Geospatial Analysis for Identifying Blackspots on National and Rural Highways in Thailand

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Abstract
Traffic accidents are a pervasive global issue. In Thailand, a Southeast Asian country, recent years have witnessed a concerning surge in such incidents. This research aims to identify accident black spots within the country. The secondary data, including accident location records on national and rural highways from Thailand's Ministry of Transport, covering the period between 2021 and 2022, was examined by analytical tools such as severity index analysis, spatial autocorrelation analysis (Moran's I), Getis-Ord Gi statistic, Cluster and Outlier Analysis, and Kernel density estimation (KDE). The findings revealed a non-random spatial distribution of accidents across Thailand's road network, characterized by spatial clustering. These clusters, both high and low severity of road accident intensity (hot spots and cold spots), exhibited a 99 percent confidence level and spanned all regions. Furthermore, accident density varied within each area, influenced by provincial size and internal characteristics. Precise identification of genuine accident black spots in each province emerged through a comprehensive overlay and analysis of these combined results. These findings support relevant agencies in assessing accident cluster levels and effectively pinpointing black spots, ultimately enhancing safety on national and rural highways in Thailand.*

Keywords: Accidents, Black Spots, GIS, Thailand, Spatial Statistics

1. Introduction

The World Health Organization (2018) has identified traffic accidents as the foremost global cause of mortality. The gravity of this issue is contingent upon the enforcement of policies and legislation within each country, encompassing aspects like speed limits, driving under the influence, helmet usage, and the utilization of car seats. Each year, 1.35 million lives are lost to road accidents, with an additional 20-30 million individuals sustaining injuries due to this cause worldwide. Notably, road accidents constitute the primary cause of fatality among individuals aged 5-29 years, particularly in developing regions such as middle-income and low-income countries. In Southeast Asia, the road traffic death rate per 100,000 people experienced an upward trajectory between 2000 and 2016. Thailand occupied the top position with the highest road traffic death rate at 32.7 deaths per 100,000 population, followed by Vietnam (26.4), Malaysia (23.6), Myanmar (19.9), Laos (16.6), Cambodia (17.7), the Philippines (12.3), Indonesia (12.2), and Singapore (2.2), respectively [1].

Between 2014 and 2021, Thailand experienced a notable increase in accident frequencies. Specifically, 19% of all accidents in Thailand occurred on the national highways, which constituted the primary public thoroughfares connecting various regions, provinces, districts, and significant locations within a comprehensive network. Within the broader context of accidents across the country, there existed a considerable 66% likelihood of encountering accident-prone zones, often termed 'black spots,' distributed as follows: 66% on straight road segments, 13% at curves, 6% at median points of cross-shaped intersections, 5% at T-shaped intersections and Y-shaped intersections, 3% at cross-shaped intersections, 2% on bridges, and 2% on steep slopes, respectively [2].

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These road accident black spots are also known as hazardous road locations, high-risk areas, accident-prone spots, hotspots, sites warranting attention, and priority investigation locations [3]. They are identified as places with heightened accident risks, often resulting in loss of life and property. Their identification is contingent upon a synthesis of road characteristics, land utilization patterns, and socio-economic considerations. Furthermore, these hotspots serve as indicators of areas marked by a disproportionately higher concentration of accidents relative to other regions [4].

Hotspot mapping is a spatial analysis technique employed to visualize the distribution of accidents across the Earth's surface, while also accounting for the varying levels of accident density in different regions [4]. This mapping method encompasses three principal analytical approaches: 1) spatial analysis, 2) interpolation, and 3) cluster mapping. Spatial analysis involves the examination of spatial data, such as coordinates, in conjunction with descriptive data. Examples include Kernel density estimation (KDE), point density estimation (PDE), and line density estimation (LDE) [5] and [6]. Interpolation, on the other hand, is a spatial estimation method that relies on the existing values within a given dataset. This entails the selection of appropriate equations for estimation, including techniques like Inverse Distance Weighting (IDW), kriging, spline, or natural neighbour [7]. Cluster mapping, the third approach, is a spatial autocorrelation analysis technique that assesses the degree of clustering of the phenomenon under investigation when compared to neighbouring areas using statistical methods [8] and [9]. The outcomes of these three analytical approaches are presented as spatial data, delineating accident risk areas and their respective risk levels. However, it is essential to acknowledge that the shape, extent, and location of these risk areas may differ according to the specific variables and indicators employed in each technique.

Utilizing all three types of hotspot analysis techniques to identify accident black spots significantly enriches our comprehension of their occurrence. The application of Global Moran's I, a spatial autocorrelation analysis, serves to grasp the comprehensive landscape of accidents. Subsequently, Getis-Ord Gi* statistic and Cluster and Outlier Analysis assessment are employed to discern accident severity levels. Employing density analysis uncovers densely clustered accident black spots. The amalgamation of these three analytical approaches aids in pinpointing hotspots, thereby contributing to the establishment of a foundational knowledge base that underpins the formulation, administration, and execution of traffic-related policies. This endeavor aims to ensure safer roads and diminish accidents within the study area [10][11] and [12]. In this research, spatial analysis is applied to identify accident black spots along Thailand's national highways. Through the utilization of hot spot analysis techniques, encompassing spatial autocorrelation analysis, Global Moran's I, Getis-Ord Gi* statistic and Cluster and Outlier Analysis, and Kernel density analysis, the outcomes are compared, enabling the effective pinpointing of accident black spots. This endeavor culminates in a spatial dataset that buttresses decision-making concerning Thailand's highway accident management.

2. Research Methodology

Thailand, situated in Southeast Asia, shares borders with Laos, Myanmar, and Cambodia. It ranks as the 20th most populous nation globally. Geographically, the country is demarcated into six regions, encompassing the northern, northeastern, eastern, western, southern, and central zones. Thailand comprises 77 provinces, as illustrated in Figure 2. The conceptual framework shows the research methodology of this study, which consists of data collection, data preparation, and data analysis processes (see Figure 1).

2.1 Research Data

The secondary dataset utilized in this analysis included accident location data within the national highway and rural highway network, covering the period from 2021 to 2022 [13], as detailed in Table 1. Thailand is geographically partitioned into six regions: the Northern Region, Central Thailand, the Northeastern Region, Eastern Thailand, and the Western and Southern Regions. Collectively, these regions encompass 77 provinces, as depicted in Figure 2, spanning a total land area of 513,120 square kilometers.

Table 1: Data used in research

Order	Information	Source
1	Accident locations on the network of national highways and rural highways	Department of Highways (2020)
2	Thailand’s administrative boundaries	Ministry of interior (2020)
3	Road networks	Ministry of Transport (2020)

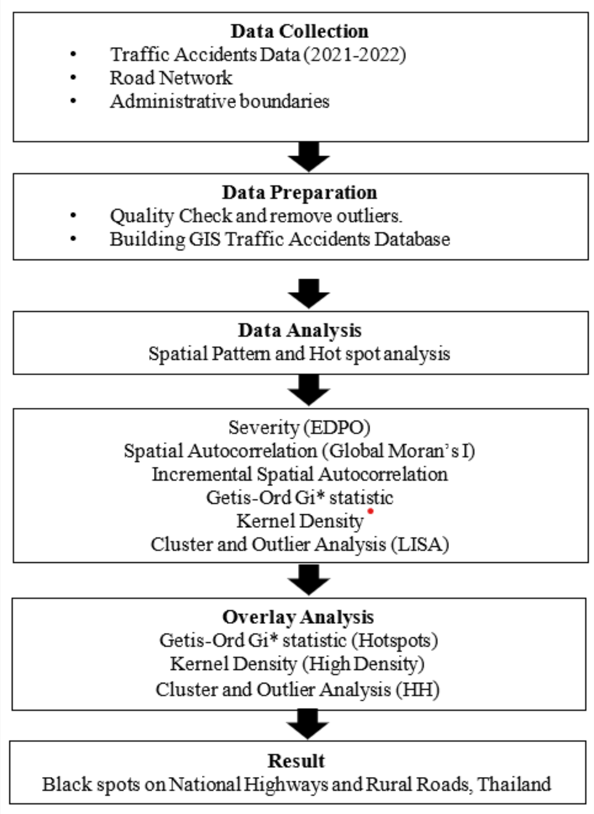

Figure 1: Conceptual framework

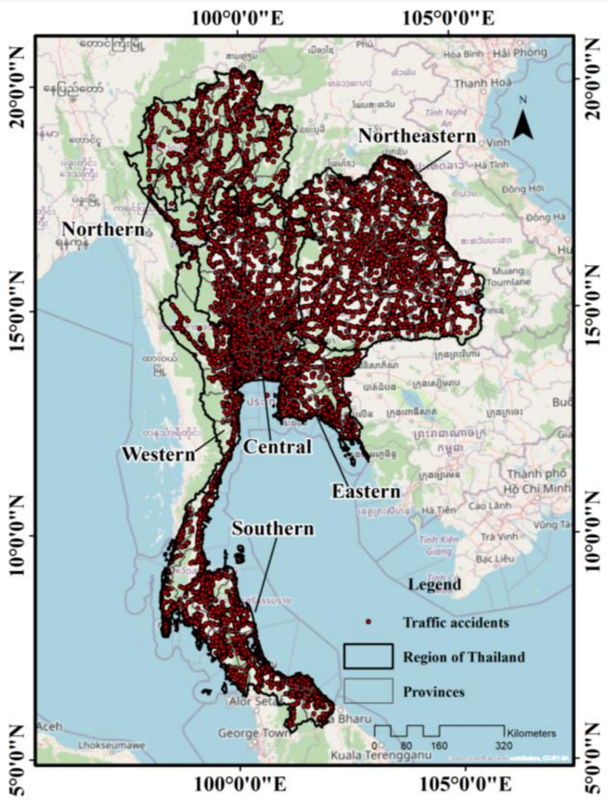

Figure 2: Administrative boundaries and locations of national highway and rural highway accidents in Thailand

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The data collection phase extended from January 1, 2021, to September 30, 2022, encompassing information on accident locations, road names, damage sustained, and the contributing causal factors for each incident. A meticulous process involving accuracy assessment, outlier identification, and subsequent removal was undertaken, resulting in the establishment of an extensive spatial accident database for Thailand's road network.

2.2 Data Analysis

In this research article, the spatial accident database of the Thai road network was analyzed to identify accident black spots on the national highways. Commenced with a spatial assessment of accidents on the Thailand Road Network, the analysis was structured into the following steps:

- Conducting a Severity Index analysis to assess the severity levels of accidents in each location.
- Determining an optimal spatial distance using Incremental Spatial Autocorrelation analysis.
- Utilizing the Global Indicator of Spatial Autocorrelation to discern the overall spatial distribution pattern of accidents on the Thai road network and categorizing them as random, dispersed, or clustered.
- Applying Kernel Density analysis to identify areas with high accident density within the road network.
- Executing Hot and Cold Spot analysis.
- Implementing Cluster and Outlier Analysis to elucidate the relationship between accident severity levels and neighbouring locations.

The details of each step are elaborated below:

2.2.1 Spatial analysis of accidents on the Thailand's road network

1) Severity Index

Analyzing the severity of road accidents provides insight into the extent of damage incurred. This research employed the concept of Equivalent Property Damage Only (EPDO) (Equation 1), which aggregates the weighted values of accident patterns along with accident frequency [14][15] and [16].

$$EDPO_i = \sum w_j f_{ij}$$

Equation 1

Where:

$EDPO_i$ = Equivalent Property Damage Only for area i

w_j = Weighting factor for accident type j as detailed in Table 2

f_{ij} = Frequency of accidents of type j in area i

Table 2: Weighting factors for different types of accident damage [14]

Severity Categories *j*	**Weight (w_j)**
Property Damage	1.0
Minor Injuries	3.5
Severe Injuries and Fatalities	9.5

2) Global Indicator of Spatial Autocorrelation

The Global Indicator of Spatial Autocorrelation measures the level and direction of spatial distribution of accidents on national and rural highways. The results of the analysis were categorized into 3 types: clustered, dispersed, and random, determined by 1) Global Moran's I for Spatial Autocorrelation, 2) z-scores, and 3) p-values (see Equation 2).

$$I = \frac{n}{W} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

Equation 2

Where:

I = Moran's I index

x_i = Observed value of area i

x_j = Observed value of area j

$\overline{x}$ = Average of observed values

n = Number of observations

w = Sum of the spatial weight matrix

w_{ij} = Spatial weight matrix

To perform the analysis, it was crucial to select an appropriate distance that would define the analysis scope for the phenomenon. Fixed distances were employed based on the principles of spatial relationships. Consequently, spatial data within a specified distance were assigned weights, while spatial data beyond that distance received a weight of 0. (Equation 3) calculated this based on the distance of the spatial data and the proximity of accident occurrences for each dataset, utilizing the distance determination method derived from Incremental Spatial Autocorrelation [17].

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

Equation 3

Where:

(X_2, Y_2) = Geographic coordinates of spot a

(X_1, Y_1) = Geographic coordinates of spot b

d = Distance between a and b

Spatial autocorrelation, as measured by Global Moran's I, fell within a range between -1 and +1. Values within the range of 0 to +1 indicated a positive spatial relationship, signifying a cohesive spatial pattern. Values within the range of 0 to -1 denoted a negative spatial relationship, indicative of a fragmented spatial pattern. Finally, when the spatial autocorrelation value of Global Moran's I equaled 0, it suggested a random spatial distribution.

3) Kernel Density Estimation

The size of the bandwidth in Kernel density estimation is a critical factor that significantly influences the outcomes of the analysis. This method estimates a smooth surface representing the density of event points within the area, and this estimation relies on the chosen bandwidth size [18][19] and [20], as shown in (Equation 4). If the chosen bandwidth size is excessively large, it results in a coarse representation, rendering the study area inadequately detailed. Conversely, opting for a bandwidth size that is too small leads to the opposite effect [21] and [22]. To ascertain the appropriate bandwidth size, we employed Incremental Spatial Autocorrelation analysis.

$$\hat{\lambda}(s) = \sum_{i=1}^{n} \frac{1}{\tau^2} k\left(\frac{s - s_i}{\tau}\right)$$

Equation 4

Where:

- $\hat{\lambda}(s)$ = Kernel density estimates
- s, s_i = Distance between S and s_i based on the observations of phenomena in the study area
- k = Weighting value of the Kernel function
- τ = Bandwidth

4) Hotspot Analysis (Getis-Ord G_i^*)

Hotspot Analysis (Getis-Ord G_i^*) was a Local Indicator of Spatial Association (LISA) method (Equation 5) used for analyzing accidents within Thailand's road network.

The results of the hot and cold spot analysis were represented with values including z-scores and p-values. This analysis involved studying a dataset at various locations in conjunction with neighboring location data. The z-score became statistically significant only when the sum of observations in each location significantly differed from the sum of observations in neighboring areas. If this difference exceeded random chance, the null hypothesis, indicating spatial aggregation, was rejected. Accepting the null hypothesis suggested the absence of spatial aggregation, offering insights into the level of clustering of the studied phenomenon [23].

In the context of hot and cold spots, their locations and surrounding spots were considered "hot spots" when they exhibited high values (positive z-scores), while "cold spots" were characterized by low values (negative z-scores) [8][17] and [22].

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{x}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2}{n-1}}}$$

Equation 5

When G_i^* represents the value of the Getis-Ord's correlation standard score at any position:

- x_j = Observation of the area j
- $\bar{x}$ = Average of the observations in area j
- w_{ij} = Weighted value between areas i and j
- S = Standard deviation of the observation values
- n = Total number of areas

The result of the G_i^* calculation must be validated using z-scores and p-values.

5) Analysis of Clusters and Outlier with Anselin Local Moran's I

The Anselin Local Moran's I method (Equation 6) for analyzing clusters and outliers determined the extent of accident clustering by visualizing hotspots. It differentiated between high and low clusters as well as spatial outliers, relying on z-scores, p-values, and identification codes for spatial cluster types to depict statistically significant cluster patterns.

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j}(x_i - \bar{x})$$

Equation 6

Where:

- x_j = Observation of the area j
- $\bar{x}$ = Average of the observations in area j
- w_{ij} = Weighted value between areas i and j

S_i^2 is determined from equation 7

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} (x_i - \bar{x})^2}{n-1}$$

Equation 7

- n = Total number of areas

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The z-score (z_{Ii}) is calculated from (Equation 8):

$$z_{Ii} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}}$$
Equation 8

$$E[I_i] = -\frac{\sum_{j=1, j\neq i}^{n} w_{ij}}{n-1}$$
Equation 9

$$V[I_i] = E[I_i^2] - E[I_i]^2$$
Equation 10

When the z-score results were positive, it indicated that the analyzed position shared similar characteristics with neighboring areas, either being consistently high or consistently low. This pointed to a clustering pattern. A negative z-score suggested that the analyzed position differed from neighboring areas in terms of characteristics, indicating an outlier pattern. In both cases, the p-value had to reach a statistically significant level. The type of cluster that emerged could be categorized as having high-high (HH) or low-low (LL) values, signifying similar characteristics among clustered areas. Conversely, high-low (HL) and low-high (LH) values represented differences in characteristics between the analyzed area and its surroundings. The confidence level was set at 95 percent to determine statistical significance [24] and [25].

2.2.2 Identifying accident black spots on Thailand's national highways

The findings of the spatial model analysis regarding accidents on Thailand's national highways were examined by integrating them with the results of Kernel density estimation. Additionally, both hot and cold spot analyses and cluster level assessments were performed. The accident blackspot was characterized by a high-density area, with a confidence level of 99 percent. The clusters were categorized as 'HH' [26].

3. Research Results

3.1 Results of Spatial Analysis of Accidents on the Thailand's Road Network

Based on the Ministry of Transport's road network accident statistics in Thailand between 2021 and 2022 [13], when classified by hazard severity, it was revealed that there were 15,738 instances of property damage only, 12,820 cases of minor injuries, and 6,912 cases of serious injuries and fatalities, totaling 35,470 incidents (see Table 3).

After conducting data management and mapping techniques to display the number of accidents on Thailand's national highways by province, classified into categories using the Quartile method, the provinces' accident types were categorized as follows: low level, ranging from 67 to 226 incidents; moderate level, ranging from 227 to 354 incidents; high level, ranging from 355 to 496 incidents; and very high level, exceeding 496 incidents (see Figure 3). The breakdown by geographical region is as follows: A very high number of accidents (>496) is observed in each region of Thailand, as indicated in Table 4.

For the spatial analysis of accidents on national highways in Thailand, weighted Spatial Autocorrelation (Moran's I) was employed, resulting in a Global Moran's I coefficient of 0.124874, a z-score of 65.509159, and a p-value of 0.000. This indicates a statistically significant spatial association model (see Figure 4).

Table 3: EDPO accident frequency

Level of severity	EDPO frequency
Property Damage Only	15,738
Minor Injuries	12,820
Severe Injuries and Fatalities	6,912
Total	**35,470**

Table 4: A significantly high number of accidents are observed in every region of Thailand

Region	Provinces
Northern Region	Chiang Mai and Phrae
Northeastern Region	Nakhon Ratchasima
Central Region	Bangkok, Pathum Thani, Phra Nakhon Si Ayutthaya, Suphan Buri, Samut Prakan, Sukhothai, Nakhon Sawan, and Phetchabun
Western Region	Kanchanaburi, Tak, and Prachuap Khiri Khan
Eastern Region	Chachoengsao, Chanthaburi, and Chonburi
Southern Region	Nakhon Si Thammarat, and Surat Thani

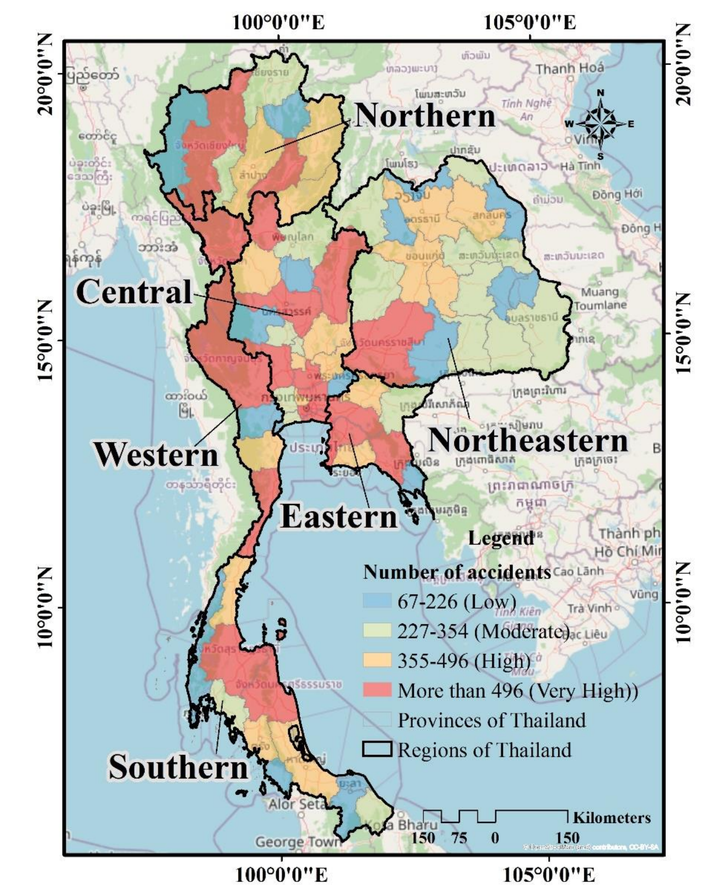

Figure 3: Number of accidents on national highways of Thailand

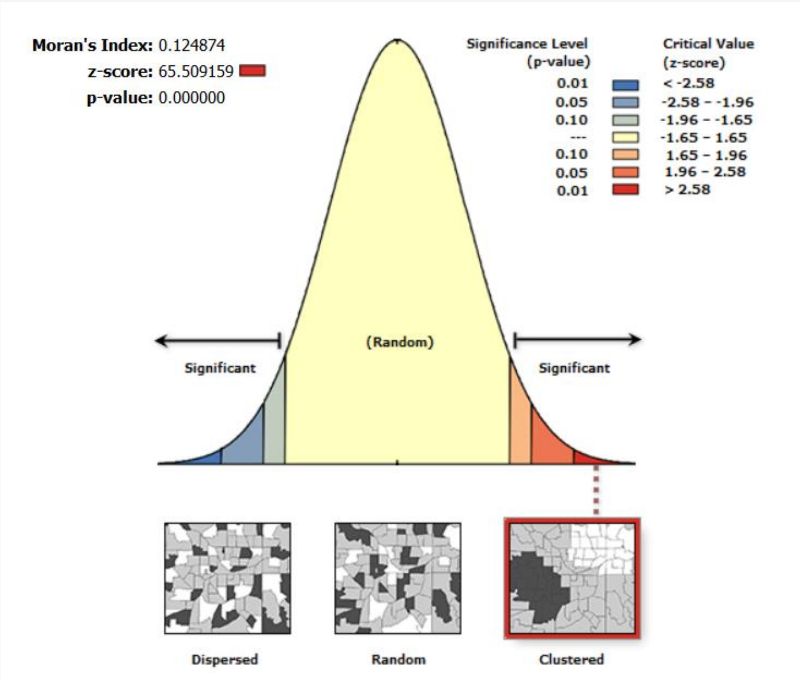

Figure 4: Global Moran's I spatial autocorrelation

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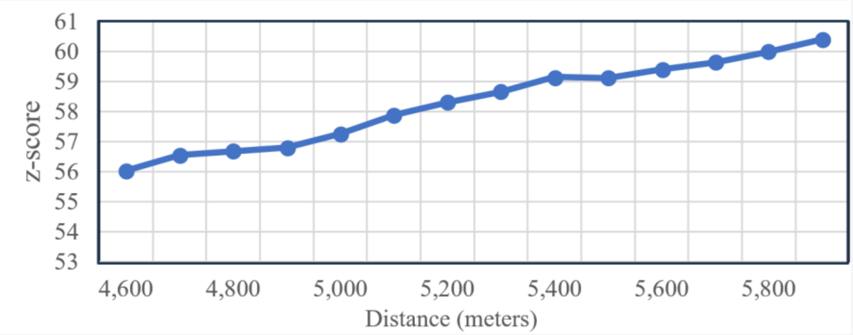

Figure 5: Incremental spatial autocorrelation

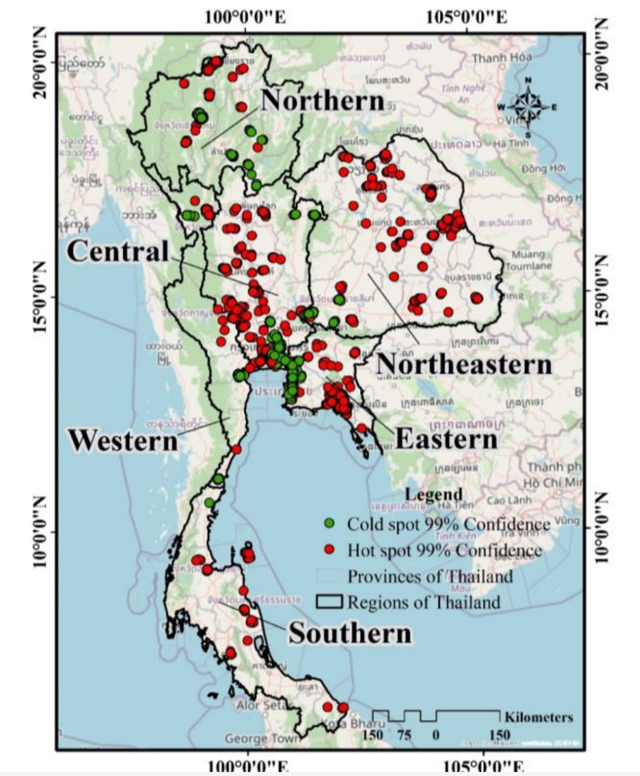

Figure 6: Identification of hot and cold spots for highway accidents with a 99% confidence level (Getis Ord G_i^*)

The results of the Incremental Spatial Autocorrelation analysis were utilized to determine the optimal distance (bandwidth) that maximizes the level of high-level cluster formation. It was observed that different distances yielded varying z-scores and levels of statistical significance (see Figure 5). Figure 5 displays a spatial autocorrelation graph for each distance, highlighting a First Peak value of 5400, a z-score of 59.1564, and a p-value of 0.000. Analysis of hot and cold spots of accidents on the Thai road network revealed that several provinces had hot spots. The top 10 provinces with the highest accident rates were led by Chanthaburi, followed by Samut Prakan, Mukdahan, Chiang Mai, Bangkok, Nonthaburi, Tak, Udon Thani, Suphan Buri, and Nakhon Sawan, respectively. In contrast, for provinces with cold spots, the confidence level was set at 99 percent. Bangkok had the highest number of cold spots, followed by Chonburi, Pathum Thani, Samut Prakan, and Chachoengsao (see Figure 6).

In the analysis of accident density on Thailand's road network, the data was divided into 4 quartile levels as depicts in Tables 5 [6] and [27]:

Table 5: Accidental density classification

Accidental density	Density classes
0	Very low
0.1 – 0.165	Low
0.166 – 0.661	Moderate
0.662 – 42.175	High

The province with the highest accident density was Nakhon Ratchasima, followed by Chiang Mai, Suphan Buri, Surat Thani, Chon Buri, Chanthaburi, Tak, Nakhon Si Thammarat, Bangkok, and Phetchabun, as shown in Figure 8.

Figure 7 displays the results of LISA statistics. It revealed 1096 locations with high severity accidents in adjacent positions (High-High: H-H). Additionally, there were 7755 low severity accidents with adjacent locations (Low-Low: L-L). The number of low severity and high severity adjacent accidents was 615 (Low-High: L-H), and the number of high severity and low severity adjacent accidents was 2269 (High-Low: H-L), while the remaining positions represented accidents that were not statistically significant.

3.2 Results of Identifying Accident Black Spots on Thailand's National Highways

Thailand, divided into 77 provinces, revealed high-density areas as hot spots with a confidence level of 99%, Clusters in the category of HH were identified in 40 provinces, with the most notable being Chanthaburi, followed by Mukdahan, Samut Prakan, Chiang Mai, Udon Thani, Nonthaburi, Nakhon Sawan, Suphan Buri, Bangkok, Tak, Sakon Nakhon, Surin, Kamphaeng Phet, Nakhon Ratchasima, Chai Nat, Nakhon Si Thammarat, Roi Et, Maha Sarakham, Surat Thani, Nong Khai, Ubon Ratchathani, Kanchanaburi, Phitsanulok, Samut Sakhon, Kalasin, Trang, Yasothon, Rayong, Sisaket, Saraburi, Chachoengsao, Prachinburi, Sa Kaeo, Ang Thong, Phayao, Chiang Rai, Narathiwat, Phrae, and Sukhothai (see Figure 9 and Table 6).

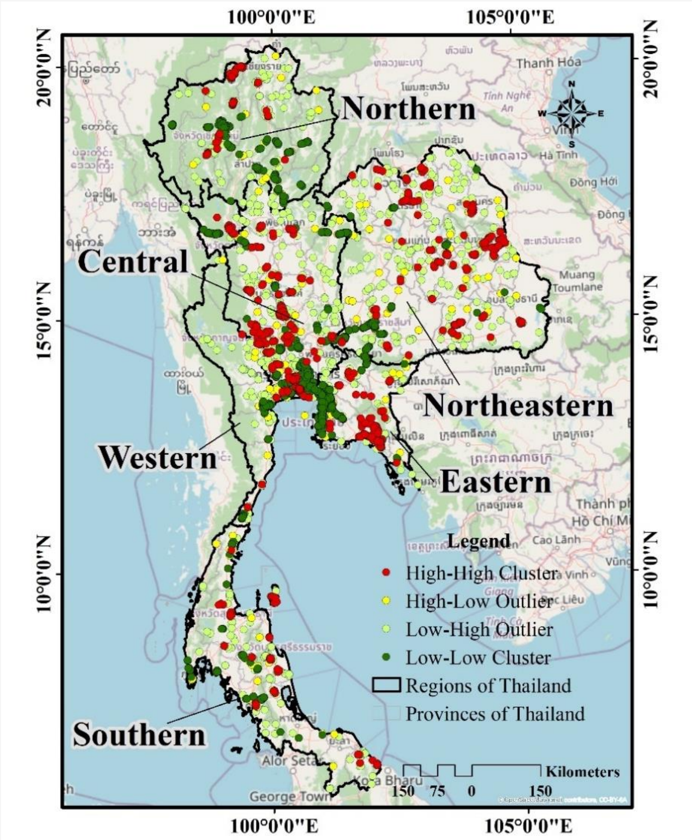

Figure 7: Identification of cluster and outlier for highway accidents (Anselin local Moran's I)

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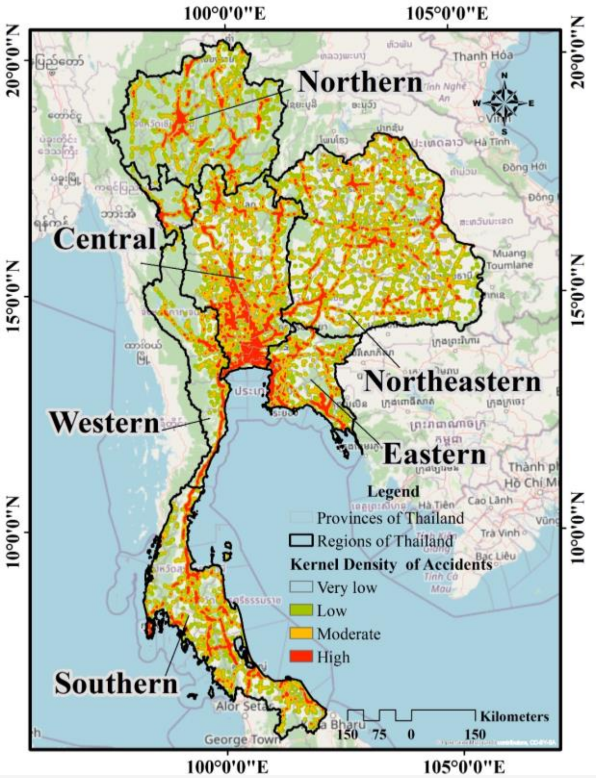

Figure 8: Results of density analysis of accidents on Thailand's road network

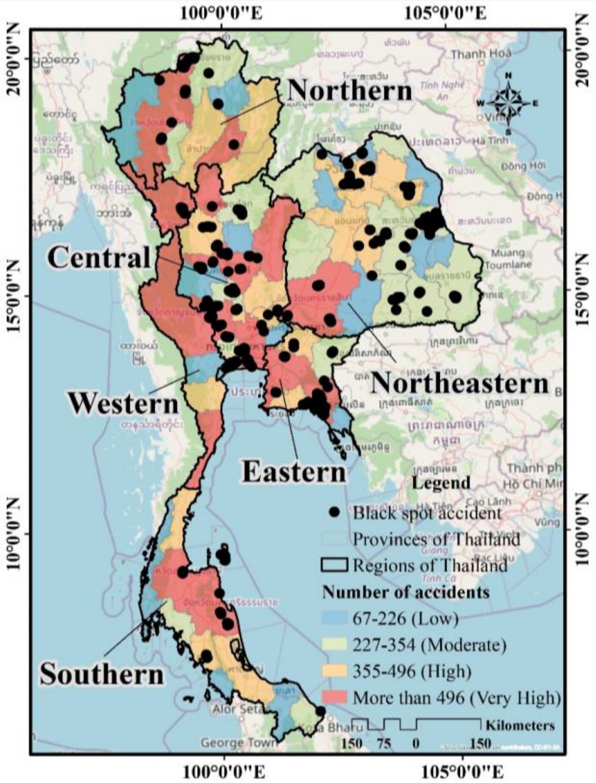

Figure 9: Accidental risks on Thailand's road network

Table 6: Number of black spots in Thailand

Province	Number of Black Spots	Province	Number of Black Spots
Chanthaburi	152	Ubon Ratchathani	11
Mukdahan	78	Kanchanaburi	10
Samut Prakan	70	Phitsanulok	10
Chiang Mai	64	Samut Sakhon	10
Ubon Thani	36	Kalasin	9
Nonthaburi	36	Rayong	7
Nakhon Sawan	34	Trang	7
Suphan Buri	31	Yasothon	7
Bangkok	26	Saraburi	6
Sakon Nakhon	24	Si Sa Ket	6
Tak	24	Chachoengsao	4
Surin	18	Prachin Buri	4
Kamphaeng Phet	15	Sa Kaeo	4
Nakhon Ratchasima	15	Ang Thong	3
Chai Nat	13	Phayao	2
Nakhon Si Thammarat	13	Chiang Rai	1
Roi Et	13	Narathiwat	1
Maha Sarakham	12	Phrae	1
Nong Khai	11	Sukhothai	1
Surat Thani	11		

4. Discussion

Spatial analysis for identifying accident risk points on national and rural highways in Thailand utilized spatial statistics to analyze and identify genuine accident risk points through four key processes: 1) accident severity analysis, 2) Kernel density estimation. 3) hot and cold spot analysis, and 4) cluster and outlier analysis [25][26] and [28]. In the analysis of accident severity, it was observed that property damage only accounted for 44.4% of accidents, minor injuries constituted 36.1%, and serious injuries and fatalities made up 19.5% of the total accidents on Thailand's national and rural highways. Notably, provinces with the highest accident frequencies within each region of Thailand were those hosting major cities or serving as crucial transportation hubs connecting important regions or provinces [29] and [30].

The analysis of hot and cold spots on the Thai road network identified Bangkok and Samut Prakan as the provinces with the highest concentration of both hot and cold spots nationwide. These provinces were densely populated urban and commercial areas with significant economic activities [21][31] and [32]. The provinces with a high density of high-level accident occurrences, included Nakhon Ratchasima, Chiang Mai, Suphan Buri, Nakhon Si Thammarat, Surat Thani, Chanthaburi, Maha Sarakham, Prachuap Khiri Khan, Chonburi, and Tak. These findings highlighted a pattern of high accident prevalence in urban areas, gradually tapering off in other regions [31] and [33].

When the results of the analysis were overlaid and examined, an intriguing finding emerged: the analytical process employed in this research paper aided in mitigating the risk of artificial accidents, as identified by Kernel density estimation. The total number of accident risk points amounted to 800, stemming from accident locations out of 35,470 instances, all characterized by severe injury or fatality. Chanthaburi ranked as the province with the highest accident risk on the road network, closely followed by Mukdahan. This observation underscored the elevated levels of accident severity, accident density, and clustering within these provinces. This constituted both a public and private concern. Local organizations could leverage the analytical framework outlined in this research paper, incorporating risk data to craft policies and enact measures aimed at curbing accidents within their respective areas [21][28] and [34].

5. Conclusion

This research paper employs spatial statistics to analyze and pinpoint accident risk points within each province of Thailand, specifically focusing on national highways and rural routes for the years 2021-2022.

The adopted approach proves to be efficient and swift, revealing a cluster of spatial patterns characterizing accidents across Thailand's road network. While hotspots and cold spots with a confidence level of 99% are distributed across all regions of the country. Remarkably, accident density correlated with provincial size and internal characteristics, with larger and more urbanized provinces exhibiting significantly higher accident densities.

The results of each analytical facet namely, accident severity analysis, Kernel density analysis, hot and cold spot analysis, and cluster and outlier analysis were integrated to accurately pinpoint the precise accident risk points within each province.

6. Recommendations

For future investigations aiming to gain a more comprehensive understanding of accidents, the temporal dimension could be incorporated. However, it is necessary to acquire consistent data throughout the research period, including information such as the number of fatalities, serious injuries, and minor injuries, as well as accident dates and causes. Alternatively, researchers may explore the integration of spatial statistics and artificial intelligence technologies to extract insights into accident patterns.

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