents and fatalities (Alharbi et al., 2022).

Conversely, cold spots for road traffic accidents tend to be concentrated in the regencies surrounding Yogyakarta City, encompassing most of Sleman, Bantul, Gunung Kidul, and Kulonprogo. The smaller the city area, the lower the traffic density (Saladié et al., 2020), resulting in lower Road Traffic Accident density. This distribution is strongly indicative of a lower frequency of road traffic accidents attributable to lower population density (Kamh et al., 2024). In densely populated areas like Yogyakarta City and the previous areas, highway accident rates are very high. Therefore, the majority of accidents in recent years have occurred on highways and in urban areas due to their high density (Islam & Dinar, 2021). As officially noted by Regional Development Planning Agency of the Special Region of Yogyakarta (2025), the population density of Yogyakarta City reaches a peak of $11,562$ persons/km^2, far exceeding that of neighboring regencies, such as Sleman at $2,052$ persons/km^2.

This finding aligns with previous research, as high population density has consistently been shown to increase accident frequency across studies (Alsahfi, 2024). The synergy of high population density and numerous public facilities consequently results in increased traffic volume and a heightened risk of road traffic accidents (Rengarasu & Arunodi, 2025). Beyond lower population density, the occurrence of cold spots is likely influenced by differing urban configurations. During the site inspection, hotspot locations are in the city center, with numerous one-way and winding roads, unlike the cold spots, which typically feature less congested, two-way regency roads. This suggests a diverse urban dynamic that mitigates the occurrence of accidents (Kamh et al., 2024). The confluence of major roads creates complex traffic dynamics that are inherently prone to accidents (Kamh et al., 2024), necessitating focused attention on traffic safety and urban planning.

3.7 Limitation and future research directions

This research, while yielding significant contributions to understanding RTA patterns in the Special Region of Yogyakarta, is subject to several inherent constraints. Firstly, the study relied primarily on self-reported accident data sourced from social media (specifically @merapi_uncover). This reliance introduces limitations regarding data reliability, uniformity, completeness, and potential under-reporting of incidents, as data capture is not based on official police or hospital records. Consequently, this constraint makes it challenging to accurately assess the true magnitude and injury severity index of all accidents that transpired. Furthermore, the analysis was deliberately constrained to a short, specific temporal window, the early onset of the rainy season (October 1st to October 22nd, 2025), to control for weather variables. While effective for isolating seasonal impact, the conclusions drawn about frequency and hotspot activity may not readily transfer to other seasons (e.g., the dry season) or to areas with vastly different traffic patterns outside the dense urban core of Yogyakarta City.

Future research should broaden the investigation's geographical and temporal scope. It is highly recommended that future studies integrate and cross-validate social media data with official governmental datasets (e.g., from the Regional Police Traffic Unit or district hospitals). Enhancing collaboration with these governmental entities could yield a more comprehensive and authoritative dataset on the actual severity and magnitude of accidents. Furthermore, subsequent studies should investigate the practical application and effectiveness of the seasonal traffic management strategies proposed based on the identified hotspots and vulnerable time periods. Finally, given the strong findings related to two-wheel vehicle vulnerability, additional research focusing specifically on legislative modifications for motorcycle safety and the integration of contemporary technology (such as bright traffic lights or advanced road monitoring systems) in managing traffic flow within the concentrated hotspot areas is essential to ensuring safer road conditions for all users in Yogyakarta. The findings of this study provide empirical evidence that can contribute to broader discussions on smart city planning, particularly in the integration of spatial risk monitoring within urban traffic management systems aimed at improving traffic safety and preventive planning strategies.

4. Conclusions

In summary, this research successfully provides critical insight into the concerning prevalence of Road Traffic Accidents (RTAs) in the Special Region of Yogyakarta Province. Clearly, it underscores the substantial influence of the early rainy season conditions on the frequency and spatial distribution of these incidents. The study meticulously revealed several significant findings regarding the circumstances of accident occurrence, with two-wheel vehicle collisions consistently recognized as the most frequent and dominant type of incident. Temporally, the highest concentration of accidents occurs during the periods leading up to the weekend on working days, with the most critical hours falling within the late evening and early morning slots (Night and Early Morning categories). Spatially, RTAs are not randomly distributed but are heavily clustered, with the resulting hotspots concentrated along major, high-volume arterial roads, specifically identified within the central urban core of Yogyakarta City and extending along the Ring Road Utara, Jalan Magelang, and Jalan HOS Cokroaminoto, covering four key kapanewon.

The aforementioned results highlight the pressing, undeniable need for enhanced, targeted traffic management during the wet season and the necessity of stricter enforcement of regulations specifically focused on the identified vulnerable hours and high-risk geographical zones. This study offers managerial suggestions that strongly emphasize upgrading traffic database systems to an integrated, centralized model and advocating the use of advanced geospatial methodologies to enhance seasonal traffic management and significantly reduce RTA rates. The adoption of improved seasonal managerial and traffic regulations is an imperative step for reducing the frequency and severity of accidents. Furthermore, the systematic use of spatial analysis techniques holds immense potential to significantly enhance road safety by moving beyond reactive responses toward proactive, location-specific intervention strategies.

Notwithstanding its valuable and substantial contributions, this research is subject to several inherent limitations, chiefly its reliance on self-reported social media data and its narrow temporal window of data collection, which limit the ability to compare findings with data from other seasons. Future research endeavors should broaden their temporal scope and improve data quality by analyzing data from other seasons for comparative analysis. Additionally, future studies must focus on the practical application of proposed strategies while simultaneously fostering closer, more effective collaboration with relevant governmental authorities. The findings presented in this research possess the potential to serve as a robust foundation for the development of more effective, data-driven strategies in tackling the alarmingly high occurrence of road traffic accidents, not only within the Special Region of Yogyakarta Province but also in similar urban areas experiencing high two-wheel vehicle usage and seasonal weather risks.

Acknowledgement
The author gratefully acknowledges all individuals and institutions that supported this research. Special appreciation is extended to data providers, reviewers, and colleagues for their valuable contributions and insights.

Author Contribution
The author solely conceived the study, collected and analyzed the data, conducted spatial and statistical analyses, interpreted the findings, prepared the manuscript, and approved the final version.

Funding
This research received no external funding

Da Ethical Review Board Statement
Not available.

Informed Consent Statement
Not available.

Data Availability Statement
The data that support the findings of this study are available. These data were derived from publicly available sources, including citizen-reported traffic incident posts from the Instagram account @merapi_uncover (https://www.instagram.com/merapi_uncover) and official climatological information from the Meteorological, Climatological, and Geophysical Agency of Yogyakarta Province.

Conflict of Interest
The author declares no conflict of interest. The research received no external funding, and all analyses and interpretations were completed independently.

Declaration of Generative AI Use
During the preparation of this work, the author used Grammarly to assist in improving grammar, clarity, and academic tone of the manuscript. After using this tool, the author reviewed and edited the content as needed and took full responsibility for the content of the publication.

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References

Aati, K., Houda, M., Alotaibi, S., Khan, A. M., Alselami, N., & Benjeddou, O. (2024). Analysis of road traffic accidents in dense cities: geotech transport and ArcGIS. *Transportation Engineering*, *16*, 100256. https://doi.org/10.1016/j.treng.2024.100256

Alam, M. S., & Tabassum, N. J. (2023). Spatial pattern identification and crash severity analysis of road traffic crash hot spots in Ohio. *Heliyon*, *9*(5). https://doi.org/10.1016/j.heliyon.2023.e16303

Al-Aamri, A. K., Hornby, G., Zhang, L. C., Al-Maniri, A. A., & Padmadas, S. S. (2020). Mapping road traffic crash hotspots using GIS-based methods: A case study of Muscat Governorate in the Sultanate of Oman. *Spatial Statistics*, *42*, 100458. https://doi.org/10.1016/j.spasta.2020.100458

Alharbi, R. J., Lewis, V., & Miller, C. (2022). A state-of-the-art review of factors that predict mortality among traumatic injury patients following a road traffic crash. *Australasian emergency care*, *25*(1), 13-22. https://doi.org/10.1016/j.auec.2021.01.005

Alkaabi, K. (2023). Identification of hotspot areas for traffic accidents and analyzing drivers' behaviors and road accidents. *Transportation research interdisciplinary perspectives*, *22*, 100929. https://doi.org/10.1016/j.trip.2023.100929

Alsahfi, T. (2024). Spatial and temporal analysis of road traffic accidents in major californian cities using a geographic information system. *ISPRS International Journal of Geo-Information*, *13*(5), 157. https://doi.org/10.3390/ijgi13050157

Ashraf, T., Ahamad, M. I., Mahmood, S., Fu, J., Mehmood, M. S., Rehman, A., ... & Zulqarnain, R. M. (2025). Exploring hotspots of traffic accidents in Chiniot-Sargodha Road, Punjab, Pakistan. *Environment, Development and Sustainability*, 1-21. https://doi.org/10.1007/s10668-025-05996-w

Black, A. W., Villarini, G., & Mote, T. L. (2017). Effects of rainfall on vehicle crashes in six US states. *Weather, climate, and society*, *9*(1), 53-70. https://doi.org/10.1175/WCAS-D-16-0035.1

Chua, R., Ng, Y. Y., Ho, A. F., & Aik, J. (2025). Association between climate variability and injury-causing road traffic accidents in Singapore–A time-stratified case-crossover study. *Urban Climate*, *59*, 102257. https://doi.org/10.1016/j.uclim.2024.102257

Gu, Z., Peng, B., & Xin, Y. (2025). Higher traffic crash risk in extreme hot days? A spatiotemporal examination of risk factors and influencing features. *International Journal of Disaster Risk Reduction*, *116*, 105045. https://doi.org/10.1016/j.ijdrr.2024.105045

Iamtrakul, P., & Chayphong, S. (2025). GIS-based analysis of spatio-temporal clustering of road traffic accidents in Bangkok Metropolitan Region (BMR), Thailand from 2012 to 2021. *Transportation Research Interdisciplinary Perspectives*, *31*, 101489. https://doi.org/10.1016/j.trip.2025.101489

Islam, M. A., & Dinar, Y. (2021). Evaluation and spatial analysis of road accidents in Bangladesh: an emerging and alarming issue. *Transportation in developing economies*, *7*(1), 10. https://doi.org/10.1007/s40890-021-00118-3

Jaroszweski, D., & McNamara, T. (2014). The influence of rainfall on road accidents in urban areas: A weather radar approach. *Travel behaviour and society*, *1*(1), 15-21. http://dx.doi.org/10.1016/j.tbs.2013.10.005

Jayasinghe, B. C., Withanage, N. C., & Mishra, P. K. (2025). Evaluating Geographical Variations of Road Traffic Accidents in Matara, Sri Lanka: A Geospatial Perspective to Policy Decisions. *Revue Internationale de Géomatique*, *34*(1). https://doi.org/10.32604/rig.2025.067395

Kamh, H., Alyami, S. H., Khattak, A., Alyami, M., & Almujibah, H. (2024). Exploring road traffic accidents hotspots using clustering algorithms and GIS-based spatial analysis. *IEEE Access*, *13*, 60944-60954. https://doi.org/10.1109/ACCESS.2024.3443245

Le, K. G., Liu, P., & Lin, L. T. (2020). Determining the road traffic accident hotspots using GIS-based temporal-spatial statistical analytic techniques in Hanoi, Vietnam. *Geo-spatial Information Science*, *23*(2), 153-164. https://doi.org/10.1080/10095020.2019.1683437

Ma, Q., Huang, G., & Tang, X. (2021). GIS-based analysis of spatial–temporal correlations of urban traffic accidents. *European transport research review*, *13*(1), 50. https://doi.org/10.1186/s12544-021-00509-y

Mirzahossein, H., Nobakht, P., Waller, T., & Lin, D. Y. (2025). Revealing crash hotspots concerning google traffic maps historical data by supervised and ensemble machine learning techniques. *Transportation Engineering*, *20*, 100326. https://doi.org/10.1016/j.treng.2025.100326

Mohammed, S., Alkhereibi, A. H., Abulibdeh, A., Jawarneh, R. N., & Balakrishnan, P. (2023). GIS-based spatiotemporal analysis for road traffic crashes; in support of sustainable transportation Planning. *Transportation research interdisciplinary perspectives*, *20*, 100836. https://doi.org/10.1016/j.trip.2023.100836

Nayak, A., & Goyal, K. (2024, April). Traffic modeling and accidental data analysis using GIS: A Review. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1327, No. 1, p. 012028). IOP Publishing. https://doi.org/10.1088/1755-1315/1327/1/012028

Novikov, I. A., Borovskoy, A. E., Gorbun, Y. V., Terentyev, A. V., & Pletney, M. G. (2021, March). Geographic information systems to improve road safety. In *2021 Systems of Signals Generating and Processing in the Field of on Board Communications* (pp. 1-6). IEEE. https://doi.org/10.1109/IEEECONF51389.2021.9416096

Nugroho, A., Susanto, N., & Fadlilah, S. (2022). Factors Associated with Traffic Accidents in Sleman, Yogyakarta, Indonesia. *International Medical Journal*, *29*(6), 366-368. https://jglobal.jst.go.jp/en/detail?JGLOBAL_ID=202302262150593696

Rengarasu, T. M., & Arunodi, H. K. I. (2025). Identification of Traffic Accident Hotspots using Network Kernel Density: Application to Galle District in Sri Lanka. *Journal of South Asian Logistics and Transport*, *5*(1). https://doi.org/10.4038/jsalt.v5i1.92

Regional Development Planning Agency of the Special Region of Yogyakarta. (2025). *Penduduk*. https://bapperida.jogjaprov.go.id/dataku/data_dasar/cetak/701-penduduk?id_skpd=251

Sadeghi, P., & Goli, A. (2024). Investigating the impact of pavement condition and weather characteristics on road accidents. *International Journal of Crashworthiness*, *29*(6), 973-989. https://doi.org/10.1080/13588265.2024.2348269

Saladié, Ò., Domínguez-Mallafré, M., Domènech, A., & Gutiérrez, A. (2023). 'Back to the past': The decline and rebound in traffic accident numbers in Catalonia in the context of COVID-19 lockdown and post-lockdown. *Norsk Geografisk Tidsskrift-Norwegian Journal of Geography*, *77*(2), 78-97. https://doi.org/10.1016/j.trip.2020.100218

Ziakopoulos, A., & Yannis, G. (2020). A review of spatial approaches in road safety. *Accident Analysis & Prevention*, *135*, 105323. https://doi.org/10.1016/j.aap.2019.105323

Zou, X., Sun, L., Lan, T., Fan, C., Liu, S., Zhao, H., & Qiu, J. (2024). The effects of weather factors on road traffic casualties: Analysis on provincial panel data of China from 2006 to 2021. *Heliyon*, *10*(17). https://doi.org/10.1016/j.heliyon.2024.e36788

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