Spatial Statistics and Severity of Highway Accidents in Nakhon Pathom, Thailand

Sae-ngow, P.* and Kulpanich, N.
Suan Sunandha Rajabhat University, Faculty of Humanities and Social Sciences, Geography and Geo-Informatics Program, Bangkok, Thailand, 10300, E-mail: pornperm.sa@ssru.ac.th*, nayot.ku@ssru.ac.th
*Corresponding Author

DOI: https://doi.org/10.52939/ijg.v19i4.2629

Abstract
The aim of this study was to use spatial statistics and geographic information systems to identify high-risk areas for highway accidents in Nakhon Pathom, Thailand. Secondary data from the Ministry of Transport on the locations of accidents in the road network between 2021-2022 was analyzed using Equivalent Property Damage Only (EPDO), Spatial Autocorrelation, Kernel Density Estimation, and hotspot analysis. The study focused on Nakhon Pathom, a province in Central Thailand, and found that high-risk areas were concentrated along major routes with heavy traffic and high population density, including both urban and community areas. The study also identified specific risk spots, with Kamphaeng Saen District and Highways NO. 321(Kamphaeng Saen-Thung Khok Road), NO. 3231(Den Makham-Bang Len Road), and NO. 3232(Nong Phong Nok - Pai Chedi Road) being particularly affected, as well as Sam Phran District and Highway NO. 375(Ban Bo-Phra Prathon Road). These findings provide important insights into the clustering of accidents and their risk spots, which can be used to improve traffic safety in Nakhon Pathom.

Keywords: Accidents, Geographic Information Systems, Nakhon Pathom, Spatial Statistics

1. Introduction

For decades, road traffic accidents have posed a significant threat to public health worldwide. Surprisingly, a staggering 1.3 million individuals lost their lives due to these accidents, with an additional 20-50 million people sustaining injuries, leading to not only physical harm but also socioeconomic damage like property damage and loss of human resources. According to the World Health Organization (WHO), a significant proportion of fatalities among individuals aged 5 to 29 are caused by road accidents, with over 90% of these deaths occurring in low-income and middle-income countries [1].

Thailand, a medium-income country, has experienced a tremendous increase in road accidents from 61,114 cases in 2012 to 99,887 cases in 2021, representing a significant 63.4 % increase over the entire period, as reported by the Bureau of Highway Safety [2]. One particular area where this increase in road accidents is notable is Nakhon Pathom, a province that connects the central region to the western region of Thailand and supports expansion of urban areas. Due to its strategic location, Nakhon Pathom plays a crucial role in the logistics system that delivers products and services to the West and South of Thailand, making highway traffic a major concern for the province. In 2021 alone, there were 1,095 cases of traffic accidents recorded in Nakhon Pathom, with 177 of them happening on highways and resulting in 50 deaths and 141 injured individuals [2]. These accidents caused significant losses to property and human resources, underscoring the importance of better traffic accident management. With this objective in view, the integration of spatial statistics and geographical information systems can be a powerful tool in enhancing decision-making and spatial risk management to effectively reduce traffic accidents [3] [4] [5] and [6].

One effective way to manage road accidents is through the use of a geographical information system (GIS), which can apply spatial statistics to identify patterns and high-risk areas. This process typically involves several stages, including data collection, storage, analysis, processing, and overlay. During the final stage, data is combined with relevant environmental variables to gain insights into the impact of spatial conditions on the likelihood of road accidents in each high-risk area [7] and [8]. Additionally, the Kernel Density Estimation is a powerful tool that can help pinpoint accident hotspots [9].

Using spatial statistics to examine accident hotspots and cold spots can offer greater insights into the nature and trends of accidents in a specific area [10] [11] [12] and [13]. These analysis results can then be leveraged to enhance decision-making, traffic management, road network planning, and accident prevention measures.

The objective of this research is to investigate the application of geographical information systems and spatial statistics, including Equivalent Property Damage Only (EPDO), Spatial Autocorrelation, Kernel Density Estimation, and hotspot analysis, to explore the patterns and severity of highway accidents in Nakhon Pathom. The expected outcome of this research is to produce maps that show the severity levels and risk spots of highway accidents, which can be used to prevent accidents on Nakhon Pathom's highways.

2. Research Methodology

The research for this study commenced with a comprehensive data collection process, after which the data was prepared and analyzed (Figure 1). During the data collection stage, information on traffic accidents that occurred between 2021 and 2022 was obtained from the Department of Highways [14]. This data was utilized to develop a geographic information system (GIS) traffic accident database, which was subsequently leveraged to examine the severity and patterns of highway accidents.

2.1 Research Data

This study utilized secondary data obtained from the Ministry of Transport as research material. The data showcases the locations of traffic accidents that occurred on the road network of the ministry from January 1, 2021, to September 30, 2022, according to the Department of Highways [14]. The study area selected was Nakhon Pathom a province in Thailand that covers an area of 2,168.327 km^2. The data provided information about the location, names of the roads where the accidents took place, the extent of the damage incurred, and the causes of the accidents. During the specified time period, there were 275 accidents location in the study area, resulting in 45 fatalities or severe injuries, 80 minor injuries, and 150 accidents causing damage to property only. Figure 2 shows the accident locations observed on the national highways and rural roads throughout the province.

2.2 Data Analysis

2.2.1 Accident severity index

In this study, the severity of accidents was analyzed using the Equivalent Property Damage Only (EPDO) method. The EPDO is calculated as sum of the frequency of accidents under category j in area i multiply by the weight of damage caused by accidents under category j [15] [16] and [17], as shown in the formula:

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

Equation 1

Where:

$EDPO_i$ = Equivalent property damage i

w_j = weighting factor for a type of accident j as shown in Table 1

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

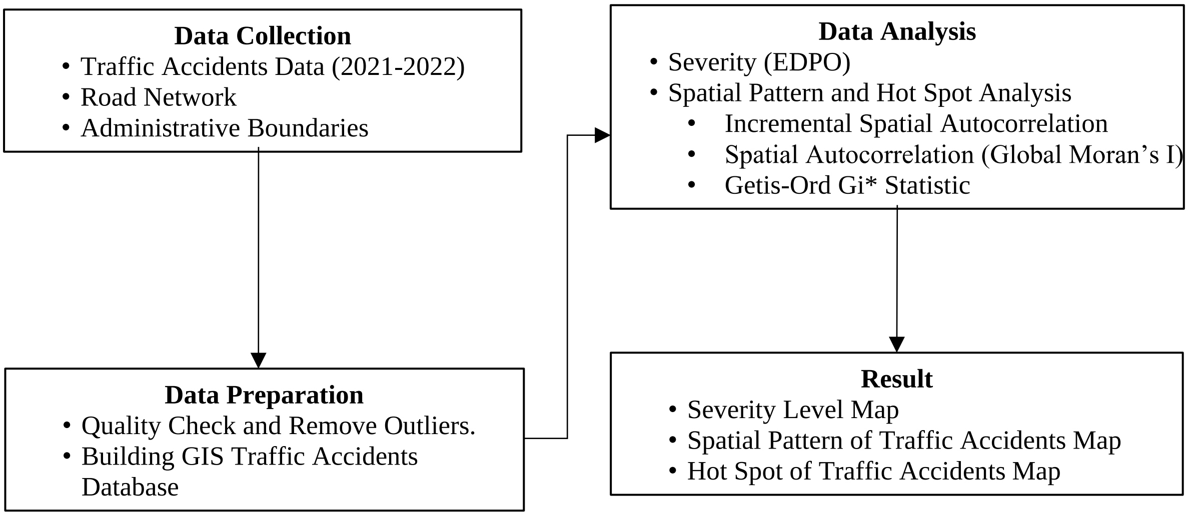

Figure 1: Methodological framework

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

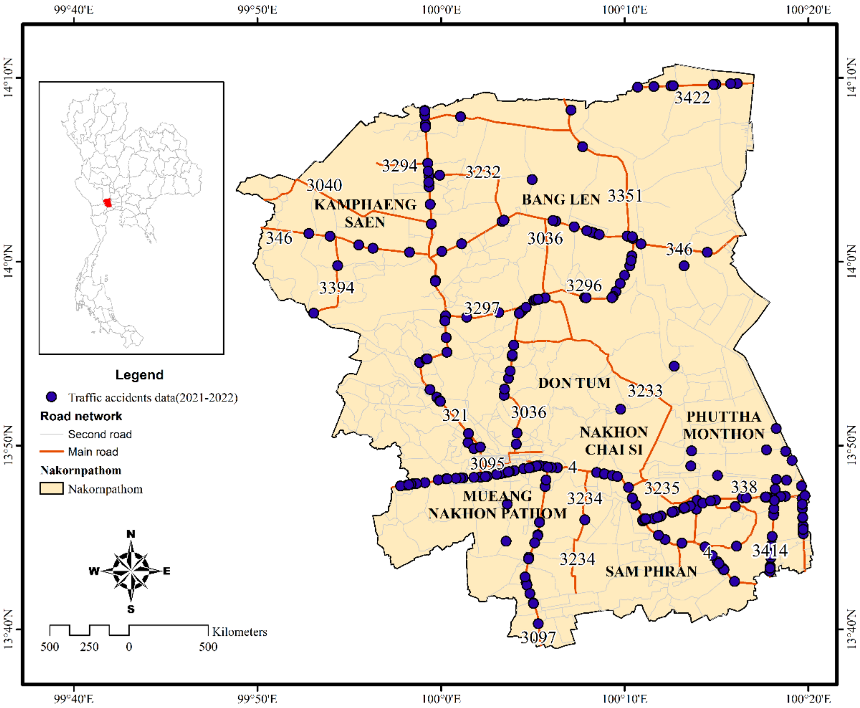

Figure 2: Accident locations on national highways and rural roads in Nakhon Pathom

Table 1: Weighting factors for different types of accident damage

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

According to Table 1, the EDPO is a method that considers the severity of injuries caused by accidents and prioritizes the more severe ones. It awards a higher value to accidents with more serious injuries. Property damage-only accidents have a value of 1, minor injury accidents have a value of 3.5, and accidents resulting in fatalities or severe injuries have a value of 9.5 [17].

2.2.2 Global spatial autocorrelation

To examine whether there was spatial autocorrelation in the dataset of highway accidents in Nakhon Pathom, the researchers employed Global Moran's I, a statistical measure frequently used in spatial analysis. This approach allowed them to quantify both the level and spatial pattern of accidents across the region's national highways and rural roads. Then, the resulting spatial patterns were categorized into three distinct groups: clustered, dispersed, and random. Through the global spatial autocorrelation analysis, they derived several key products, including the Moran's I Index, z-score, and p-value, the calculation formula is:

$$I = \frac{n}{w} * \frac{\sum\sum w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum(x_i - \bar{x})^2}$$

Equation 2

Where:

I = Moran’s I Index
x_i = observed value of area i
x_j = observed value of area j
$\bar{x}$ = average of observed values
n = number of observations
w = the aggregate of the spatial weight matrix
w_{ij} = spatial weight matrix

A fixed distance was used, based on the principles of spatial relationships. Therefore, spatial data within the specified distance was weighted. Spatial data outside of the specified distance was given a weight of 0. The distance was calculated using the Euclidean distance formula (Equation 3) for neighboring spatial data. The distance was determined by analyzing Incremental Spatial Autocorrelation [18], as shown in the formula:

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

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

The Global Moran's I index for spatial autocorrelation ranges from -1 to +1. Values between 0 and +1 indicate a positive spatial relationship, where similar features are clustered together. Values between 0 and -1 indicate a negative spatial relationship, where similar features are dispersed.

2.2.3 Kernel Density Estimation
The kernel density analysis method is an approach to estimate the density of events that occur within an area by smoothing a surface. This is done by applying a kernel function to each point, and then summing the results. The calculation describes this method [19] [20] and [21], as shown in the formula:

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

Equation 4

Where:
$\hat{\lambda}(s)$ = kernel density estimate
s, s_i = distance between s and s_i based on observation of study area
k = kernel function
τ = bandwidth

The selection of bandwidth size is important and affects the kernel density analysis because if the bandwidth is too large, the resulting output will not be able to explain the study area in detail, and if the bandwidth is too small, it will cause an opposite effect [12] and [19]. In this analysis, the bandwidth size was determined using Incremental Spatial Autocorrelation to obtain the appropriate bandwidth size that matched the spatial pattern of the accidents occurring on highways and rural roads in Nakhon Pathom.

2.2.4 Hotspot analysis (Getis-Ord Gi)*
Getis-Ord Statistics is a method used for analyzing local spatial associations (LISA), to explain the clustering level of a phenomenon studied in a neighboring area as a statistical inference. Basically, the results will be hypothetically tested, and if the null hypothesis is accepted, it means that there is no spatial clustering. If data that has the same high value clustering together, it is called a "hot spot" (with a positive z-score), and if there is clustering of data with the same low value, it is called a "cold spot" (with a negative z-score). The results of the analysis of hot and cold spots are explained by the z-score and p-value. The dataset to be studied is analyzed at each location along with data from neighboring locations. The occurrence of hot and cold spots is determined by whether the observed values at each location and its surrounding area are high or low together. The z-score is statistically significant when the sum of the observations at each location and its surrounding area differs from the sum of the expected values at each location and its surrounding area. When the difference is too large to be random, the null hypothesis is rejected, which means that there is a spatial clustering [13] [18] and [23], as shown in the formula:

$$Z(G_{i*}) = \frac{\sum_{j=1}^{n} w_{ij} x_{j-\bar{x}} * \sum_{j=1}^{n} w_{ij}}{s * \sqrt{n * \sum_{j=1}^{n} w_{ij^2} - (\sum_{j=1}^{n} w_{ij})^2}}$$

Equation 5

Where:
G_{i*} = z-score of Getis-ord at any location
x_j = observed value of area j
$\bar{x}$ = average of area j
w_{ij} = weight between i and j
s = standard deviation of observed value
n = number of total areas

The calculated value of G_{i*} should be verified by the standard score (z-score) and the probability value (p-value).

3. Research Results

3.1 Severity Index
The severity levels of accidents were analyzed using the Equivalent Property Damage Only (EPDO) method, and a damage index was calculated for each location. This information was then linked to data on national highways and rural roads. The severity levels of the accidents were classified into quartiles based on their EPDO values, which ranged from 0 (no severity) to 0.01-1.00 (low severity), 1.01-2.70 (moderate severity), 2.71-3.50 (high severity), and 3.51-9.50 (very high severity). Table 2 shows that out of 37 roads, 24 roads on national highways and rural roads were found to have EPDO values indicating accident severity. Thirteen of the routes had non-severe accidents, while the remaining roads had very high severity levels resulting in deaths and serious injuries.

The roads with high severity levels included National Highway NO. 4, Highway NO. 321, Highway NO. 3097, Rural Road NPT 4, Highway NO. 338, Highway NO. 346, Highway NO. 3310, Highway NO. 3422, Highway NO. 3316, Highway NO. 3414, Highway NO. 3296, Rural Road NPT 3, National Highway NO. 3232, National Highway NO. 3036, Rural Road NPT 6, National Highway NO. 3415, National Highway NO. 3294, National Highway NO. 3297, National Highway NO. 3235, National Highway NO. 3394, National Highway NO. 3231, National Highway NO. 3351, and National Highway NO. 3234. Accordingly, Figure 3 illustrates a map of different routes with different levels of highway accident severity in Nakhon Pathom.

Table 2: Level of highway accident severity in Nakhon Pathom

Highway NO.	Level of Accident Severity			
	Low	**Moderate**	**High**	**Very High**
4	20.522	9.364	2.850	8.456
321	5.471	3.611	6.551	4.550
3097	2.380	0.598	0.630	4.067
NPT.4	0.310	0.000	2.473	3.011
338	13.084	1.732	0.968	2.228
346	5.178	0.889	2.522	2.013
3310	2.269	0.193	1.894	1.107
3422	0.030	0.840	2.236	1.059
3316	1.041	0.000	0.000	0.720
3414	2.332	0.754	0.280	0.639
3296	0.863	0.000	0.405	0.453
NPT.3	0.000	0.000	1.242	0.408
3232	0.000	0.000	0.000	0.241
3036	3.780	1.234	0.171	0.138
NPT.6	0.000	0.000	1.318	0.000
3415	0.000	0.000	0.838	0.000
3294	0.000	0.000	0.826	0.000
3297	0.000	0.000	0.668	0.000
3235	0.000	0.000	0.569	0.000
3394	0.741	0.000	0.309	0.000
3231	0.000	0.000	0.149	0.000
3351	1.288	0.000	0.000	0.000
3094	1.061	0.000	0.000	0.000
3234	0.623	0.000	0.000	0.000
3040	0.000	0.000	0.000	0.000
3095	0.000	0.000	0.000	0.000
3098	0.000	0.000	0.000	0.000
3233	0.000	0.000	0.000	0.000
NPT.1	0.000	0.000	0.000	0.000
NPT.2	0.000	0.000	0.000	0.000
NPT.5	0.000	0.000	0.000	0.000
NBI.1	0.000	0.000	0.000	0.000
NBI.3	0.000	0.000	0.000	0.000
RBR.3	0.000	0.000	0.000	0.000
SKM4	0.000	0.000	0.000	0.000
SKM5	0.000	0.000	0.000	0.000
SPB.4	0.000	0.000	0.000	0.000

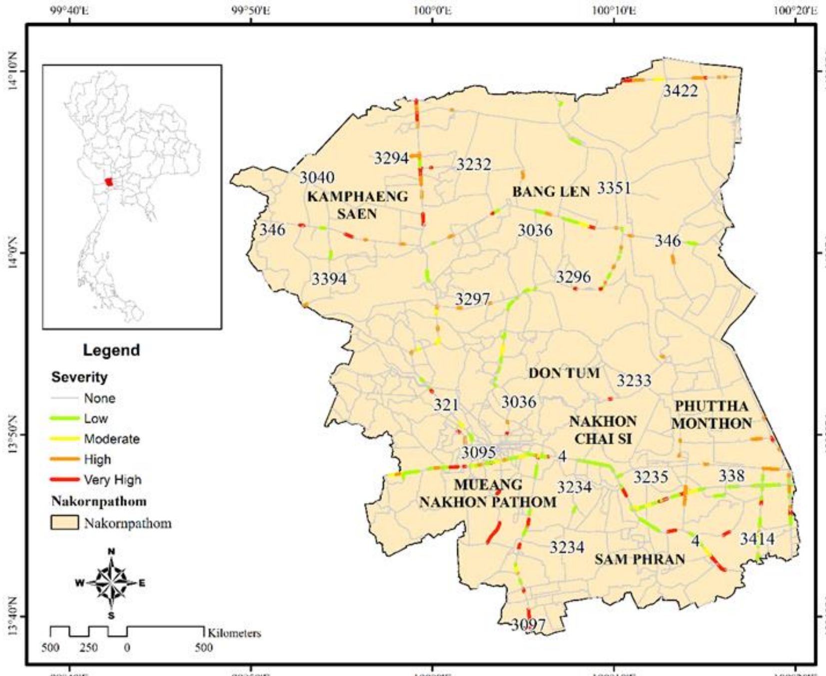

Figure 3: Highway accident severity map of Nakhon Pathom

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

3.2 Spatial Pattern of Accidents

3.2.1 Global spatial autocorrelation

The spatial patterns of accidents that occurred on highways and rural roads in Nakhon Pathom province were analyzed using Spatial Autocorrelation (Moran's I). The analysis showed that the Global Moran's I spatial autocorrelation value was 0.05455, with a z-score of 3.523 and a p-value of 0.000426, as shown in Figure 4. Therefore, the spatial autocorrelation value of Global Moran's I ranges from 0 to +1. Positive spatial autocorrelation occurs when there is a significant clustering of accidents in a particular direction. Figure 4 also shows the statistically significant cluster of accidents.

3.2.2 Incremental spatial autocorrelation

Incremental Spatial Autocorrelation was applied to analyze spatial autocorrelation by using different distance ranges, called bandwidths. Each bandwidth gave a z-score and statistical significance level, as shown in Table 3. According to Figure 5, the graph displays the values of spatial autocorrelation for each bandwidth. The max peak value was 8,000.00, with a z-score of 4.057380 and a p-value of 0.000050. Therefore, within a distance of 8,000.00 meters, there was a highly significant cluster of accidents. This value was then used as the bandwidth to analyze the kernel density of accidents on highways and rural roads in Nakhon Pathom.

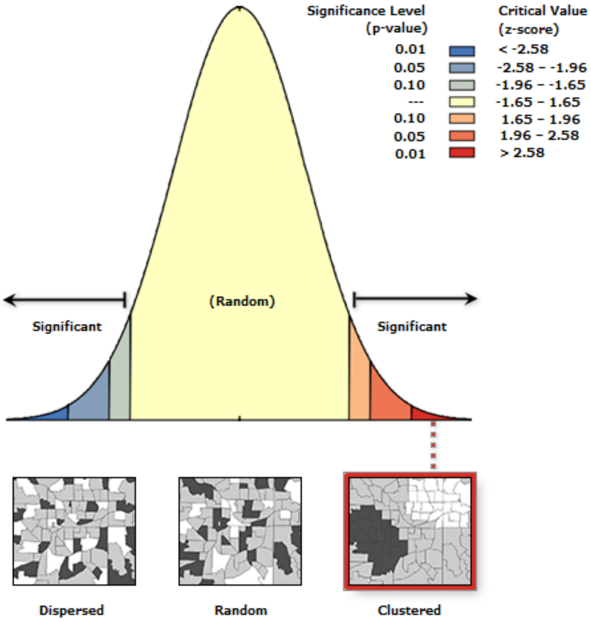

Figure 4: Global Moran's I analysis

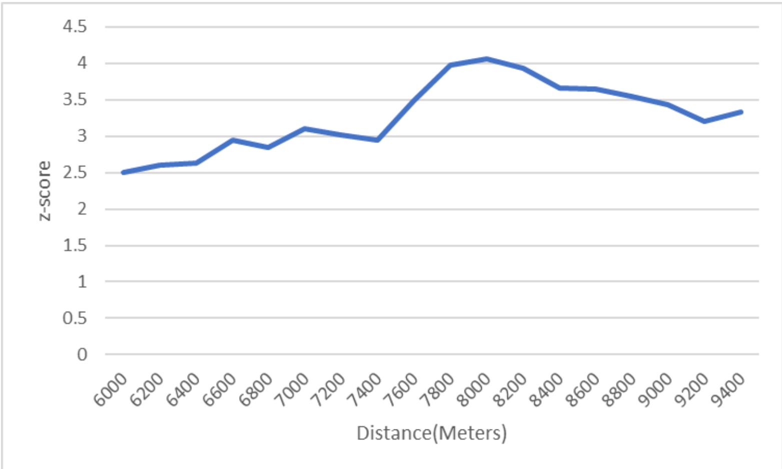

Figure 5: Incremental spatial autocorrelation

ISSN: 1686-6576 (Printed) | ISSN 2673-0014 (Online) | © Geoinformatics International

Table 3: Incremental spatial autocorrelation results

Distance	Moran's Index	Expected Index	Variance	z-score	*p*-value
6000	0.048095	-0.003745	0.000427	2.508417	0.012127
6200	0.04917	-0.003745	0.000412	2.608047	0.009106
6400	0.048399	-0.003745	0.000393	2.629055	0.008562
6600	0.052245	-0.003745	0.000362	2.94122	0.003269
6800	0.049268	-0.003745	0.000348	2.842786	0.004472
7000	0.052426	-0.003745	0.000329	3.096916	0.001955
7200	0.04966	-0.003745	0.000314	3.013485	0.002583
7400	0.047484	-0.003745	0.000303	2.944934	0.00323
7600	0.055001	-0.003745	0.000283	3.494622	0.000475
7800	0.061394	-0.003745	0.000267	3.983511	0.000068
8000	***0.061529***	***-0.003745***	***0.000259***	***4.05738***	***0.00005***
8200	0.057862	-0.003745	0.000246	3.929968	0.000085
8400	0.052522	-0.003745	0.000236	3.663853	0.000248
8600	0.051055	-0.003745	0.000226	3.649176	0.000263
8800	0.048786	-0.003745	0.000219	3.550758	0.000384
9000	0.045889	-0.003745	0.00021	3.428715	0.000606
9200	0.041777	-0.003745	0.000202	3.204645	0.001352
9400	0.042785	-0.003745	0.000195	3.335501	0.000851

3.2.3 Kernel density estimation

The density analysis of accidents that occurred on the highways in Nakhon Pathom using kernel density estimation was illustrated in Figure 6. It was found that there was a high density of accidents in certain areas, namely:

- Areas of Mueang Nakhon Pathom District, including Highway NO. 4 (Nakhon Chai Si-Phra Prathon Road and Phra Prathon-Sa Kathiam Road), Highway NO. 321 (Nakhon Pathom-Nong Pla Lai Road), Highway NO. 3036 (Nakhon Pathom-Don Tum Road), Highway NO. 3 0 9 5 (Nakhon Pathom-Department of Animal Army Road), Highway NO. 3097 (Ban Bo-Phra Prathon Road), Rural Road NPT. 1 (NO. 1003 and NO. 1008), Rural Road NPT. 4 (NO. 4002, NO. 4017, and NO. 4021-4024), Rural Road NPT. 5 (NO. 5021, and NO. 5022), and Rural Road NPT. 6 (NO. 6022).
- Areas of Kamphaeng Saen District, including Highway NO. 321 (Kamphaeng Saen-Thung Khok Road), Highway NO. 3231 (Den Makham -Bang Len Road), Highway NO. 3232 (Nong Phong Nok-Pai Chedi Road), Highway NO. 3294 (Yak Ban Sa-Lat Pla Khao Road), and Rural Road NPT. 3 (NO. 3009-3010, and NO. 3027).
- Areas of Bang Len District, including Highway NO. 3296 (Don Tum-Bang Len Road).
- Areas of Nakhon Chai Si District, including Highway NO. 4 (Nakhon Chai Si-Phra Phaton Road, a flyover at Tha Tamnak, and the Om Yai-Nakhon Chai Si Road), Highway NO. 338 (Phutthamonthon Sai 4-Nakhon Chai Si Road, and a flyover at Tha Tamnak), Highway NO. 3094 (entrance to Nakhon Chai Si District Road), Highway NO. 3233 (Nakhon Chai Si-Don Tum Road), Highway NO. 3235 (Nakhon Chai Si-Along the Nakhon Chai Si River Road), Rural Road NPT.1 (NO. 1033), Rural Road NPT.4 (NO. 4006, and NO. 4017)
- Areas of Sam Phran District, including Highway NO. 4 (Om Yai-Nakhon Chai Si Road), Highway NO. 338 (Phutthamonthon Sai 4-Nakhon Chai Si Road), Highway NO. 3097 (Phra Prathon-Ban Bo), Highway NO. 3098 (entrance to Sam Phran District), Highway NO. 3310 (Krathum Lom-Putthamonthon Road), Highway NO. 3235 (Nakhon Chai Si-Along the Nakhon Chai Si River Road), Highway NO. 3414 (Om Noi-Salaya Road), Highway NO. 3415 (Sampran-Nakhonchaisri River), Highway NO. 3316 (Rai Khing-Trong Kong Road), and Rural Road NPT. 1 (NO. 1034).
- Areas of Phutthamonthon District, including Highway NO. 338 (Phutthamonthon Sai 4-Nakhon Chai Si Road), Highway NO. 3310 (Krathum Lom-Putthamonthon Road), Highway NO. 3414 (Om Noi-Salaya Road), Rural Road NPT.3 (NO. 3004), Rural Road NPT.4 (NO. 4006), and Rural Road NBI.1 (NO. 1011).

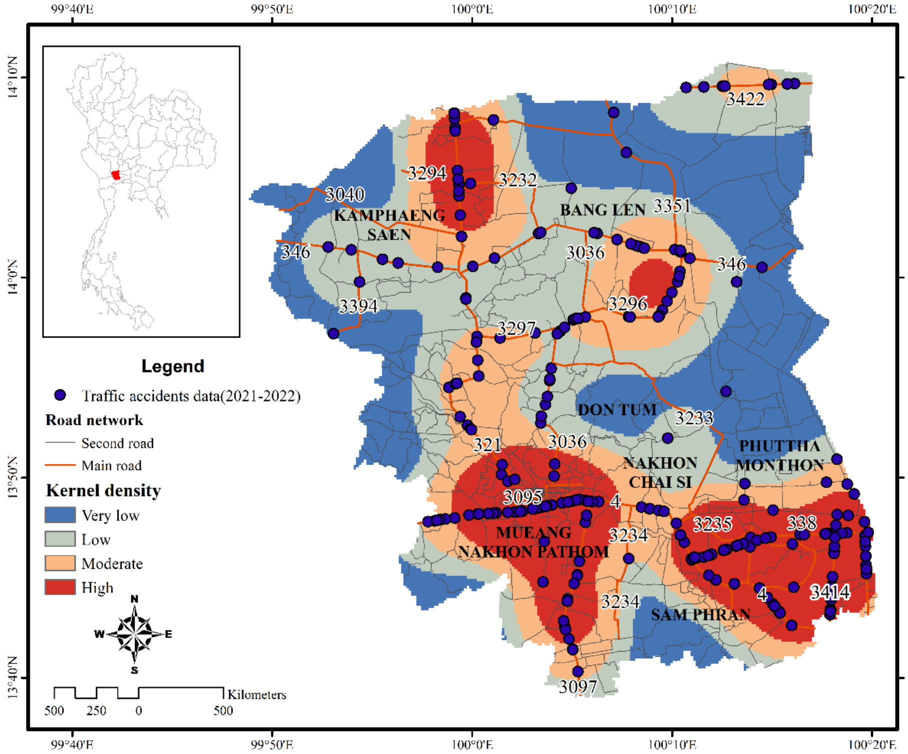

Figure 6: Kernel density map of highway accidents in Nakon Pathom

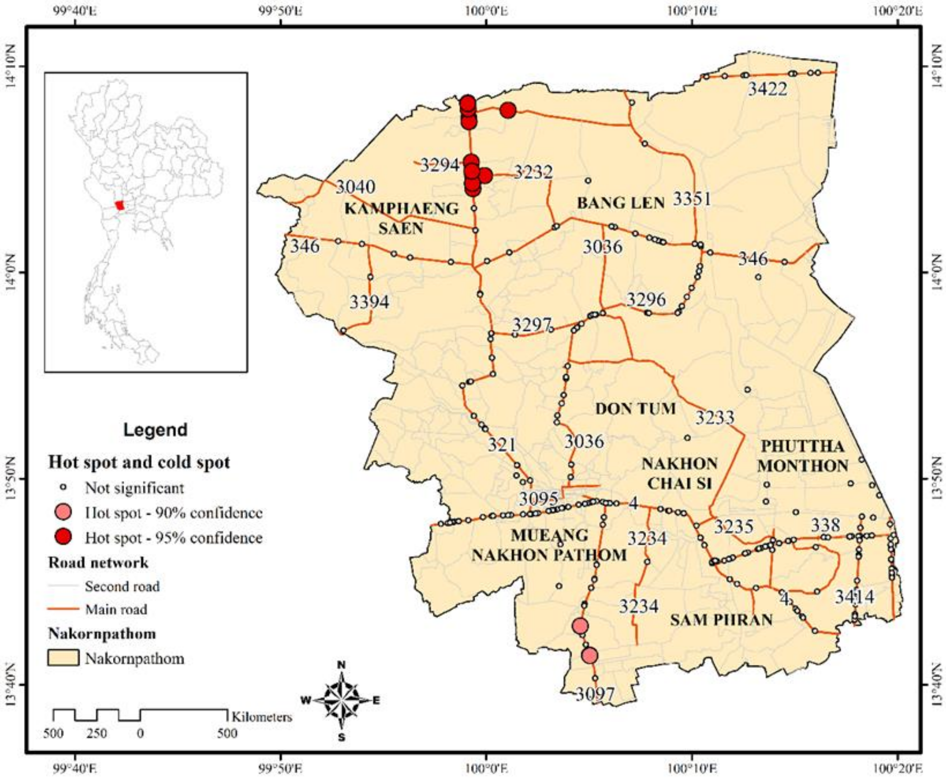

Figure 7: Hot and cold spots of accidents

3.2.4 Hotspot analysis (Getis-Ord Gi)*

The analysis of hotspots and cold spots for highway accidents in Nakhon Pathom revealed that accident hotspots were primarily concentrated in Kamphaeng Saen District, particularly on Highway 321 (Kamphaeng Saen-Thung Khok Road), Highway 3231 (Den Makham-Bang Len Road), and Highway 3232 (Nong Phong Nok-Pai Chedi Road) at a 95% confidence level. Additionally, hotspots were identified in Sam Phran District, specifically on Highway 375 (Ban Bo-Phra Prathon Road) at a 90% confidence level. Figure 7 illustrates the distribution of hotspots and cold spots of accidents on the highways in Nakhon Pathom.

4. Discussion

The application of geographic information systems (GIS), spatial statistics, and the severity level of accidents by EPDO could statistically explain and identify the aftermath of accidents on important routes. By analyzing the spatial density using a kernel density estimator and automatic spatial association, the areas with high density and agglomeration of accidents could be determined. Clearly, analyzing the hot and cold spots of accidents could help identify the risk areas of accidents on the highways in Nakhon Pathom.

The analysis conducted using the EPDO showed that areas with high accident severity were typically found in places where U-turns, flyovers, turns, and intersections occur on highways. The accidents that occurred in these dangerous areas were often related to overturned cars, crashes off-road, rear-end collisions, and head-on collisions (without lane changing). It is interesting to note that the majority of accidents that happened in these high-risk areas were caused by drivers exceeding the speed limit [13] and [24].

The results of the Spatial Autocorrelation (Moran's I) analysis indicate that highway accidents in Nakhon Pathom exhibited a clustered pattern with a spatial relationship, extending to adjacent areas in the same direction, suggesting the existence of accident-prone zones. However, the hotspots and cold spots analysis identified only a few areas with significant accident risks: namely, Highway NO. 321 (Kamphaeng Saen-Thung Khok), Highway NO. 3231 (Den Makham-Bang Len), Highway 3232 (Nong Phong Nok-Pai Chedi Road) in Kamphaeng Saen District, and Highway NO. 375 (Ban Bo-Phra Prathon) in Sam Phran District, which were statistically significant accident-prone areas on the provincial highways. The kernel density estimation analysis also revealed a high density of accidents in these areas. These highways were main routes for traveling across the province, indicating the need for targeted interventions to enhance road safety in these high-risk zones. The accidents often occurred on straight routes that passed through densely populated urban and community areas [25].

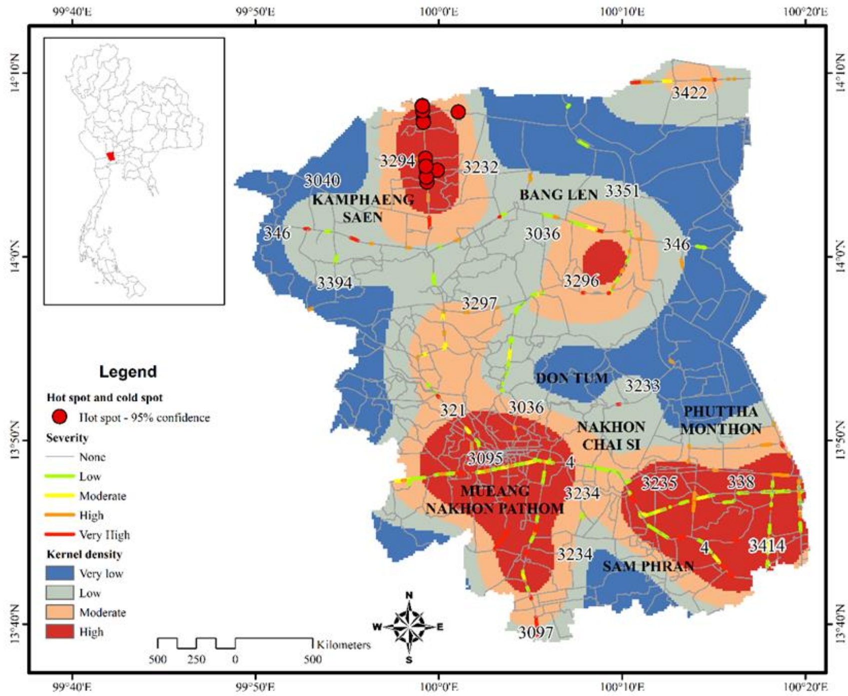

Figure 8: Data overlays of analysis results

Based on the data overlays of the analysis results (which combined accident severity analysis using EPDO, kernel density analysis, and hotspot analysis), it can be inferred from Figure 8 that while highway accidents in Nakhon Pathom were spatially clustered, the highest accident density was observed in almost every district of the province. However, statistically significant accident-prone areas were found at six very high-risk spots, six high-risk spots, and two low-risk spots in Kamphaeng Saen District, as well as one very high-risk spot and two low-risk spots in Sam Phran District. Overall, the analysis identified a total of 17 locations out of 275 that were statistically significant at a 95% confidence interval, including 14 points.

5. **Conclusion**

This study employed spatial statistics to analyze the severity of highway accidents in the Nakhon Pathom region, examining a total of 275 accidents that occurred between 2021 and 2022 in various locations. Among these accidents, 45 resulted in fatalities or severe injuries, 80 caused minor injuries, and 150 involved only property damage. The analysis categorized these accidents under EPDO, which identified the most hazardous highways, particularly those falling into the extremely high danger category, as major national routes such as National Highway NO. 4 and National Highway NO. 321. These highways were primarily used for inter-provincial travel, suggesting that travelers on these roads are at a higher risk of experiencing severe accidents. These findings underscore the need for further safety measures and interventions to reduce the incidence of accidents and improve road safety in these high-risk areas.

This study utilized a spatial pattern, including global spatial autocorrelation, kernel density estimation, and hotspot analysis, to examine the occurrence of highway accidents in Nakhon Pathom. By weighting the severity of accidents, it was possible to predict the patterns of accidents that might occur on both national highways and rural roads in the region. Analysis revealed that the Kamphaeng Saen District was the most statistically significant risk area, with several extremely dangerous spots and a high density of accidents and hotspots. The study's findings can provide valuable insights for relevant agencies in developing targeted policies and interventions to effectively prevent highway accidents in Nakhon Pathom.

6. Recommendations

To better understand the patterns of accidents, future studies should analyze the data in time intervals, which requires detailed information about the number of fatalities, injuries, and minor injuries, the date of the accident, and the cause of the accident. This can be achieved through the application of spatial statistics and artificial intelligence technology to extract knowledge about accidents.

Acknowledgment

This research was financially supported by the Institute for Research and Development, Suan Sunandha Rajabhat University in the fiscal year 2022. It was successfully completed with the assistance of students as well as cooperation and guidance from the faculty members of the Geography and Geo-Informatics Program, Faculty of Humanities and Social Sciences, Suan Sunandha Rajabhat University.

References

[1] World Health Organization, (2018). *Global Status Report on Road Safety 2018* [Online]. Available: https://www.who.int/publications/i/item/9789241565684 [Accessed Dec. 20, 2022].

[2] Bureau of Highway Safety, (2022). *Traffic Accident on National Highways in 2021* [Online]. Available: http://bhs.doh.go.th/files/accident/64/report_accident_2564.pdf [Accessed Dec. 20, 2022].

[3] Kumaresan, V., Vasudevan, V. and Nambisan, S. S., (2009). Development of a GIS-based Traffic Safety Analysis System. *In Annual ESRI International User Conference, San Diego, CA, USA*,13-17. https://proceedings.esri.com/library/userconf/proc09/uc/papers/pap_1402.pdf.

[4] Mohaymany, A. S., Shahri, M. and Mirbagheri, B., (2013). GIS-Based Method for Detecting High-Crash-Risk Road Segments Using Network Kernel Density Estimation. *Geo-Spatial Information Science*, Vol. 16(2), 113-119. https://doi.org/10.1080/10095020.2013. 766396.

[5] Dereli, M. A. and Erdogan, S., (2017). A New Model for Determining the Traffic Accident Black Spots Using GIS-Aided Spatial Statistical Methods. *Transportation Research Part A: Policy and Practice*, Vol. 103, 106-117. https://doi.org/10.1016/j.tra.2017.05.031.

[6] Harirforoush, H. and Bellalite, L., (2019). A New Integrated GIS-Based Analysis to Detect Hotspots: A Case Study of the City of Sherbrooke. *Accident Analysis & Prevention*, Vol. 130, 62-74. https://doi.org/10. 1016/j.aap.2016.08.015.

[7] Aguero-Valverde, J. and Jovanis, P. P., (2006). Spatial Analysis of Fatal and Injury Crashes in Pennsylvania. *Accident Analysis & Prevention*,

Vol. 38(3), 618-625. https://doi.org/ 10.1016/j.aap.2005.12.006.
[8] Lloyd, C., (2010). *Spatial Data Analysis: An Introduction for GIS Users*. Oxford University Press.
[9] Vemulapalli, S. S., Ulak, M. B., Ozguven, E. E., Sando, T., Horner, M. W., Abdelrazig, Y. and Moses, R., (2017). GIS-Based Spatial and Temporal Analysis of Aging-Involved Accidents: A Case Study of Three Counties in Florida. *Applied Spatial Analysis and Policy*, Vol. 10, 537-563. https://doi.org/10.1007/s12061-016-9192-4.
[10] Prasannakumar, V., Vijith, H., Charutha, R. and Geetha, N., (2011). Spatio-Temporal Clustering of Road Accidents: GIS Based Analysis and Assessment. *Procedia-Social and Behavioral Sciences*, Vol. 21, 317-325. https://doi.org/10.1016/j.sbspro.2011.07.020.
[11] Chen, H., (2012). Black Spot Determination of Traffic Accident Locations and its Spatial Association Characteristic Analysis Based on GIS. *Journal of Geographic Information System*, Vol. 4(6), 608-617. http://dx.doi.org/10.4236/jgis.2012.46063.
[12] Lakshmi, S., Srikanth, I. and Arockiasamy, M., (2019). Identification of Traffic Accident Hotspots Using Geographical Information System (GIS). *International Journal of Engineering and Advanced Technology*, Vol. 9(2), 4429-4438. http://dx.doi.org/10.35940/ijeat.B3848.129219.
[13] Mesquitela, J., Elvas, L. B., Ferreira, J. C. and Nunes, L., (2022). Data Analytics Process Over Road Accidents Data—A Case Study of Lisbon City. *ISPRS International Journal of Geo-Information*, Vol. 11(2), 143. https://doi.org/10.3390/ijgi11020143.
[14] Department of Highways, (2020). *Traffic Accident on National Highways* [Online]. Available: https://data.go.th/th/dataset/gdpublish-roadaccident [Accessed Dec. 20, 2022].
[15] PIARC, (2003). *Road Safety Manual*, Permanent International Association of Road Congresses, World Road Association, Paris.
[16] Rodrigues, D. S., Ribeiro, P. J. G. and da Silva Nogueira, I. C., (2015). Safety Classification Using GIS in Decision-Making Process to Define Priority Road Interventions. *Journal of Transport Geography*, Vol. 43, 101-110. https://doi.org/10.1016/j.jtrangeo.2015.01.007.
[17] Karimi, A. and Kashi, E., (2018). Investigating the Effect of Geometric Parameters Influencing Safety Promotion and Accident Reduction (Case study: Bojnurd-Golestan National Park Road). *Cogent Engineering*, Vol. 5(1). https://doi.org/10.1080/23311916.2018.1525812.
[18] Hazaymeh, K., Almagbile, A. and Alomari, A. H., (2022). Spatiotemporal Analysis of Traffic Accidents Hotspots Based on Geospatial Techniques. *ISPRS International Journal of Geo-Information*, Vol. 11(4). https://doi.org/10.3390/i jgi11040260.
[19] Anderson, T. K., (2009). Kernel Density Estimation and K-Means Clustering to Profile Road Accident Hotspots. *Accident Analysis & Prevention*, Vol. 41(3), 359-364. https://doi.org/10.3390/ijgi11040260.
[20] Grekousis, G. and Photis, Y. N., (2014). Analyzing High-Risk Emergency Areas with GIS and Neural Networks: The case of Athens, Greece. *The Professional Geographer*, Vol. 66(1), 124-137. https://doi.org/10.1080/00330124.2013.765300.
[21] Jientrakul, R., Yuangyai, C., Boonkul, K., Chaicharoenwut, P., Nilsang, S. and Pimsakul, S., (2022). Integrating Spatial Risk Factors with Social Media Data Analysis for an Ambulance Allocation Strategy: A Case Study in Bangkok. *Sustainability*, Vol. 14(16). https://doi. org/10.3390/su141610247.
[22] dos Santos, A. M., Santos, B. R. I., da Silva, C. F. A., de Almeida Junior, P. M. and Falcão, V. A., (2022). Spatio-Temporal Analysis of Accident Hotspots on Federal Highways in the State of Goiás, Brazil. *GeoJournal*, Vol. 87(5), 3839-3854. https://doi.org/10.1007/s10708-021-10472-9.
[23] Getis, A. and Ord, J. K., (1992). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis*, Vol. 24(3), 189-206. https://doi.org/10.1111/j.1538-4632.1992.tb00261.x.
[24] Hisam, F. N. S. A., Halim, M. B. A., Naharudin, N. and Hashim, N., (2022). GIS Analysis on Road Accident and Road Safety: A Case Study of Road Geometry in Kajang, Selangor. *International Journal of Geoinformatics*, Vol. 18(4), 45-50. https://doi.org/10.52939/ijg.v18i4.2257.
[25] Le, K. G., Liu, P. and 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*, Vol. 23(2), 153-164. https://doi.org/10.1080/10095020.2019.1683437.