Temporal Analysis of Road Traffic Accidents at Major Intersections in Khon Kaen Province, Thailand: A Time Series Investigation from 2012 to 2021

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Abstract
This research paper presents a comprehensive analysis of accidents at 23 intersections within Muang Khon Kaen district over the period from 2012 to 2021. The 10 years data were collected and analyzed utilizing Global Moran's I to investigate the existence of spatial autocorrelation among the intersections. And Anselin Local Moran's I was adopted to identify the cluster of the accidents at the intersections. The result found that the spatial pattern did not exist, which indicates that the accident numbers at each intersection is independent from each other. However, a hotspots and high outliers were found at Mitraparp-Bankok (MB) and Sricharn-Chatapadoong (SC) intersections, respectively, in 2020. The study identifies 2018 as the year with the highest incidence of accidents, followed by a notable decline post-2018, potentially influenced by the onset of the COVID-19 pandemic in early 2020. The analysis of accident hotspots reveals the Sricharn-Chatapadoong (SC) intersection as the most accident-prone location, contrasting starkly with the absence of incidents at the Prachasamosorn-Bakham (PB) and Robbueng-Srithat (RS) intersections. The MB intersection ranks second in accidents, consistent with hotspot identification in cluster analysis. Additionally, intersections ML and MS tie for third place in accident frequency. Temporal analysis uncovers a peak in accidents between 2:00 AM and 4:00 AM, likely attributable to driving under the influence (DUI) compounded by the closure of entertainment venues nationwide at 2:00 AM. Accidents are predominantly observed among males aged 18 to 25 years, frequently involving motorcycles as their primary mode of transportation. The concentration of educational institutions along Sricharn road contributes to heavy traffic flow, particularly during peak hours, increasing the risk of accidents, notably among adolescent motorcycle commuters. Consequently, the SC intersection emerges as a high-risk area, necessitating intensified surveillance and accident prevention measures. In conclusion, this study offers valuable insights into road safety challenges within Muang Khon Kaen district, providing evidence-based recommendations to reduce accidents. Decision-makers and authorities can leverage this information to implement targeted interventions and enhance road safety measures, locally and beyond.

Keywords: Cluster Analysis, Intersection, Khon Kaen, Road Accident, Time Series Analysis

1. Introduction

Thailand, like many developing countries, grapples with significant challenges related to road traffic accidents. Despite efforts to improve road safety measures, the country continues to face a high rate of accidents, injuries, and fatalities on its roads [1]. One of the contributing factors to the prevalence of road traffic accidents in Thailand is the rapid motorization of the country.

As more people afford vehicles, roads become congested, and the risk of accidents increases. Additionally, inadequate infrastructure, poorly maintained roads, and inconsistent enforcement of traffic laws further exacerbate the problem. Motorcycles are a popular mode of transportation in Thailand, particularly in urban areas, and they are involved in a disproportionate number of accidents [2] and [3]. Factors such as reckless driving, lack of helmet use, and disregard for traffic laws contribute to the high rate of motorcycle accidents. Drunk driving is another significant issue contributing to road accidents in Thailand. Despite strict laws and campaigns to deter drunk driving, many motorists continue to drive under the influence, putting themselves and others at risk. The Thai government has taken various measures to address the problem of road traffic accidents, including implementing stricter penalties for traffic violations, improving road infrastructure, and promoting road safety education and awareness campaigns. However, continued efforts and investment in comprehensive road safety strategies are necessary to effectively reduce the incidence of accidents and ensure safer roads for all road users in Thailand.

Road traffic accidents pose a significant public health and safety concern globally, with developing countries like Thailand experiencing a particularly high burden [4]. Despite efforts to improve road safety measures, Thailand continues to grapple with a concerning rate of accidents, especially at junctions. These intersections, where multiple streams of traffic converge, present complex traffic dynamics and a heightened risk of collisions. Thailand's road traffic accident situation reflects broader challenges associated with rapid urbanization, motorization, and infrastructure development [5]. The country's bustling urban centers, such as Khon Kaen Province, witness heavy traffic volumes and intricate road networks, amplifying the likelihood of accidents, particularly at junctions. Khon Kaen Province, situated in northeastern Thailand, serves as a microcosm of the nation's road safety concerns [6]. Its expanding urban areas, coupled with the interplay of various transportation modes, contribute to a dynamic traffic environment prone to accidents, especially at junctions. Investigating accidents at junctions is crucial for several reasons:

- High Risk Locations: Junctions are inherently high-risk locations where multiple streams of traffic converge, increasing the likelihood of collisions. Understanding the factors contributing to accidents at junctions can help identify strategies to mitigate these risks and improve overall road safety.
- Complex Dynamics: Junctions exhibit complex traffic dynamics, involving interactions between vehicles, pedestrians, and cyclists, as well as factors such as traffic signals, road signage, and road layout. Investigating accidents at junctions allows researchers to analyze these interactions and dynamics to identify patterns and potential areas for intervention.
- Frequency of Accidents: Accidents at junctions are among the most common types of road traffic accidents. By focusing on these locations, researchers can target efforts where they are most needed to have a significant impact on reducing the overall number of accidents and associated injuries and fatalities.
- Impact on Traffic Flow: Accidents at junctions can disrupt traffic flow, leading to congestion and delays for motorists, pedestrians, and public transportation. Investigating junction-related accidents can help identify strategies to improve traffic flow and minimize disruptions, benefiting both road users and the broader community.
- Preventive Measures: Understanding the causes and contributing factors of accidents at junctions enables the development of preventive measures and interventions. This may include improvements to road infrastructure, changes to traffic management strategies, enhanced enforcement of traffic laws, and educational campaigns targeting road users' behavior at junctions.

Therefore, investigating accidents at junctions is essential for enhancing road safety, reducing the number of accidents and associated injuries and fatalities, and improving the overall efficiency and effectiveness of transportation systems. The objectives of the study entitled "Temporal Analysis of Road Traffic Accidents at Major Intersections in Khon Kaen Province, Thailand: A Time Series Investigation from 2012 to 2021" are as follows:

1. To Identify Temporal Trends: Analyze the temporal patterns of road traffic accidents at major intersections in Khon Kaen Province over the period from 2012 to 2021, focusing on variations in the frequency and severity of accidents over time.
2. To Explore Age Distribution: Investigate the age distribution of individuals involved in road traffic accidents at major intersections, aiming to identify age groups that are disproportionately affected and discern any

temporal changes in age-related accident patterns.

3. To Analyze Accidental Time Patterns: Investigate the temporal distribution of road traffic accidents at major intersections throughout the day, week, month, and year, aiming to identify peak accident times and temporal variations in accident occurrence.
4. To Investigate Vehicle Type Involvement: Explore the involvement of different vehicle types in road traffic accidents at major intersections, analyzing temporal trends and variations in the types of vehicles involved in accidents over the study period.
5. To Explore Gender Disparities: Examine gender disparities in involvement in road traffic accidents at major intersections, analyzing temporal variations and trends in gender-related accident patterns over the study period.
6. To Utilize Cluster Analysis: Adopt cluster analysis techniques to identify distinct clusters or patterns within the temporal data on road traffic accidents at major intersections, aiming to uncover underlying patterns, associations, and potential risk factors contributing to different types of accidents.

By addressing these objectives, the study aims to provide a comprehensive understanding of the temporal dynamics and determinants of road traffic accidents at major intersections in Khon Kaen Province, Thailand, thereby informing the development of targeted interventions and policies to improve road safety and reduce the incidence and severity of accidents in the region.

2. Literature Reviews

Geographic Information Systems (GIS) have become indispensable tools for comprehensively understanding and addressing traffic-related challenges, offering robust spatial analysis capabilities that support informed decision-making processes. By amalgamating spatial data with accident records, GIS empowers researchers and policymakers to pinpoint high-risk areas, discern underlying patterns, and devise targeted interventions to bolster road safety. Notably, GIS has been widely employed in numerous studies focusing on road accident analysis.

For instance, least squares and spatial analysis techniques were utilized to investigate the impact of road intersection geometry, traffic volume, and traffic light waiting times on road accidents, high-risk areas at junctions within the study area were successfully identified from such techniques [7]. Similarly, Getis Ord Gi* was adopted to analyze hotspots of road accident in Selangor, Malaysia, the relationship between road geometries and accident-prone areas, with T-intersections emerging as the most frequent accident sites [8] Furthermore, in Nakhon Pathom, Thailand, cluster analysis techniques, kernel density estimation (KDE), and spatial autocorrelation analysis were utilized to pinpoint hotspots of highway accidents witin the study area, the results reveal a prevalence of high-risk areas along major roads characterized by heavy traffic flow and dense concentrations of population [9].

Cluster analysis incorporating both Global Moran’s I and Anselin's Local Moran’s I was employed to detect hotspots, coldspots, and outliers among intersections in Khon Kaen Municipality, Thailand, focusing on the top ten intersections with the highest occurrences of road traffic accidents (RTAs). The analysis integrates various factors related to RTAs, such as gender, age group, vehicle types involved, victim demographics, and the time of day of accidents. However, the study revealed a spatially random distribution of RTAs, suggesting an absence of discernible spatial patterns or clustering [10]. In GIS, kernel density estimation (KDE) emerges as a pivotal spatial analysis technique employed to estimate the density of point features across geographic areas. By calculating the density of points within a defined search radius or kernel around each location on a grid, KDE proves instrumental in identifying hotspots or areas of high point density, such as crime-prone zones, wildlife habitats, or clusters of road accidents [2] and [11].

Recognizing speeding and inadequate awareness of driver safety and driving skills as significant contributors to traffic accidents in Thailand, there is an urgent need to enhance road safety, particularly at high-risk sites. The identification of black spots—intersections or road segments characterized by an unusually high frequency of traffic accidents—thus becomes crucial [4][12]and [13]. Through a review of previous studies on road accident investigation utilizing GIS, it is evident that GIS plays a paramount role in comprehensively understanding and addressing road safety challenges. By facilitating spatial analysis, GIS enables the identification of accident patterns and hotspots within geographic areas. GIS assists in pinpointing high-risk locations or black spots where accidents are more prevalent [14]. Additionally, visual representation of accident data on maps aids authorities in recognizing frequent accident sites and understanding the spatial relationship between accidents and various factors such as road geometry, traffic flow, and environmental conditions [15]. GIS facilitates the integration of diverse datasets, including road infrastructure, traffic volume, weather conditions, and driver behavior data, enabling the identification of contributing factors to accidents, such as poorly designed intersections, inadequate signage, speeding, or impaired visibility due to environmental factors [16]. Moreover, by analyzing historical accident data, GIS helps prioritize resources for targeted interventions and road safety enhancement measures [17].

3. Study Area

Khon Kaen, Thailand, stands out as an ideal setting for studying road accidents utilizing GIS technology, for several compelling reasons. Nestled in the northeastern region of Thailand, Khon Kaen emerges as one of the country's largest and most populous provinces. Its significance as a bustling transportation hub is underscored by its extensive road networks and diverse traffic patterns. With bustling urban centers, industrial zones, and expansive agricultural areas, Khon Kaen experiences a varied range of traffic conditions, spanning from congested city streets to sprawling rural highways, thus presenting a multifaceted landscape of road safety challenges. Geographically, Khon Kaen province is situated within the Khorat plateau, boasting an elevation of approximately 167 meters. Its coordinates lie at a latitude of 16°26′48″N and longitude of 102° 49′ 58″E [10]. The population numbers in Muang Khon Kaen district is the highest compared to the other districts as illustrated in Figure 1(a). It is evident that the population in Muang Khon Kaen district is the highest among all other districts. Therefore, the study focused on Muang Khon Kaen district, assuming that higher population numbers correlate with higher accident rates. Moreover, the province is traversed by Highway No. 2, also known as the Mittraphap (Friendship) highway as shown in Figure 1(b), which holds significance as one of Thailand's four primary highways [6]. This strategic placement, coupled with its diverse terrain and traffic dynamics, renders Khon Kaen an exemplary locale for investigating road accidents, especially concerning their spatial distribution and underlying determinants through the lens of Geographic Information Systems (GIS).

4. Data Used and Methodology

4.1 Data Used

The accidental road data spanning from 2012 to 2021 were sourced from the Accident Information Center of Thailand, available at https://www.thairsc.com/. However, the data collection period actually extends until 2021.

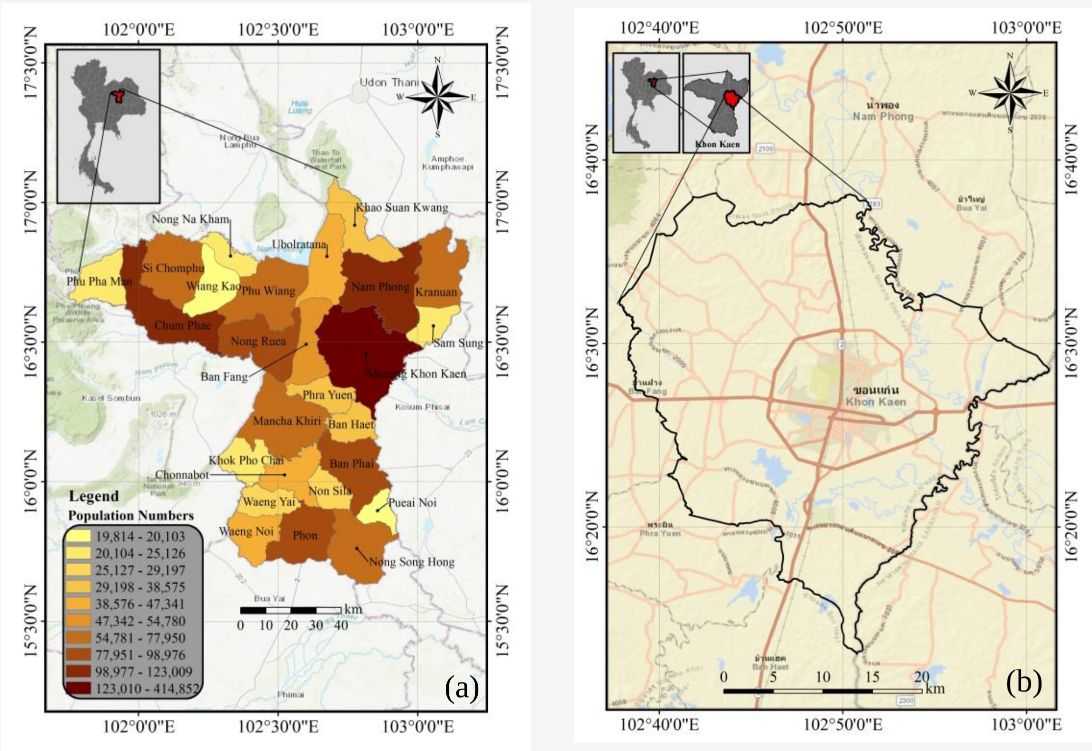

Figure 1: (a) Khon Kaen populations (b) Muang Khon Kaen municipality

Furthermore, the coordinates for 23 intersection points within the research area were obtained from Google Maps at https://www.google.com/maps/. These intersections, which were analyzed in the study, are detailed in Table 1. Additionally, the locations of the 23 intersections depicts in Figure 2.

Table 1: Intersections within the study area

No.	Intersection names	Abbreviation
1	Mitraparp-Laonadee	ML
2	Sricharn-Chatapadoong	SC
3	Bakham-Sricharn	BS
4	Prachasamosorn-Bakham	PB
5	Robbueng-Srithat	RS
6	Kasikornthungsang-Jomphon	KJ
7	Nikornsamran-Srinuan	NS
8	Mitraparp-Maliwan-Prachasamoson	MMP
9	Mitraparp-Sricharn	MS
10	Mitraparp-Bankok	MB
11	Srichan-Robmuang	SR
12	Namuang-Reunrom	NR
13	Kasikornthungsang-Nai Muang	KN
14	Prachasamosorn-Sricharn	PS
15	Tedsabarn-Sricharn-Teparak	TST
16	Railway station roundabout	RR
17	Klangmuang-Laonadee	KL
18	Maliwan- entrance KKU	ME
19	Sricharn-Klangmuang	SK
20	Prachasamosorn-Chatapadoong	PC
21	Sricharn-Anamai	SA
22	Sricharn-Langmuang	SL
23	Prachasamosorn-Langmuang	PL

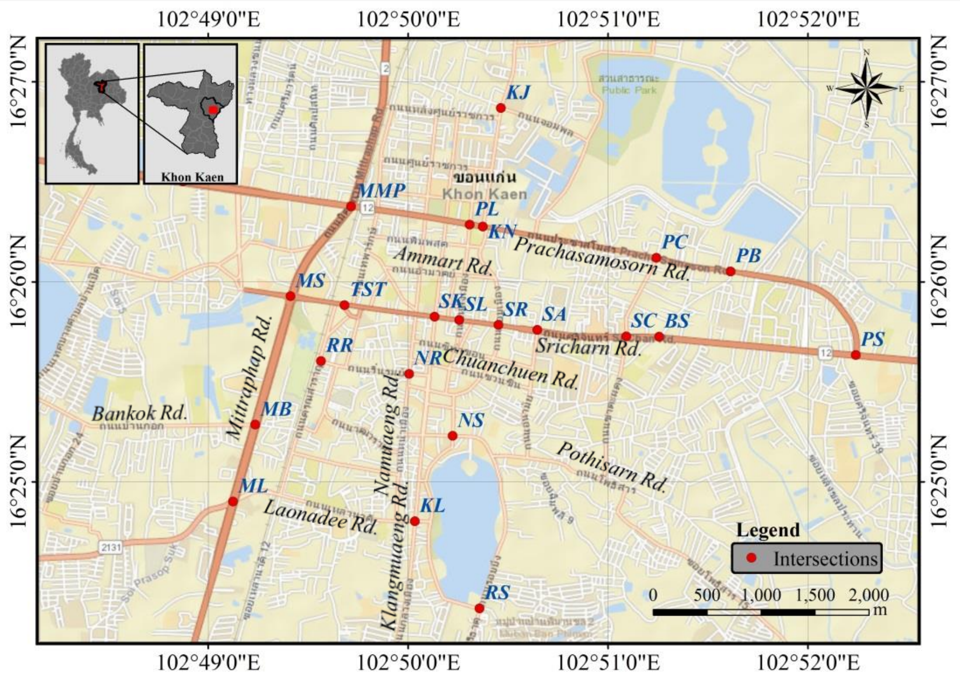

Figure 2: Locations of the 23 intersections in the study area

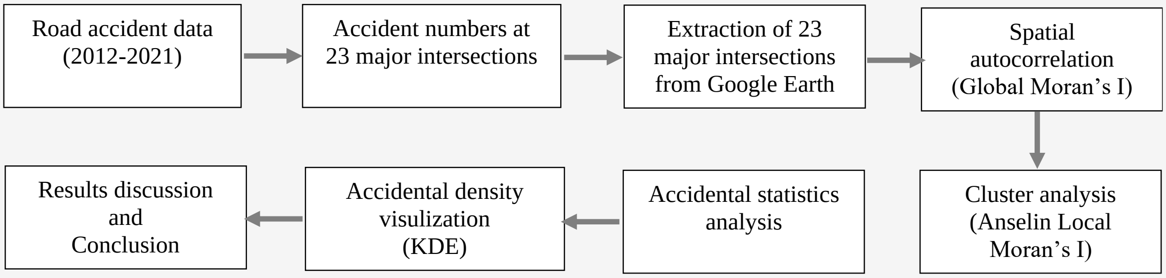

Figure 3: Research workflow

4.2 Methodology

4.2.1 Study workflow

This flowchart in Figure 3 outlines the methodology for analyzing road accident data over a ten-year period (2012-2021) focusing on 23 major intersections. Here is a detailed explanation of each step in the flowchart:

- Road accident data (2012-2021): Collect and compile road accident data from the years 2012 to 2021. The collected raw data necessary for further analysis.
- Accident numbers at 23 major intersections: Identify and extract the number of accidents occurring at 23 major intersections. The analysis is focused on specific critical points within the study area.
- Extraction of 23 major intersections from Google Earth: Use Google Earth to accurately locate and extract geographical information on the 23 major intersections to ensures precise spatial data for the intersections in the study area.
- Spatial autocorrelation (Global Moran’s I): Perform spatial autocorrelation analysis using Global Moran’s I statistic to identify the overall spatial distribution pattern of accidents. And to investigate whether the accident occurrences are clustered, dispersed, or randomly distributed.
- Cluster analysis (Anselin Local Moran’s I): Conduct cluster analysis using Anselin Local Moran’s I to identify specific clusters or hotspots of accidents at a local level. Furthermore, Anselin Local Moran’s I result used to pinpoints exact locations with higher accident densities for targeted interventions.
- Accidental statistics analysis: Provides a comprehensive understanding of the accident patterns and contributing factors.
- Accidental density visualization (KDE): Use Kernel Density Estimation (KDE) to visualize the density of accidents spatially and also to Creates a visual representation of accident hotspots and their intensities.
- Results discussion and Conclusion: Discuss the findings of the analysis, interpret the results, and draw conclusions, as well as summarizes the study’s insights and provides recommendations for future actions or studies.

This structured methodology ensures a thorough analysis of road accidents at major intersections, combining spatial analysis, statistical evaluation, and visual representation to draw meaningful conclusions and inform safety measures.

4.2.2 Global Moran's I

Spatial autocorrelation within the dataset is assessed using Global Moran’s I, which yields values ranging from -1 to +1. A positive Moran’s I denotes positive spatial autocorrelation or clustering of similar values, whereas a negative value signifies clustering of dissimilar values. A value near zero indicates a random pattern within the dataset. Equation 1 can be employed to discern spatial patterns within the dataset [18].

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{S_0 \sum_{i=1}^{n} z_i^2}$$

Equation 1

Where:

- I is Global Moran’s I
- n is the feature numbers
- $w_{i,j}$ is matrix of spatial weight
- z_i is the difference between the observation and its mean at location i
- S_0 is the sum of all weights, as defined in Equation 2.

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}$$

Equation 2

Global Moran's I operates as an inferential statistic, necessitating interpretation with respect to its null hypothesis. This statistic's null hypothesis suggests that the attribute being analyzed is randomly distributed across the features within the study area.

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A statistically significant p-value signifies the rejection of this null hypothesis (H_0) as follows: H_0: Spatial autocorrelation does not exist, and H_a: Spatial autocorrelation exist

4.2.3 Anselin's Local Moran's I

Anselin's Local Moran's I, named after Luc Anselin who introduced it in the 1990s, is a spatial statistic used in spatial analysis to identify spatial clusters or outliers in a dataset. Unlike Global Moran's I, which measures overall spatial autocorrelation, Local Moran's I calculates spatial autocorrelation for each feature in a dataset by considering its neighboring features. This helps to detect local clusters of high or low values, providing more detailed insights into spatial patterns within the data. Local Moran's I computation entails contrasting the attribute value of each feature with the average attribute value of its neighboring features. This process is iterated across all features in the dataset, yielding a Local Moran's I value for each. Subsequently, these values are categorized into four categories: Clustered-High (Hotspot), Clustered-Low (Cold spot), High outlier, and Low outlier. Hotspots and cold spots indicate positive spatial autocorrelation, where similar values cluster, while outliers denote negative spatial autocorrelation, where dissimilar values cluster [10] and [18].

4.2.4 Kernel Density Estimation (KDE)

Kernel Density Estimation (KDE) is a non-parametric statistical technique employed to estimate the probability density function of a random variable using a set of observed data points. It is particularly valuable for visualizing and analyzing the distribution of data across multiple dimensions. KDE provides a smoothed representation of the underlying distribution without assuming a specific parametric form, making it versatile for various applications such as data visualization, spatial analysis, and machine learning for exploratory data analysis and pattern recognition. In the context of road accident analysis, KDE serves as a robust tool by generating spatially explicit representations of accident data. This capability enables stakeholders to make well-informed decisions and implement targeted interventions aimed at enhancing road safety. KDE is utilized in road accident analysis for several reasons:

- Visualization of Accident Hotspots: KDE helps in visualizing the spatial distribution of road accidents. By estimating a smooth density surface from the accident data points, KDE can highlight regions with higher concentrations of accidents (hotspots) and areas with fewer accidents (coldspots) [19].
- Identifying High-Risk Areas: KDE allows analysts to identify specific locations or stretches of road where accidents are most likely to occur. This information is crucial for prioritizing interventions such as road improvements, traffic calming measures, or increased enforcement [20] and [21].
- Data-Driven Decision Making: Instead of relying on intuition or anecdotal evidence, KDE provides a statistically grounded method to objectively assess accident patterns. Decision makers can use KDE outputs to allocate resources more effectively and target interventions where they are most needed.
- Comparison and Trend Analysis: KDE can be used to compare accident patterns over different time periods or across different regions. This helps in identifying changes in accident density, understanding the effectiveness of implemented measures, and planning future interventions [20].
- Integration with Geographic Information Systems (GIS): KDE outputs can be easily integrated into GIS platforms, allowing for spatial analysis in conjunction with other geographic data (e.g., road network, population density). This integration enhances the ability to derive meaningful insights from accident data [22].
- Adjustment for Population Density: KDE can normalize accident densities by accounting for underlying population or traffic density. This adjustment helps in identifying areas where the accident rate is disproportionately high relative to the number of people or vehicles present [23] and [24].

5. Results

5.1 Global Moran's I

The Global Moran's I was utilized to examine the presence of spatial autocorrelation within the dataset. A P-value of less than 0.05 for the Global Moran's I suggests the existence of spatial autocorrelation or clustered areas within the study area, with further identification of these cluster areas possible. The Global Moran's I results for the years 2012 to 2021 are presented in Table 2. Table 2 reveals that accidents at intersections were generally independent, with no spatial autocorrelations detected between 2012 and 2021, except for 2020, where a clustering pattern emerged with a P-value of 0.035. Consequently, further investigation into the identification of these clustering areas is warranted. The cumulative accident numbers from 2012 to 2021 were tallied, and Global Moran's I was employed to ascertain the presence of spatial autocorrelation.

As indicated in the last row of Table 2, the absence of spatial autocorrelation suggests that clustering areas (hotspots and cold spots) could not be discerned. Thus, the occurrences of accidents at intersections appear to be independent of each other.

5.2 Anselin Local Moran's I

According to the results in the previous section, the cluster pattern was identified in 2020, therefore, the clustering areas for this year were further analyzed utilizing Anselin Local Moran's I. The result is depicted in Figure 4. Figure 4 illustrates the intersections where accidents clustered in 2020. It is evident that the Mitraparp-Bankok (MB) intersection emerged as a notable accident hotspot, surrounded by a high frequency of accidents. Consequently, it is imperative to implement mitigation and prevention measures at this intersection. Similarly, the Sricharn-Chatapadoong (SC) and Klangmuang-Laonadee (KL) intersections exhibit elevated accident rates, juxtaposed with adjacent intersections experiencing lower accident frequencies. Conversely, cold spots were identified at intersections along Sricharn road, namely Sricharn-Langmuang (SL), Srichan-Robmuang (SR), and Sricharn-Anamai (SA), while the remaining intersections did not exhibit significant patterns.

Table 2: Analysis of Global Moran's I for each individual year

Year	Moran's I	Z-score	P-value	Pattern
2012	0.047466	0.710102	0.477641	Random
2013	- 0.040623	0.036815	0.970632	Random
2014	0.170841	1.579556	0.114209	Random
2015	0.066689	0.870755	0.383888	Random
2016	0.140659	1.338837	0.180624	Random
2017	0.154653	1.481476	0.138480	Random
2018	-0.004482	0.531559	0.595031	Random
2019	0.144801	1.553899	0.120208	Random
2020	0.243917	2.110829	0.034787	Clustered
2021	0.067450	0.924037	0.355467	Random
2012-2021	0.100670	1.095740	0.273193	Random

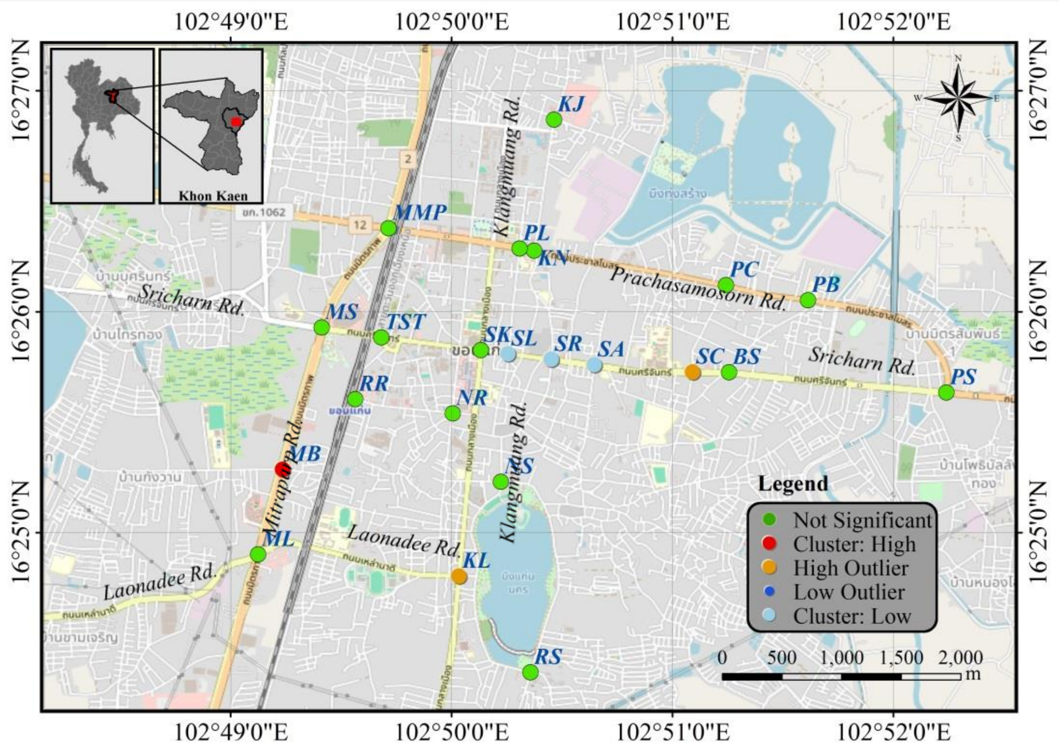

Figure 4: Cluster analysis (Anselin local Moran's I) of 2020

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5.3 Accidental Statistics from 2012 to 2021

5.3.1 Number of accidents

The accidents that occurred in Muang Khon Kaen district, Khon Kaen province, from 2012 to 2021depicts in Figures 5 and 6. Figure 5 provides an overview of the accident numbers, indicating an approximate monthly average of 40 incidents in the study area. Peaks occurred notably in March 2013 and January 2020. Moreover, 2018 stands out as a year with higher accident numbers compared to others. Figure 6 further dissects the annual accident data, corroborating the observation from Figure 5 that 2018 witnessed the highest incidence of accidents. The fluctuating nature of annual accident trends hampers detailed investigation; however, a decline in accidents is discernible post-2018, potentially influenced by the onset of the COVID-19 pandemic in early 2020. Notably, accident figures for 2020 and 2021 resembled those of 2015 and 2016, indicating a relative downturn compared to other years. Figure 7 illustrates that the Sricharn-Chatapadoong (SC) intersection had the highest accumulated accidents from 2012 to 2021. Conversely, no accidents occurred at the Prachasamosorn-Bakham (PB) and Robbueng-Srithat (RS) intersections during the same period.

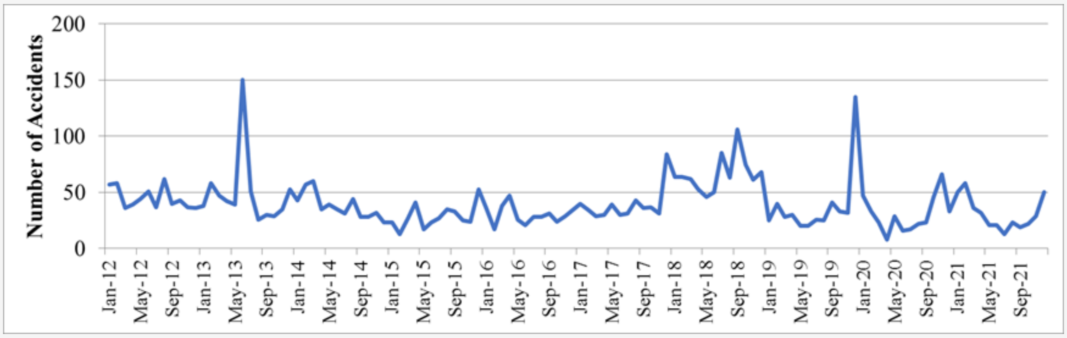

Figure 5: Number of accidents from 2012 to 2021

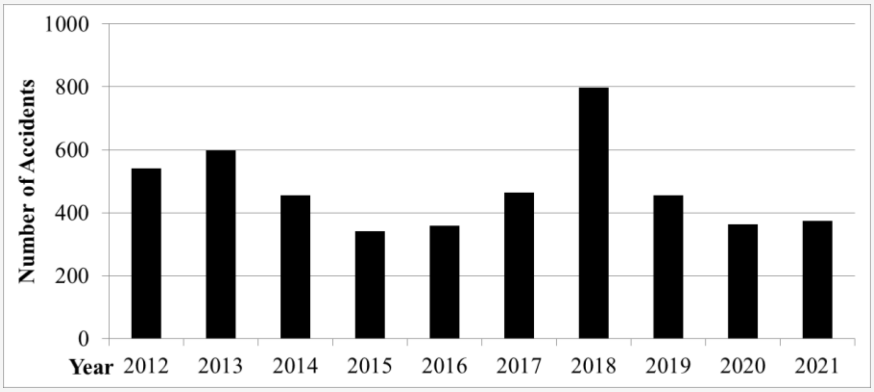

Figure 6: Annual accident numbers from 2012 to 2021

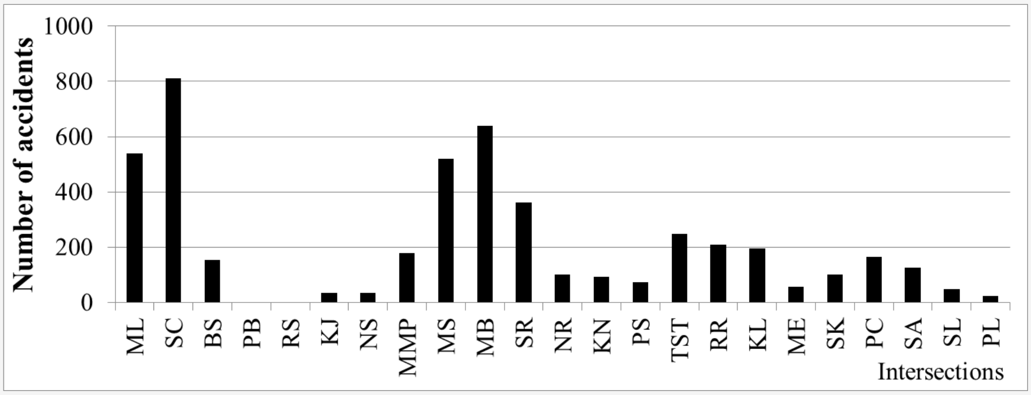

Figure 7: Accumulated accident figures at each intersection from 2012 to 2021

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This finding is consistent with the Anselin Local Moran's I analysis, which identified a high outlier (high accident numbers surrounded by low accident numbers) at the SC intersection in 2020. The MB intersection ranked second in terms of accident numbers, corroborating the hotspot identified in the cluster analysis detailed in section 5.2. The accumulated accident numbers at ML and MS intersections were identical, both ranking third. Meanwhile, accidents at SR, TST, and RR intersections ranged between 200 to 400 incidents, with the remaining intersections experiencing fewer than 200 incidents from 2012 to 2021.

5.3.2 Time of accident

The time of accident and the accumulated accident numbers illustrates in Figure 8. Figure 8 reveals that the majority of accidents occur between 2:00 AM and 4:00 AM, with a significant decrease afterward, reaching the lowest numbers between 6:00 AM and 7:00 AM. This pattern is likely influenced by the closure of entertainment venues such as nightclubs at 2:00 AM nationwide in Thailand, suggesting a higher likelihood of accidents due to Driving Under the Influence (DUI) during this period [25]. Accidents during the hours of 7:00 AM to 3:00 PM are scattered. However, after 3:00 PM, there is a gradual increase in accidents until 10:00 PM, followed by a slight decrease until 11:00 PM, and then a sharp increase from midnight to 1:00 AM. The accident numbers decrease between 1:00 AM and 2:00 AM to a level similar to that observed between 11:00 PM and midnight. Thus, it can be inferred that accidents predominantly occur between 2:00 AM and 4:00 AM due to DUI behavior.

5.3.3 Age ranges and accumulated accident numbers

The age ranges and accumulated accident numbers collected from 2012 to 2021 depicts in Figures 9 and 10. Figure 9 indicates that the majority of accidents occurred among road users aged 18 to 25 years from 2012 to 2021. However, in 2013, the number of accidents among those aged 11 to 18 surpassed that of the 18 to 25 age group. Moreover, Figure 10 highlights that accidents predominantly involved adolescents (aged 18-25 years). The trend depicted in Figure 10 demonstrates that accidents were initially observed in the 11-18 age group and increased significantly within the 18-25 age range. Subsequently, the incidence of accidents tends to decrease with increasing age.

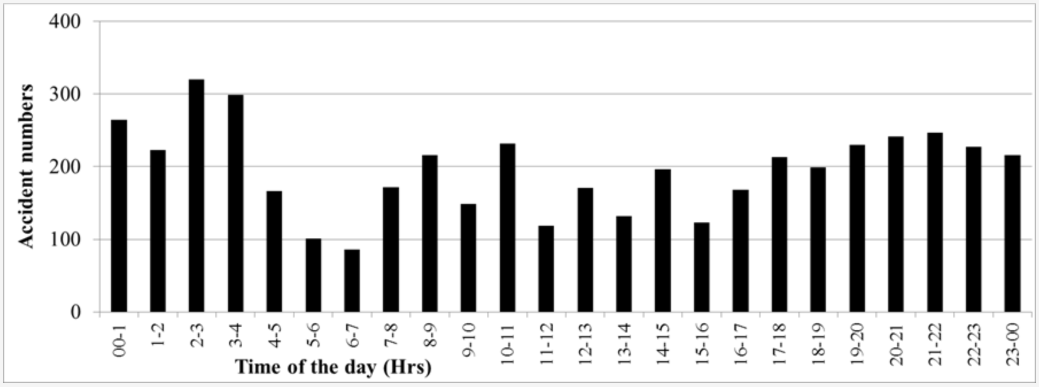

Figure 8: Accumulated accident numbers and the time of accident

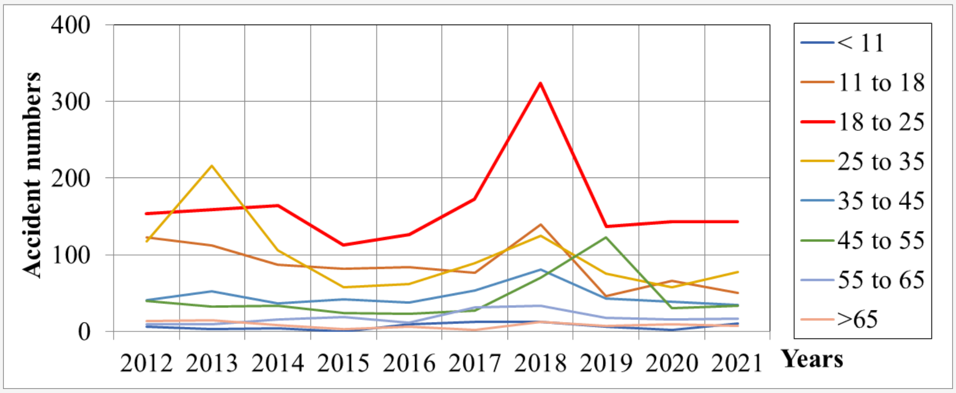

Figure 9: Relation between accident numbers and age range

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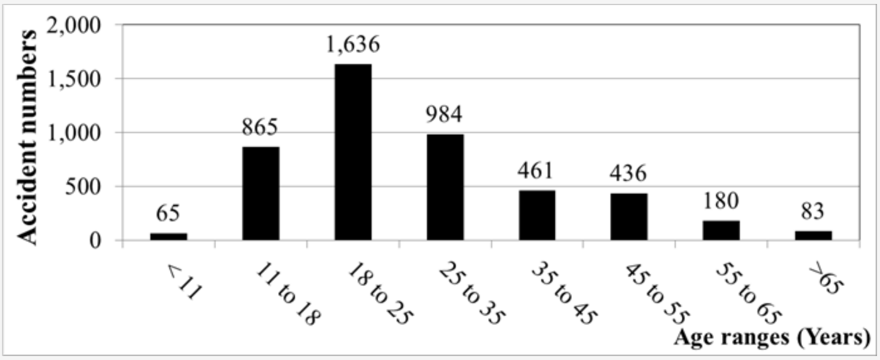

Figure 10: Age ranges and cumulative accident numbers from 2012 to 2021

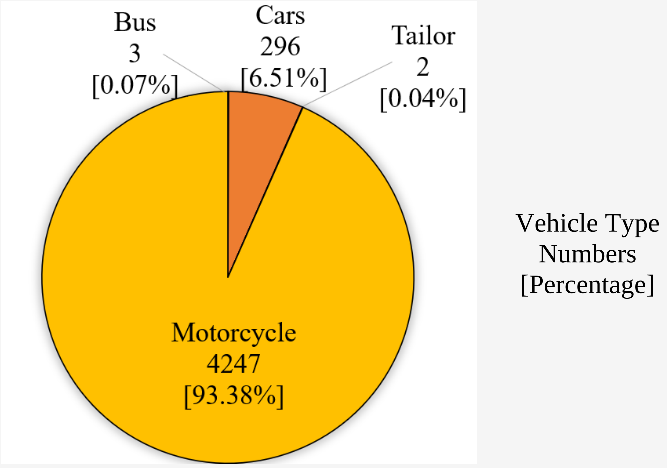

Figure 11: Accident occurrences and vehicle types

5.3.4 Vehicle types involved in accidents

Figure 11 illustrates that motorcycles account for the majority of accidents, followed by cars, buses, and trailers, respectively. This aligns with the findings in the previous section, which indicated that the age range of 18-25 years old had the highest number of accidents. The following explanations elucidate the relationship between adolescents and accident numbers.

- *Risk-taking behavior*: Adolescents often exhibit higher levels of risk-taking behavior compared to. This can manifest in reckless driving, speeding, and not wearing proper safety gear while riding motorcycles, increasing their susceptibility to accidents [26].
- *Inexperience*: Many adolescents lack experience in handling motor vehicles, including motorcycles. Inexperience with the nuances of riding, such as balancing, cornering, and reacting to hazards, can contribute to a higher likelihood of accidents [3].
- *Peer influence*: Adolescents may be influenced by their peers to engage in risky behaviors, including unsafe motorcycle riding practices. Peer pressure can lead to adolescents taking unnecessary risks or attempting dangerous maneuvers while riding, increasing the chances of accidents.
- *Lack of awareness*: Adolescents may have limited awareness of road safety rules and regulations. This lack of awareness can result in poor decision-making while riding motorcycles, such as ignoring traffic signals, overtaking recklessly, or riding without proper training or licenses.
- *Accessibility and affordability*: Motorcycles are often more accessible and affordable for adolescents compared to other vehicles. This accessibility may lead to a higher proportion of adolescents choosing motorcycles as their primary mode of transportation, thereby increasing their exposure to the risk of accidents.
- *Protective measures*: Adolescents may be less likely to prioritize safety measures such as wearing helmets and other protective gear while riding motorcycles. This reluctance to use safety equipment can significantly increase the severity of injuries in the event of an accident.

Overall, the relationship between adolescents and motorcycle accidents underscores the importance of comprehensive road safety education, enforcement of traffic laws, and promoting responsible behavior among young riders to reduce the incidence of accidents and mitigate their consequences.

5.3.5 Gender and accident numbers

Figure 12 illustrates that males tend to have higher accident numbers than females. The figure indicates that 61% of the accumulated accidents from 2012 to 2021 involved males, while 39% involved females.

The higher accident numbers among males compared to females can be attributed to several factors as follow:

- *Driving behavior*: Research indicates that males tend to engage in riskier driving behaviors compared to females. This includes behaviors such as speeding, aggressive driving, and not wearing seat belts. Risk-taking behavior increases the likelihood of accidents [27].
- *Risk perception*: Males often perceive risks differently than females. They may underestimate the dangers of certain driving behaviors or overestimate their driving abilities, leading to increased risk-taking on the road.
- *Mileage and exposure*: Males typically drive more miles than females and spend more time on the road. Increased exposure to driving situations naturally increases the likelihood of being involved in accidents [28].
- *Vehicle choice*: Males are more likely to drive vehicles associated with higher accident risks, such as sports cars or motorcycles. These types of vehicles are often faster and less stable, increasing the likelihood of accidents.
- *Age*: Younger male drivers, particularly adolescents and young adults, have higher accident rates compared to their female counterparts of the same age group. This may be due to factors such as inexperience, impulsivity, and peer influence [19].
- *Social and cultural factors:* Societal norms and cultural expectations may influence male driving behavior. For example, there may be pressure for males to demonstrate masculinity through assertive and sometimes risky driving behaviors.

Addressing these factors through targeted education, enforcement of traffic laws, and promoting safer driving practices can help reduce the gender gap in accident rates.

5.4 Identifying Surveillance Intersections

The Kernel Density Estimation (KDE) technique was employed to generate density representations of accidents across 23 intersections. Annual density surfaces of accidents at these intersections were generated individually. Subsequently, these 23 surfaces were combined using raster calculation tools. The overlaid KDE results are depicted in Figure 13. From Figure 13, it is evident that Sricharn-Chatapadoong (SC) stands out as a focal point within the study area, as it exhibits a notably high density of accidents spanning a 10-year period. This observation aligns with the results of the cluster analysis, which also identified this intersection as a high outlier. Sricharn-Chatapadoong (SC) marks the convergence of National Highway no.12, known as "Sricharn" road, linking Muang Khon Kaen to Mahasarakham province, and Chatapadoog road, which connects Sricharn road to Prachasamosorn road, as depicted in Figure 14.

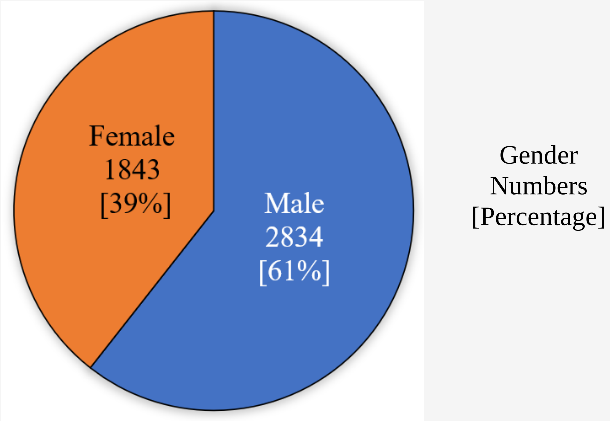

Figure 12: Accident occurrences and gender

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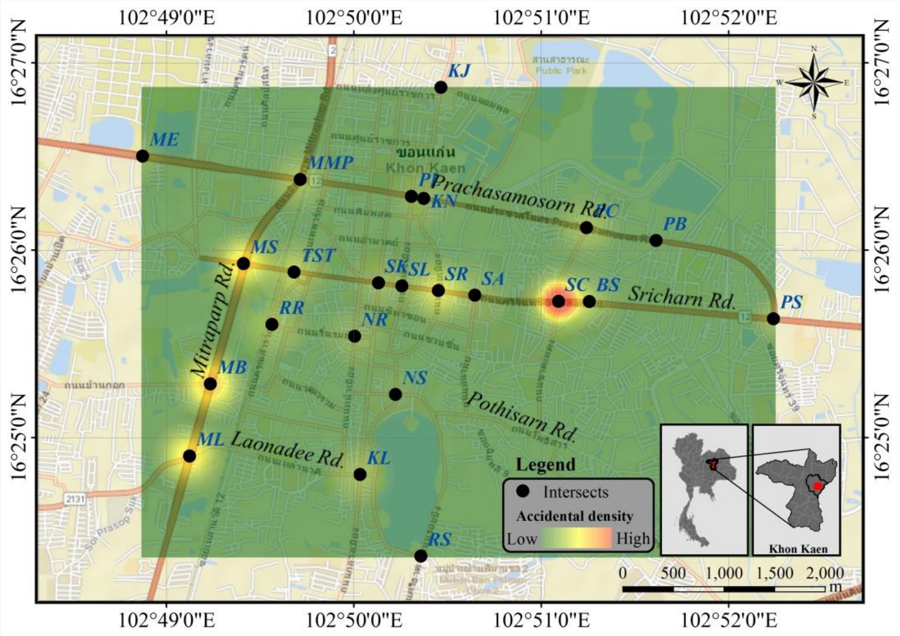

Figure 13: Surveillance points of accident detection at the intersections

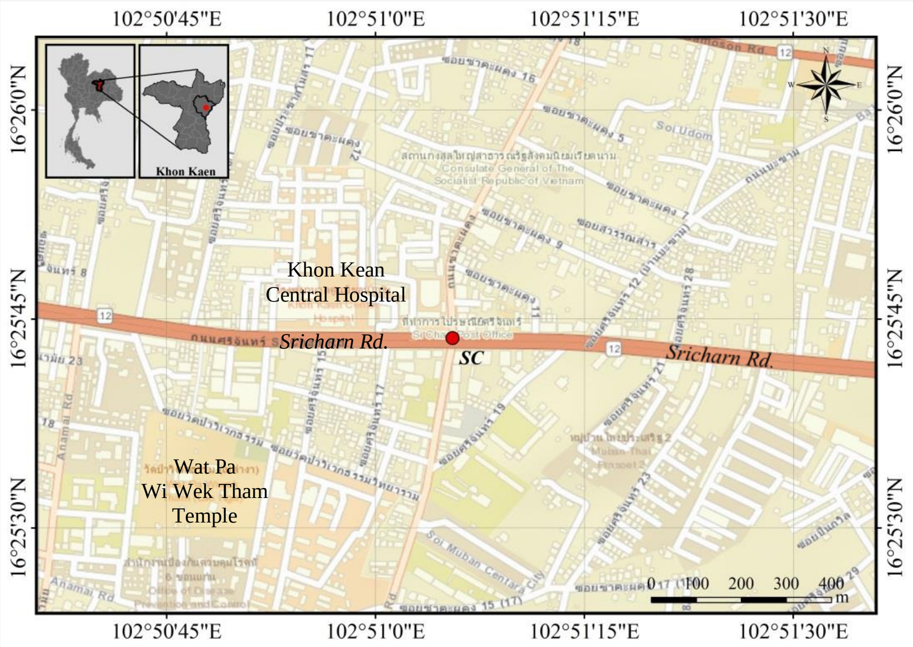

Figure 14: Sricharn-Chatapadoong (SC) intersection

Along Sricharn road, several educational institutions such as Khon Kaen Technical College, Sripatum University, and Rajamangala University of Technology Isan are situated, alongside the prominent Khon Kaen Hospital. Consequently, this thoroughfare experiences significant traffic volume, particularly during rush hours. Compounded by the fact that students residing near these educational hubs often opt for motorcycles as their mode of transportation, the likelihood of accidents along this route is heightened. This pattern is further supported by the age-range analysis, which reveals a concentration of accidents among adolescents. Given these factors, the Sricharn-Chatapadoong (SC) intersection emerges as a high-risk area. Intensive surveillance and accident prevention measures should therefore be implemented at this intersection to mitigate potential hazards.

6. Conclusion

In conclusion, the spatial autocorrelation investigation spanning 10 years (2012-2021) across 23 intersections in Muang Khon Kaen district reveals an absence of spatial autocorrelation pattern among the intersections, indicating independent accident occurrences at each intersection. However, notable hotspots and high outliers were identified at the MB and SC intersections, respectively, in 2020. The year 2018 marked the highest incidence of accidents, followed by a discernible decline post-2018, potentially influenced by the onset of the COVID-19 pandemic in early 2020.

Further analysis highlights the Sricharn-Chatapadoong (SC) intersection as the site with the highest number of accidents, contrasting starkly with the absence of incidents at the Prachasamosorn-Bakham (PB) and Robbueng-Srithat (RS) intersections. The MB intersection ranked second in accidents, consistent with hotspot identification in the cluster analysis. Additionally, intersections ML and MS tied for third place in accident frequency, while others exhibited varying incident counts. Temporal analysis reveals a peak in accidents between 2:00 AM and 4:00 AM, potentially due to driving under the influence (DUI), compounded by the closure of entertainment venues at 2:00 AM nationwide. Moreover, accidents were predominantly observed among males aged 18 to 25 years, often involving motorcycles as their primary mode of transportation. The concentration of educational institutions along Sricharn road contributes to heavy traffic flow, particularly during peak hours, elevating the risk of accidents, especially among adolescent motorcycle commuters. Consequently, the SC intersection emerges as a high-risk area, warranting intensified surveillance and accident prevention measures.

Overall, this study provides valuable insights into road safety challenges within Muang Khon Kaen district, offering evidence-based recommendations to reduce accidents. Decision-makers and authorities can leverage this information to implement targeted interventions and improve road safety measures, not only locally but also on a broader scale.

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