Geojournal of Tourism and Geosites
ISSN 2065-0817, E-ISSN 2065-1198

Year XVIII, vol. 60, no. 2spl, 2025, p.1067-1077
DOI 10.30892/gtg.602spl04-1480

IDENTIFICATION OF ROAD CRASH ZONES, SPATIAL PATTERNS, AND EMERGING HOT SPOTS OF ROAD TRAFFIC INJURY SEVERITY IN PHUKET, THAILAND

Pornperm SAE-NGOW [1], Nayot KULPANICH [1*], Morakot WORACHAIRUNGREUNG [1], Nuttakorn SITTARACHU [2], Kunyaphat THANAKUNWUTTHIROT [3], Phonpat HEMWAN [4]

[1]Suan Sunandha Rajabhat University, Faculty of Humanities and Social Sciences, Geography and Geo-Informatics Program, Bangkok, Thailand; pornperm.sa@ssru.ac.th (P.S.N.); nayot.ku@ssru.ac.th (N.K.); morakot.wo@ssru.ac.th (M.W.)
[2]Silpakorn University, Department of Innovation and Academic, Bureau of Digital Technology, Nakornpathom, Thailand; sittarachu_n@su.ac.th (N.S.)
[3]Suan Sunandha Rajabhat University, Faculty of Fine and Applied Arts, Digital Design and Innovation Field of Study, Bangkok, Thailand; kunyaphat.th@ssru.ac.th (K.T.)
[4]Chiang Mai University, Department of Geography, Faculty of Social Sciences, Chiang Mai, Thailand; phonpat.h@cmu.ac.th (P.H.)

Citation: Sae-Ngow, P., Kulpanich, N., Worachairungreung, M., Sittarachu, N., Thanakunwutthirot, K., & Hemwan, P. (2025). Identification of road crash zones, spatial patterns, and emerging hot spots of road traffic injury severity in Phuket, Thailand. *Geojournal of Tourism and Geosites*, 60(2spl), 1067–1077. https://doi.org/10.30892/gtg.602spl04-1480

Abstract: Road traffic accidents are a critical global concern. Thailand, a middle-income country, has the highest road traffic mortality rate in Southeast Asia. Phuket, which generates the second-highest tourism revenue in the country after Bangkok, faces road traffic accidents as one of the leading causes of death among both residents and tourists. This study aims to apply space-time cube (STC) analysis to identify high-risk road crash zones in Phuket. Secondary data on road accident locations from 2017 to 2023 were utilized for analysis. The methodological framework included the Severity Index analysis, Spatial Autocorrelation (Moran's I), Hotspot Analysis (Getis-Ord Gi*), and space-time cube (STC) analysis. The findings indicated an overall increase in road accidents across Phuket's road network, characterized by a rise in minor accidents and a decline in major accidents. This trend resulted in a yearly reduction in the average severity index from 2017 to 2023. Spatial analysis revealed that road accidents in Phuket exhibited a clustered pattern. The distribution of hot and cold spots was predominantly spatially random, accounting for 91.3% of all accident locations. The proportion of hot spots (4.710%) was higher than that of cold spots (3.995%). The spatial analysis of road accidents in Phuket Province, conducted using Getis-Ord statistics, identified Mueang Phuket District as the area with the highest concentration of accident hotspots, particularly in Rawai and Karon Subdistricts. Kathu District ranked second, with the majority of hotspots located in Patong Subdistrict. Thalang District followed, with Pa Khlok Subdistrict exhibiting the highest density of hotspots in that area Furthermore, the spatial distribution of road accidents suggests a strong correlation between high-risk zones and urban zones. The space-time cube (STC) analysis further identified both consecutive hot spots and sporadic hot spots, particularly in urban and built-up areas. These results offer empirical evidence to support spatially targeted traffic safety interventions. The integration of spatial and temporal perspectives highlights the dynamic nature of road crash patterns, enabling local authorities to prioritize areas for immediate and long-term interventions. This study contributes to the growing field of geospatial health by applying advanced spatial-temporal techniques to road safety analysis in a developing tourism context.

Keywords: traffic accidents, spatiotemporal patterns, space-time cube analysis, Getis-Ord Gi*, severity, Phuket, Thailand

* * * * * *

INTRODUCTION

Thailand is classified as a middle-income country (WHO, 2019; Korwatanasakul, 2023). Road safety is one of the most significant public health issues in the country and a critical concern for the Thai government (Road Safety Operation Center (RSOC) by Department of Disaster Prevention, 2023). Although Thailand has had a national road safety plan in place since 2013, its implementation has yet to achieve the desired outcomes (Thailand Development Research Institute, 2017). According to the 4th Global Status Report on Road Safety, Thailand recorded a road traffic fatality rate of 32.7 deaths per 100,000 population in 2018. Based on World Health Organization (WHO)'s estimation, this rate was the highest in Southeast Asia and ranked ninth among its 175 member countries. In 2016, there were 22,491 road traffic fatalities in Thailand, averaging 60 deaths per day. The most affected groups were individuals aged 15 to 29 and motorcyclists, who accounted for 74% of all road traffic fatalities (WHO, 2019). According to data from the Thailand Development Research Institute (TDRI), the economic losses from road traffic accidents in 2019 were estimated at 642,743.3 million baht (approximately 18.87 billion USD), equivalent to 5.9% of the GDP (Thailand Development Research Institute, 2017).

Thailand's primary income sources are tourism and agriculture (Sitthiyot, 2023). Phuket ranks as the second-highest province in tourism revenue, following Bangkok, among Thailand's 77 provinces, and is a major destination for international (Vongurai, 2018; Kongcharoen et al., 2021; Ministry of Tourism and Sports, 2024). However, road traffic

[*] Corresponding author

accidents are one of the leading causes of death in Phuket, resulting in significant loss of life and property and posing a substantial barrier to economic development. Road traffic fatalities in Phuket have shown a continuous upward trend, with an annual average of 135 deaths (approximately 11 per month). The situation is becoming increasingly severe, with the majority of fatalities involving motorcyclists who did not wear helmets, lacked driver's licenses, or included tourists using rental vehicles (Kongcharoen et al., 2021; Phuket Disaster Prevention and Mitigation, 2023).

The repeated occurrence of accidents in nearby areas identifies these locations as road traffic accident risk zones. Analyzing accident risk zones using spatial statistics, such as hotspot and coldspot analysis, involves identifying hotspots—locations specifically associated with frequent accidents resulting in loss of life and property. Hotspots are typically areas with a high concentration of accidents influenced by factors such as road characteristics, land use, and socio-economic conditions. Hotspots indicate zones where accident clusters occur more frequently compared to other areas within the study area. Meanwhile, coldspots exhibit characteristics entirely opposite to those of hotspots (Sae-Ngow et al., 2024). These findings support the work of relevant agencies by enabling the use of techniques and methods for efficient and rapid analysis and processing. This facilitates informed decision-making and policy formulation for managing road safety safety (Le et al., 2020; Tippayanate et al., 2024).

The application of GIS with accident location data to analyze road traffic accident risk zones using geostatistical analysis techniques has gained widespread popularity. This approach is particularly favored because its results can be presented visually as maps. Among the commonly used methods are Moran's I and Getis-Ord statistics, which effectively describe the spatial patterns of accidents and the degree of clustering of accident occurrences. A Moran's I index value of -1 indicates a dispersed spatial pattern, while a value of 0 reflects a random spatial pattern, and a value of +1 signifies a clustered spatial pattern (Getis & Ord, 1992; Amiri et al., 2021; Hazaymeh et al., 2022). Meanwhile, the Getis-Ord statistics, a local spatial analysis method of spatial autocorrelation, examines the relationship between neighboring phenomena to identify accident risk zones and provide detailed insights into the clustering levels of both hotspots and coldspots (Sababhi et al., 2024). In addition to the previously mentioned methods, there is also the 'space-time cube (STC) analysis,' which integrates spatial and temporal dimensions to identify hotspots and coldspots.

This method generates a three-dimensional map where the study area is represented on the horizontal axes (x and y) as a two-dimensional space, while the z-axis depicts changes over time (Khan et al., 2023). The results provide spatial patterns, spatial relationships, and temporal changes over the study period (Alam & Tabassum, 2023). This study utilized accident location data from Phuket's road network to assess accident risk. Spatial pattern analysis was employed to identify accident hotspots and cold spots. Additionally, a space-time cube analysis was conducted to examine spatiotemporal patterns and their evolution over time. To enhance the analysis, multiple time slices were defined, enabling a comparative evaluation of temporal variations in hotspot distributions (Hamami & Matisziw, 2021; Wu et al., 2021; Feizizadeh et al., 2022).

MATERIALS AND METHODS

Study Area

Phuket Province is located in the southern part of Thailand, specifically between latitudes 7°45′ and 8°15′ north and longitudes 98°15′ and 98°40′ east. It is the largest island in the country, situated in the Andaman Sea. To the north, it is connected to Phang Nga Province by the Sarasin Bridge and the Srisoonthorn Bridge. To the east, it is adjacent to Phang Nga Province, with the entire island surrounded by the Indian Ocean. It also includes islands within its jurisdiction to the south and east. The total area is 543.034 square kilometers, with a population of 423,599 people (Department of Provincial Administration, Ministry of the Interior, 2021). The population density is 780.05 people per square kilometer, ranking it fifth in Thailand. This study follows a research methodology based on a research design that includes data collection, data preparation, and data analysis, with detailed information presented in Figure 1.

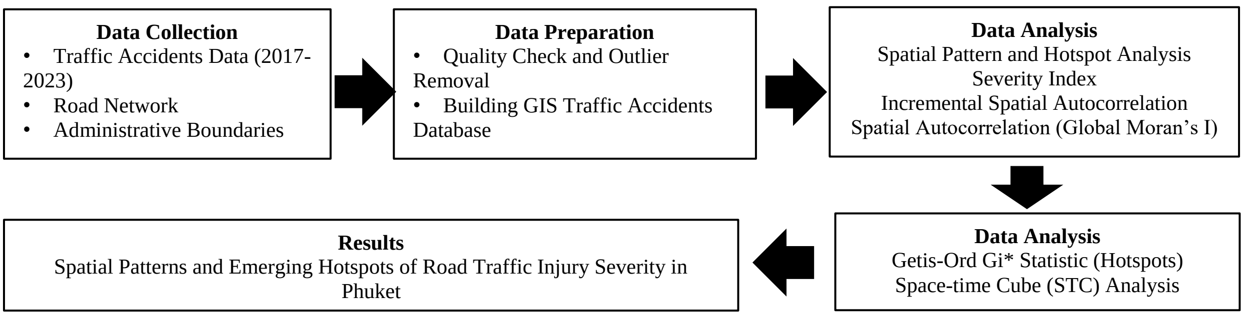


Figure 1. Conceptual framework

RESEARCH DATA

1. Data Preparation for Analysis

The secondary data used for analysis consists of road accident location data from the road network spanning from 2017 to 2023 (Department of Highways, 2023), as shown in Table 1. The study area is Phuket Province, and the data collection period is from January 1, 2017, to December 31, 2023. The details of the data include coordinates, road names, damage information, and causes leading to accidents. The researcher verified the accuracy of the data, removed any outliers, and then constructed a spatial accident database for the road network.

Table 1. Research data

NO.	Data	Resolution	Source
1.	Road accident location data on national highways and rural roads	Coordinates	Department of Highways
2.	Administrative boundaries of Phuket Province	1:25,000	Ministry of Interior
3.	Road transportation routes	1:25,000	Ministry of Transport
4.	Land Use of Phuket Province	1:25,000	Land Development Department

In this article, the spatial accident data on Phuket's road network were analyzed to identify accident-prone areas in the province. The analysis process was divided into several steps. First, the severity index analysis was conducted to determine the severity level of accidents at each location. Next, incremental spatial autocorrelation analysis was used to define the distance and determine the optimal distance for spatial pattern analysis. Following this, a global indicator of spatial autocorrelation analysis was carried out to identify the overall spatial pattern of accidents on Phuket's road network, whether it was random, dispersed, or clustered. Additionally, hotspot and coldspot analysis (Hot Spot Analysis - Getis-Ord Gi*) was used to identify the occurrence of hot and cold spots of accidents. Finally, emerging hotspots analysis examined hot and cold spots in relation to time using space-time cube (STC) analysis.

2. Spatial pattern analysis of accidents on the road network

i. Crash Severity Analysis

The severity of road accidents was assessed using the Crash Severity Index (CSI). This index assigns weights to different types of collisions to determine their overall severity. A fatal collision is weighted as 3.0, a serious injury collision as 1.8, a slight injury collision as 1.3, and a property damage-only collision as 1.0, as shown in Equation (1) (Tola et al., 2021).

$$SI = 3.0 * X1 + 1.8 * X2 + 1.3 * X3 + 1.0 * X4 \quad (1)$$

Where: X1 is fatal crashes, X2 is serious injury crashes, X3 is slight injury crashes, and X4 is property-damage-only crashes respectively.

ii.Global Indicator of Spatial Autocorrelation (Global Moran's I Analysis)

The Global Indicator of Spatial Autocorrelation (Global Moran's I) measured the level and direction of the spatial distribution of accidents on the road network. The results were classified into three patterns: clustered, dispersed, or random. This analysis used the Global Moran's I spatial autocorrelation value, the z-score, and the p-value to describe the relationships. The formula for calculating Global Moran's I is provided in Equation (2) Getis & Ord, 1992).

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

Where: I is Moran's I Index, x_i is the observed value of area i, x_j is the observed value of area j, $\bar{x}$ is the average of observed values, n is the number of observations. w is the aggregate of the spatial weight matrix and w_{ij} is the spatial weight matrix. For the analysis, an appropriate distance was selected to define the analysis boundary. A fixed distance was determined based on the principles of spatial autocorrelation. Spatial data within this distance were assigned weights, while data beyond this distance were assigned a weight of zero. The Euclidean distance, as shown in Equation (3), was employed to calculate the distance between accident locations and neighboring data points. The specific distance was determined through Incremental Spatial Autocorrelation analysis (Hazaymeh et al., 2022).

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

Where: (X_2, Y_2) are the geographic coordinates of spot a, (X_1, Y_1) are the geographic coordinates of spot b and d is the distance between a and b. The Global Moran's I coefficient for spatial autocorrelation ranges from -1 to +1. A positive spatial autocorrelation, represented by values between 0 and +1, indicates a clustered spatial pattern. In contrast, a negative spatial autocorrelation, represented by values between 0 and -1, indicates a dispersed spatial pattern. A value of 0 signifies a random spatial pattern.

iii. Hotspot Analysis (Getis-Ord Gi*)

The Hotspot Analysis (Getis-Ord Gi*) of road accidents in Thailand's network utilized spatial autocorrelation at the local level, specifically employing the Local Indicator of Spatial Association (LISA). This inferential approach involved hypothesis testing to examine the observed spatial patterns of accident data.

The results of the hotspot and coldspot analysis are explained using the z-score and p-value. The analysis examines each location in the dataset along with the surrounding locations. The z-score becomes statistically significant when the sum of observations at each location and its neighboring area differs from the sum of predicted values for each location and its neighboring area. If the difference is large enough to indicate that the pattern is not random, the null hypothesis is rejected, indicating a spatial clustering. If the null hypothesis is accepted, meaning there is no spatial clustering, the level of spatial grouping can be explained relative to the neighboring areas (Anselin, 1995).

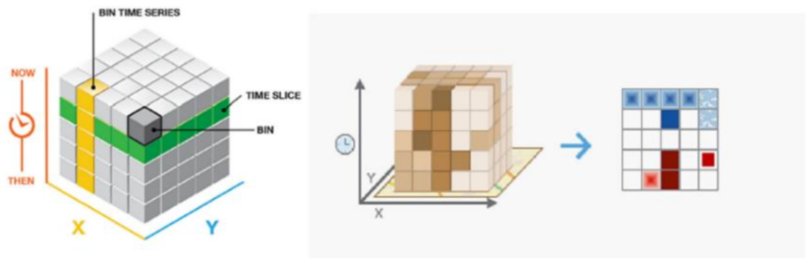
For hotspot and coldspot occurrences, if the observation points and surrounding points have high values, this is considered a hotspot (with a positive z-score). If the values are low, this is considered a cold spot (with a negative z-score) (Getis & Ord, 1992; Hazaymeh et al., 2022; Mesquitela et al., 2022). The formula for Getis-Ord Gi* is:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{5}$$

Where: G_{i*} is the Getis-Ord Gi* score at any location, x_j is the observed value at location j, $\bar{x}$ is the average of the observed values, w_{ij} is the weight between locations i and j, s is the standard deviation of the observed values and n is the total number of areas. The result of the calculation of G_{i*}must be verified with the z-score and p-value.

iv. Space-Time Cube Analysis

Space-time cube (STC) analysis is a method for comparing spatial and temporal patterns of accidents in the form of a cube, where the X and Y axes represent spatial dimensions, and the t-axis represents the time dimension. In this research, a grid cell size of 340*340 meters was used, covering the entire road network of Phuket Province with a total of 3,417 grids. The temporal dimension was used to compare accident occurrences over 90-day and 180-day periods in order to track the changes in hot spots and cold spots over time. Figure 2 illustrates the space-time cube (STC) analysis, which compares the spatial and temporal occurrence of accidents in the form of a cube, with the X and Y axes representing spatial dimensions and the t-axis representing time.



(a) (b)

Figure 2. Structure of STC from emerging hotspot analysis: (a) Space-time cube (STC) 3D and (b) Generated bins in 2D (Source: Environmental Systems Research Institute, 2024a; Khan et al., 2023)

RESULTS AND DISCUSSION

1. A study of the changes in road accidents in Phuket Province from 2017 to 2023

According to the accident report system of the Ministry of Transport, there were a total of 44,458 road accidents from 2017 to 2023 in Phuket. These accidents resulted in 447 deaths, 7,198 serious injuries, 36,322 minor injuries, and 491 cases of property damage. The occurrence of road accidents has shown a general increase each year, with the only exception being during the COVID-19 pandemic, when accidents decreased. However, after the country reopened and the COVID-19 situation subsided, the trend of increasing accidents resumed.

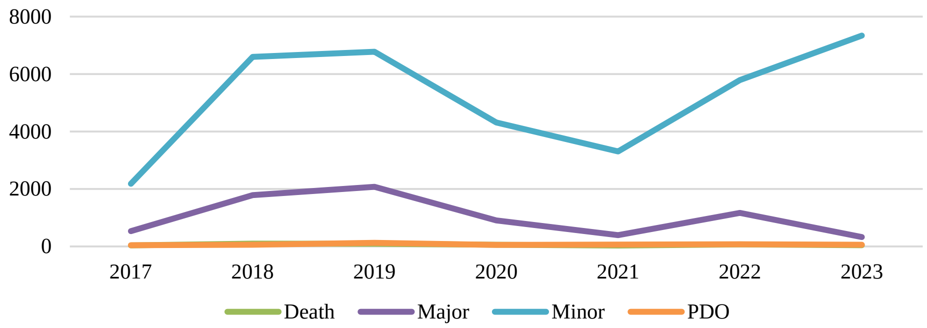


Figure 3. The annual number of accidents in Phuket (2017-2023) (Source: Author's own work)

From Figure 3 and Table 2, the average severity level of each collision type is shown along with the number of accidents in Phuket Province. The number of accidents involving minor injuries shows an increasing trend, while accidents involving serious injuries have decreased. The average severity level decreased each year from 2017 to 2023, respectively.

Table 2. The Annual Number of Accidents in Phuket (2017-2023) (Source: Author's own work)

Years	Average of SI	Death	Major	Minor	PDO	Total
2017	1.41355	38	533	2,181	45	2,797
2018	1.42227	101	1,785	6,600	63	8,549
2019	1.42837	97	2,077	6,777	127	9,078
2020	1.40146	61	909	4,318	54	5,342
2021	1.36071	31	395	3,309	65	3,800
2022	1.39671	74	1,172	5,794	78	7,118
2023	1.32860	45	327	7,343	59	7,774

2. Frequency of Road Accidents by Month from January to December in Phuket (2017-2023)

Road accidents from 2017 to 2023, when analyzed month by month, revealed a gradual increase in the overall number of accidents starting in August, peaking in December and January, before gradually decreasing until April. The mid-year period, from May to September, coincided with the rainy season, which is not a peak tourist season in Phuket. The details are illustrated in Figure 4.

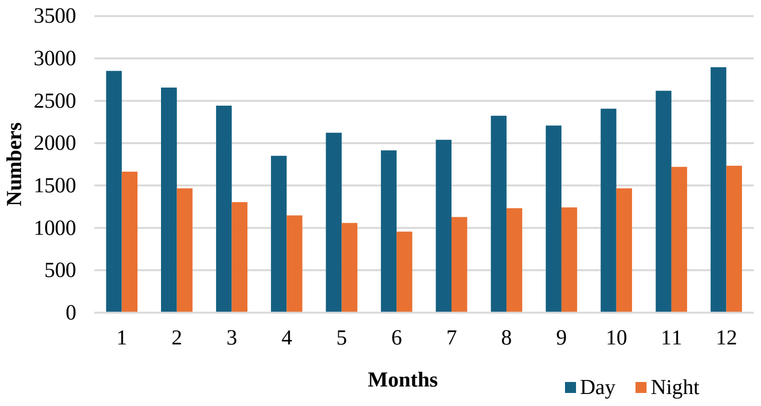


Figure 4. The number of traffic accidents in Phuket by month (2017-2023) (Source: Author’s own work)

The number of accidents by subdistrict in Phuket Province from 2017 to 2023, classified by standard deviation, shows that the subdistrict with the highest number of accidents was Wichit Subdistrict in Mueang Phuket District, followed by Talat Yai Subdistrict in Mueang Phuket District, Kathu Subdistrict in Kathu District, and Ratsada Subdistrict in Mueang Phuket District. The map (Figure 5) illustrates that accidents in Phuket Province were more concentrated in the central area than in other regions.

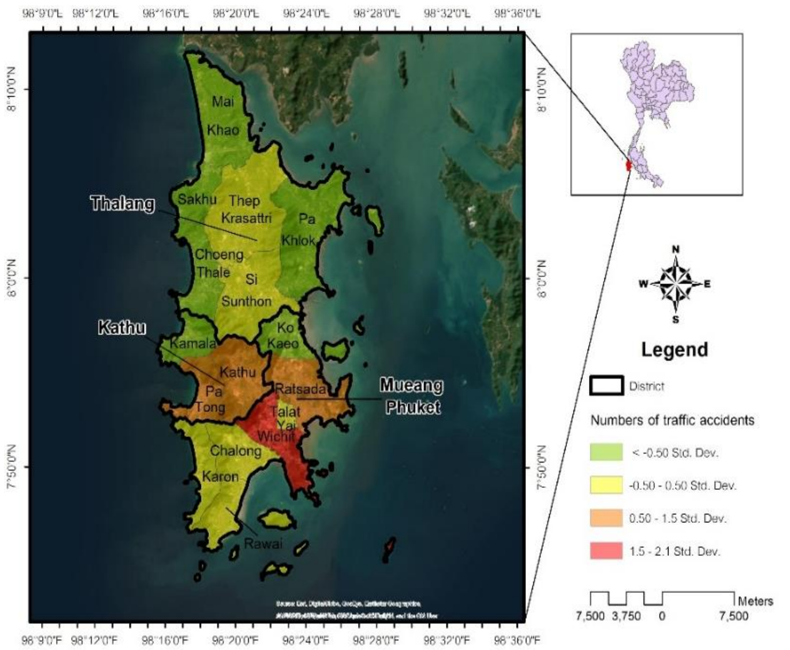
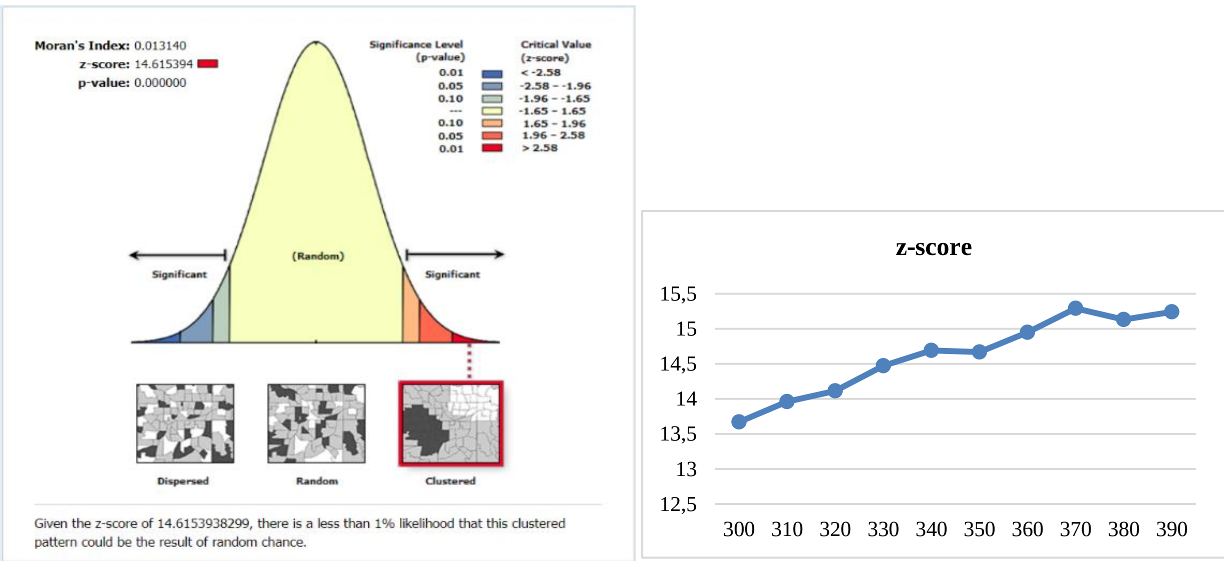


Figure 5. Number of accidents by subdistrict in Phuket (2017-2023), classified by standard deviation (Source: Author’s own work)

3. Spatial Pattern Analysis of Road Accidents in Phuket

The analysis results, based on the locations of road accidents, revealed the trend of spatial patterns using the level of spatial autocorrelation. The Global Moran's I index was found to be 0.013140, with a p-value of 0. Considering the z-score of 14.615, this indicates less than a 1% probability that this spatial pattern was a random outcome. Therefore, it is concluded that the pattern was clustered (Figure 6).

For tracking the spatial pattern of road accidents in Phuket Province using the Getis-Ord statistic, the results from Incremental Spatial Autocorrelation analysis were used to determine the appropriate distance for the analysis.



(a) (b)

Figure 6. Results of (a) global spatial autocorrelation and (b) incremental spatial autocorrelation analyses

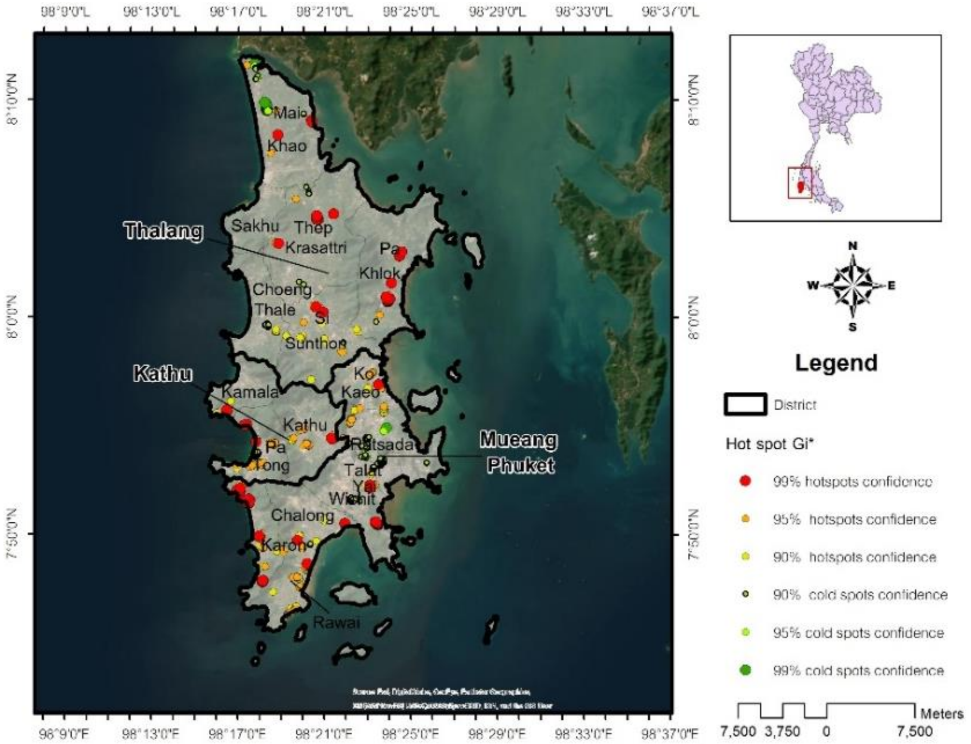


Figure 7. Monthly hotspot Gi* analysis for Phuket (2017-2023) (Source: Author's own work)

The z-scores and p-values for each accident location were categorized into red, green, or gray points with statistical significance, taking into account the severity of accidents in the surrounding areas. For instance, red points indicate severe accidents surrounded by statistically significant similar values, meaning they represent major accidents. Green points indicate minor accidents surrounded by statistically significant minor accidents, while gray points represent locations with no statistical significance, surrounded by randomly distributed severity values. Both hotspots (red) and coldspots (green) were divided into three levels: 90%, 95%, and 99%. The analysis of the spatial pattern of road accidents in Phuket Province using Getis-Ord statistics revealed that the highest number of hotspots occurred in Mueang Phuket District, particularly in Rawai Subdistrict and Karon Subdistrict. The second highest number of hotspots was found in Kathu District, specifically in Patong Subdistrict, followed by Thalang District, where the highest concentration of hotspots occurred in Pa Khlok Subdistrict, as shown in Figure 7. According to Table 3 and Table 4, when the results of the Getis-Ord spatial autocorrelation analysis were used to create a correlation table to study the characteristics of hotspots and coldspots in relation to road accidents in Phuket Province, it was found that 91.3% of road accidents in Phuket from 2017 to 2023 occurred in a spatially random pattern.

Table 3. Hotspots and coldspots by subdistrict in Phuket

District	Subdistrict	Coldspots			None	Hotspots			
		99%	95%	90%	Not significant	90%	95%	99%	Total
Kathu	Kamala				824	8		3	835
	Kathu				4.247	40	58	6	4.351
	Pa Tong		13	440	3.297	160	59	4	3.973
Kathu Total			**13**	**440**	**8.368**	**208**	**117**	**13**	**9.159**
Mueang Phuket	Chalong			17	3.207	17	1	3	3.245
	Karon				2.001	81	63	166	2.311
	Ko Kaeo				1.296	35	49	1	1.381
	Ratsada	1	153	207	3.717	44	19		4.141
	Rawai				1.968	243	563	1	2.775
	Talat Nuea			3	2.306	8	20	2	2.339
	Talat Yai		287	504	4.064				4.855
	Wichit			22	5.584	38	34	61	5.739
Mueang Phuket Total		**1**	**440**	**753**	**24.143**	**466**	**749**	**234**	**26.786**
Thalang	Choeng Thale			31	1.731	47			1.809
	Mai Khao	48	10	26	979	1	15	5	1.084
	Pa Khlok			1	578	5	21	91	696
	Sakhu				526				526
	Si Sunthon			4	2.260	83	10	2	2.359
	Thep Krasattri			9	2.003		5	22	2.039
Thalang Total		**48**	**10**	**71**	**8.077**	**136**	**51**	**120**	**8.513**
Province Total		**49**	**463**	**1.264**	**40.588**	**810**	**917**	**367**	**44.458**

Table 4 shows that the average of severity levels (SI) for hotspots and coldspots differed. The average of SI for hotspots was higher than that for cold spots, and the proportion of hot spots was greater than that of cold spots, at 4.710% and 3.995%, respectively. The spatial patterns observed were statistically significant as follows:

i. Coldspots (99% CI) had an average SI of 1.118 (0.11%)
ii. Coldspots (95% CI) had an average SI of 1.354 (1.04%)
iii. Coldspots (90% CI) had an average SI of 1.360 (2.84%)
iv. Not significant had an average SI of 1.391 (91.30%)
v. Hotspots (90% CI) had an average SI of 1.465 (1.82%)
vi. Hotspots (95% CI) had an average SI of 1.463 (2.06%)
vii. Hotspots (99% CI) had an average SI of 1.578 (0.83%)

Table 4. Characteristics of traffic accidents

Class	Number of traffic accidents	Average of SI	Percent	Death	Major	Minor	PDO
Cold spot (99% CI)	49	1.118	0.11	0	2	14	33
Cold spot (95% CI)	463	1.354	1.04	1	50	407	5
Cold spot (90% CI)	1.264	1.360	2.84	4	141	1.115	4
Not significant	40588	1.391	91.30	374	6.446	33.348	420
Hot spot (90% CI)	810	1.465	1.82	23	199	573	15
Hot spot (95% CI)	917	1.463	2.06	22	233	649	13
Hot spot (99% CI)	367	1.578	0.83	23	127	216	1
Grand Total	44.458	-	100.00	447	7.198	36.322	491

The space-time cube (STC) analysis compared the spatial and temporal patterns of accidents by defining a 340-meter bandwidth, resulting in 3,471 cubes which covered the transportation routes in Phuket Province. This method identified six distinct spatial-temporal patterns of accident occurrences. Time slices of 90 and 180 days were used to examine how hotspots and coldspots changed over time. The findings showed that the majority of accidents in Phuket during both time periods displayed no distinct pattern, accounting for 97.29% and 97.98%, respectively. The sporadic pattern followed, with 2.42% and 1.53%, while consecutive patterns accounted for 0.29% and 0.49%, respectively.

From Figures 8-10, it can be observed that during the time slice of 90 days and 180 days, the number of Consecutive Hotspots increased, while the number of Sporadic Hotspots decreased. Additionally, the number of No Pattern occurrences increased slightly. Out of the total 3,471 cubes in the space-time cube, 47.1% were in Thalang, 39.7% in Mueang Phuket, and 13.0% in Kathu. Consecutive hotspots were found only in Mueang Phuket and Kathu. A temporal comparison between the 90-day and 180-day time slices revealed changes in the Emerge Cube Hotspots.

Table 6-7 illustrates the changes in hotspots of traffic accidents in Phuket Province from the 90-day to the 180-day time slice, showing shifts in space-time patterns as follows: Sporadic Hotspots (irregular occurrences) changed to Consecutive Hotspots (continuous occurrences), with 11 hotspots. Sporadic Hotspots transitioned to No Pattern (no distinct spatial pattern), with 20 hotspots. Consecutive Hotspots changed to No Pattern, with 4 hotspots.

Table 5. Names and definitions of the space-time patterns (Source: Environmental Systems Research Institute, 2024b; Khan et al., 2023)

Patterns	Patterns Name	Definition
	Consecutive Hot/Cold Spot	A location with a single uninterrupted run of statistically significant hot/cold spot bins in the final time-step intervals. The location has never been a statistically significant hot/cold spot before the final hot/cold spot run and fewer than 90% of all bins are statistically significant hot/cold spots.
	Sporadic Hot/Cold Spot	A location that is an on-again off-again hot/cold spot. Fewer than 90% of the time-step intervals have been statistically significant hot/cold spots and none of the time-step intervals have been statistically significant cold/hot spots.
	No Pattern Detected	Does not fall into any of the defined hot or cold spot patterns.

Table 6. Traffic accident hotspots in Phuket between the 90-day and 180-day time slices

District	Consecutive 90d	Consecutive 180d	No Pattern 90d	No Pattern 180d	Sporadic 90d	Sporadic 180d
Kathu	2 (0.06%)	6 (0.17%)	431 (12.42%)	432 (12.45%)	21 (0.61%)	16 (0.46%)
Mueang Phuket	8 (0.23%)	11 (0.32%)	1318 (37.97%)	1339 (38.58%)	53 (1.53%)	29 (0.84%)
Thalang	0 (0%)	(0%)	1628 (46.90%)	1630 (46.96%)	10 (0.29%)	8 (0.23%)
Total	10 (0.29%)	17 (0.49%)	3377 (97.29%)	3401 (97.98%)	84 (2.42%)	53 (1.53%)

Table 7. Changes in hotspots of traffic accidents in Phuket from the 90-day to the 180-day time slice

The 90-day time slice	The 180-day time slice			
	Consecutive Hot Spot	No Pattern	Sporadic Hot Spot	Total
Consecutive Hot Spot	6	4	0	10
No Pattern	0	3377	0	3377
Sporadic Hot Spot	11	20	53	84
Total	17	3401	53	3471

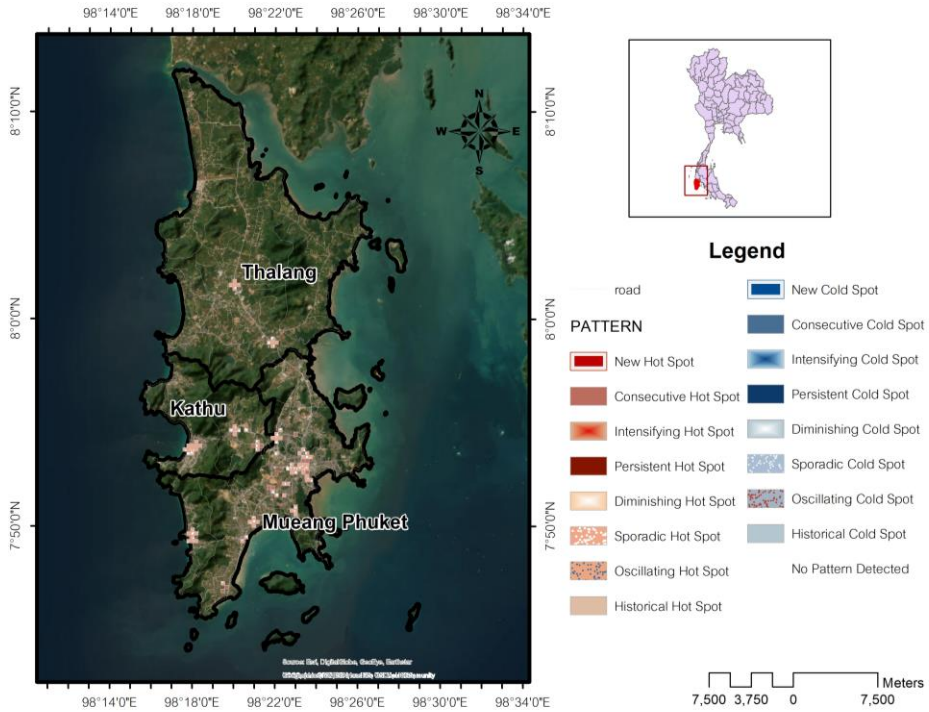


Figure 8. Space-time patterns with a time slice of 90 days for traffic accidents in Phuket

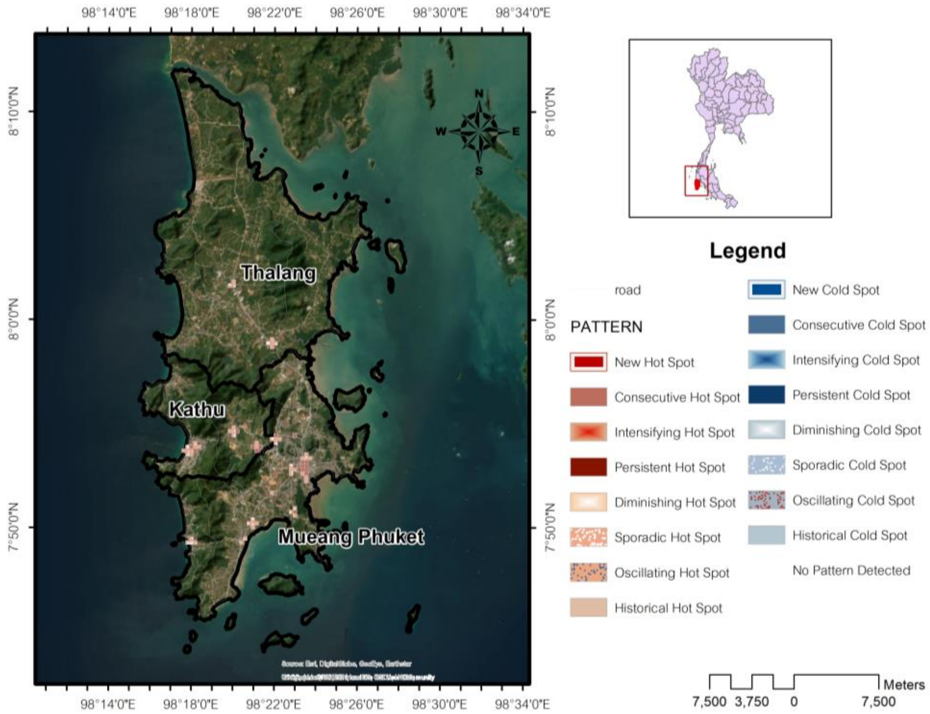


Figure 9**.** Space-time patterns with a time slice of 180 days for traffic accidents in Phuket

The analysis of traffic accident changes in Phuket between 2017 and 2023, along with the examination of monthly accident frequency from January to December of the same years, showed that accidents with lower severity tended to occur in areas with higher traffic density due to the lower speeds. This is in contrast to accidents resulting in fatalities, which tended to occur in areas with lower traffic density. Additionally, most accidents in Phuket involved motorcycles.

According to vehicle registration statistics in Phuket, motorcycles accounted for 61% of all registered vehicles in the province (Phuket Provincial Disaster Prevention and Mitigation Office, 2024). This is because motorcycles were affordable, highly maneuverable, and well-suited for use in densely trafficked urban areas in Thailand (Kongcharoen et al., 2021, Sirikup, 2016). Furthermore, the geographic characteristics of Phuket, being an island with limited space, alongside traffic congestion, leaded both local residents and international tourists to choose motorcycles for daily travel. This fostered a significant relationship between motorcycle-related commercial activities, services, and repairs, particularly with regard to foreign tourists (Prueksakorn et al., 2018; Sirikup, 2016).

(a)

(b)

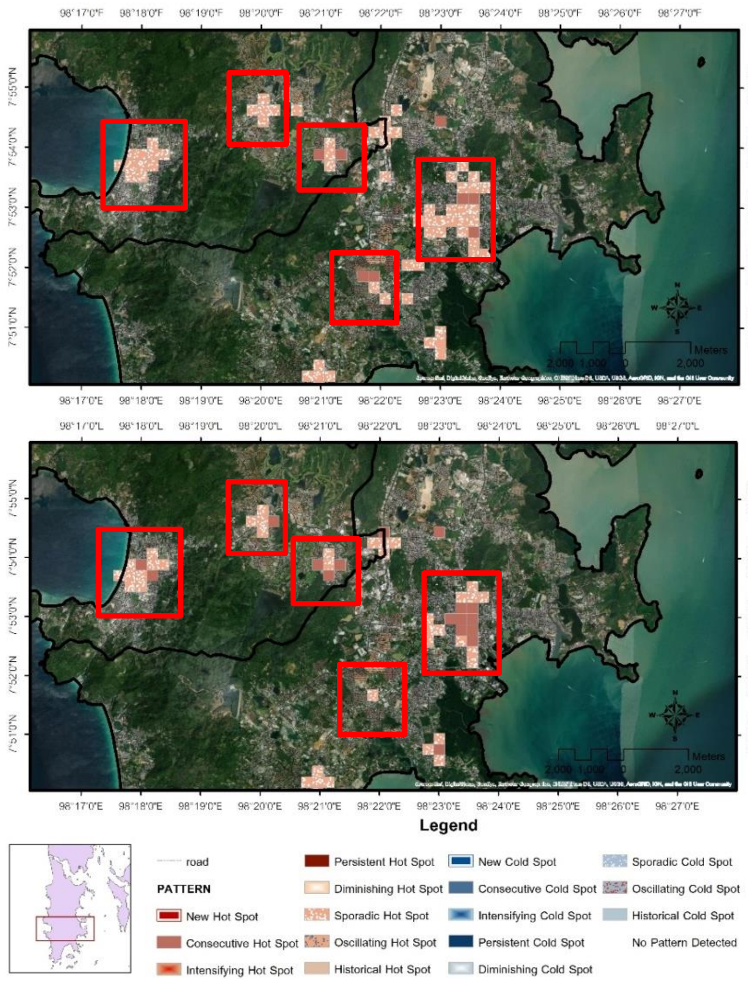


Figure 10. Changes in hotspots of traffic accidents in Phuket from the 90-day to the 180-day time slice:
(a) Space-time patterns with a time slice of 90 days (b) Space-time patterns with a time slice of 180 days (Source: Author's own work)

The results of the spatial pattern analysis of traffic accidents in Phuket indicated that the accident patterns were clustered, with a cluster distance of 340 meters. The hotspot and coldspot analysis revealed that the highest concentration of hotspots and coldspots was in the central area of the province. The most significant hotspot was located in the Mueang Phuket District, specifically in the Rawai and Karon Subdistricts. In the Kathu District, the highest concentration of hotspots was found in the Patong Subdistrict, while in Thalang District, the hotspots were most concentrated in the Pa Khlok Subdistrict, as shown in Figure 11. These areas were urban zones, central to residential areas, commerce, services, and heavy traffic (Alsahfi, 2024; Ma et al., 2021; Özcan & Küçükönder, 2020; Prueksakorn et al., 2018).

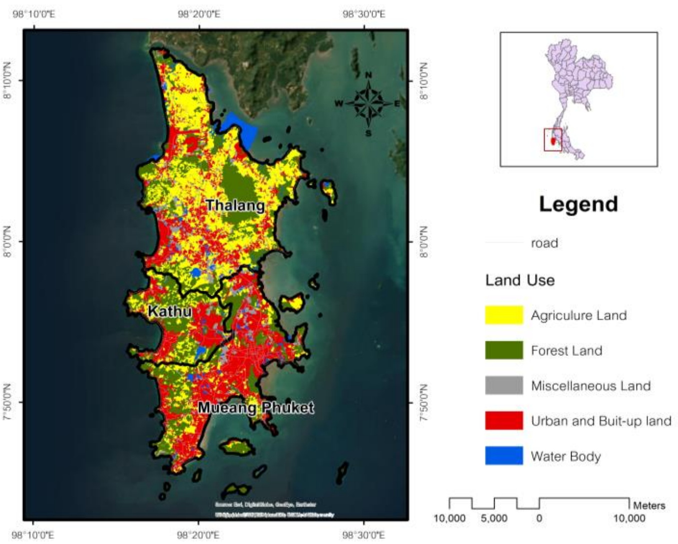


Figure 11. Land use map of Phuket (Source: Land Development Department, 2022)

For the comparison of spatial patterns over time, between 90 and 180-day periods, both time slices predominantly exhibited the "No Pattern" pattern, followed by "Sporadic," and lastly "Consecutive." The addition of time conditions in the space-time cube (STC) analysis resulted in the following changes: (1) an increase in "Consecutive Hotspots," (2) a decrease in "Sporadic Hotspots," and (3) a slight increase in "No Pattern." Furthermore, the analysis revealed the following transitions: (a) "Consecutive Hotspots" to "No Pattern," (b) "Sporadic Hotspots" to "No Pattern," and (c) "Sporadic Hotspots" to "Consecutive Hotspots." In region (a) and (b) reveal distinct temporal patterns when analyzed using a 90-day time slice in a space-time cube (STC) framework. Region (a) consistently exhibits hot spots, indicating a sustained pattern. In contrast, region (b) displays intermittent hot spots suggesting a more sporadic occurrence. However, when the time slice is extended to 180 days, neither region presents a clear spatiotemporal pattern. This implies that the events occurring in these areas may be random or influenced by factors not captured within the analyzed timeframe.

In region (c), during the 90-day time slice, events or incidents tend to occur intermittently, with a surge in hot spots observed in the final period. Less than 90% of all points within this time slice are statistically significant hot spots, and no statistically significant cold spots are detected. However, when the time slice is extended to 180 days, a persistent pattern of statistically significant hot spots emerges in the final period. This region had not previously exhibited significant hot spots. Moreover, less than 90% of all points within the 180-day time slice are statistically significant hot spots. These findings suggest a propensity for events to occur towards the end of the 180-day time slice. The patterns of consecutive and sporadic hot spots remain consistent across both 90-day and 180-day time slices. This indicates that the likelihood of accidents occurring within these regions remains unchanged, regardless of the analysis window. For instance, sporadic hot spots continue to exhibit alternating periods of high and low accident rates every 90 or 180 days. Similarly, consecutive hot spots maintain their tendency to experience a surge in accidents towards the end of the 90-day or 180-day period, making them more prone to accidents compared to regions transitioning from consecutive or sporadic hot spots to no pattern.

CONCLUSION

The overall number of traffic accidents on Phuket's road network had increased, with a rise in minor accidents and a decrease in major accidents. As a result, the average severity level of accidents decreased each year between 2017 and 2023. The analysis of Global Moran's I, combined with the severity levels of accidents, revealed that accidents on Phuket's road network exhibited a clustered spatial pattern. Hotspot analysis using the Getis-Ord Gi* method identified accident-prone areas, showing the severity levels at these hotspots and their surrounding regions, including both hot and cold spots. This approach provides a more accurate understanding of the spatial patterns and severity levels of road accidents than tabular data, which only includes details of accidents and their coordinates. Additionally, space-time cube analysis was used to compare spatial and temporal patterns of accidents, allowing for the identification of changes, trends, and the severity levels of accidents over time. The findings of this research provide valuable insights into accident occurrences on Phuket's road network, highlighting the clustering of accidents in various areas of the province and trends in the changing frequency of accidents. These results can serve as a foundation for enhancing road safety initiatives, supporting traffic engineering efforts, and informing policy decisions related to traffic regulation enforcement.

Author Contributions: Conceptualization, P.S. and N.K.; methodology, P.S. and N.K.; software, P.S. and N.S.; validation, P.S., N.K and M.W.; formal analysis, P.S., N.K. and M.W.; investigation, P.S., N.K. and P.H.; data curation, P.S., N.K., M.W. and K.T.; writing - original draft preparation, P.S. and N.K.; writing - review and editing, P.S., N.K., M.W., K.T. and P.H; visualization, P.S., N.K., M.W., N.S. and K.T.; supervision, P.S., N.K., M.W. and P.H.; project administration, P.S. and N.K. All authors have read and agreed to the published version of the manuscript.

Funding: Not applicable.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study may be obtained on request from the corresponding author.

Acknowledgments: This research was financially supported by the Institute of Research and Development, Rajabhat Suan Sunandha University in the fiscal year 2023. It was successfully completed with the assistance of students as well as cooperation and guidance from the faculty members of the Department of Geography and Geospatial Information, Rajabhat Suan Sunandha University.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

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

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

Amiri, A. M., Nadimi, N., Khalifeh, V., & Shams, M. (2021). GIS-based crash hotspot identification: A comparison among mapping clusters and spatial analysis techniques. *International Journal of Injury Control and Safety Promotion*, 28(3), 325–338. https://doi.org/10.1080/17457300.2021.1925924

Anselin, L. (1995). Local indicators of spatial association - LISA. *Geographical Analysis*, 27(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Ben-Hamouche, M., Al-Janahi, A., & Al-Madani, H. (2011). Traffic accidents in Bahrain: A statistical and spatial GIS-based analysis. *Journal of King Saud University*, 23(1), 1–18.

Department of Highways. (2023). *Traffic accidents on national highways*. Retrieved 20.12.2023. https://data.go.th/th/dataset/gdpublish-roadaccident

Department of Provincial Administration, Ministry of the Interior. (2021). *Announcement of the Central Registration Office, Department of Provincial Administration: Number of people throughout the Kingdom, classified by Bangkok Metropolis and other provinces according to the registration record as of December 31, 2021.* [PDF]. http://stat.bora.dopa.go.th/stat/pk/pk_64.pdf

Esri. (2024a). *Emerging hot spot analysis (space time pattern mining)*. Retrieved September 18, 2024. https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/emerginghotspots.htm

Esri. (2024b). *How Emerging Hot Spot Analysis work)*. Retrieved September 18, 2024. https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/learnmoreemerging.htm

Feizizadeh, B., Omarzadeh, D., Sharifi, A., Rahmani, A., Lakes, T., & Blaschke, T. (2022). A GIS-Based Spatiotemporal Modelling of Urban Traffic Accidents in Tabriz City during the COVID-19 Pandemic. *Sustainability*, 14(12), 7468. https://doi.org/10.3390/su14127468

Getis, A., & Ord, J. K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24(3), 189–206. https://doi.org/10.1111/j.1538-4632.1992.tb00261.x

Hamami, A., & Matisziw, T. (2021). Measuring the spatiotemporal evolution of accident hot spots. *Accident; analysis and prevention*, 157, 106133 . https://doi.org/10.1016/j.aap.2021.106133.

Hazaymeh, K., Almagbile, A., & Alomari, A. H. (2022). Spatiotemporal analysis of traffic accidents hotspots based on geospatial techniques. *ISPRS International Journal of Geo-Information*, 11(4), 260. https://doi.org/10.3390/ijgi11040260

Khan, I. U., Vachal, K., Ebrahimi, S., & Wadhwa, S. S. (2023). Hotspot analysis of single-vehicle lane departure crashes in North Dakota. *IATSS Research*, 47(1), 25–34. https://doi.org/10.1016/j.iatssr.2022.12.003

Kongcharoen, J., Onmek, N., Karrila, S., & Seksan, J. (2022). Risk factors related to road traffic accidents in Phuket Province, Southern Thailand: A confirmatory factor analysis. *Transactions on Transport Sciences*, 13(1), 17–25. https://doi.org/10.5507/tots.2021.020

Korwatanasakul, U. (2023). Thailand and the middle-income trap: An analysis from the global value chain perspective. *Institutions and Economies*, 15(4), 7–33. https://doi.org/10.22452/IJIE.vol15no4.1

Land Development Department. (2022). Land use map of Phuket. Retrieved September 18, 2024, from https https://dinonline.ldd.go.th/

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

Ma, Q., Huang, G., & Tang, X. (2021). GIS-based analysis of spatial–temporal correlations of urban traffic accidents. *European Transport Research Review*, 13, 1–11. https://doi.org/10.1186/s12544-021-00509-y

Mesquitela, J., Elvas, L. B., Ferreira, J. C., & Nunes, L. (2022). Data analytics process over road accidents data - a case study of Lisbon city. *ISPRS International Journal of Geo-Information*, 11(2), 143. https://doi.org/10.3390/ijgi11020143

Ministry of Tourism and Sports. (2024). *Tourism statistics 2023*. Bangkok: Ministry of Tourism and Sports. https://www.mots.go.th/news/category/704

Özcan, M., & Küçükönder, M. (2020). Investigation of spatiotemporal changes in the incidence of traffic accidents in Kahramanmaraş, Turkey, using GIS-based density analysis. *Journal of the Indian Society of Remote Sensing*, 48(7), 1045–1056. https://doi.org/10.1007/s12524-020-01137-0

Phuket Disaster Prevention and Mitigation. (2023). *Phuket road safety action plan 2024*. Phuket: Phuket Disaster Prevention and Mitigation. Retrieved September 18, 2024, from https://pkt.disaster.go.th/pkt/cms/inner_2921?id=99243

Phuket Provincial Disaster Prevention and Mitigation Office. (2024). *Lessons learned from the prevention and reduction of road and sea accidents during the Songkran Festival BE 2567*, Phuket Province [Report No. 2921]. Retrieved September 18, 2024, from https://pkt.disaster.go.th/pkt/cms/2921?id=110294

Prueksakorn, K., Gonzalez, J. C., Keson, J., Wongsai, S., Wongsai, N., & Akkajit, P. (2018). A GIS-based tool to estimate carbon stock related to changes in land use due to tourism in Phuket Island, Thailand. *Clean Technologies and Environmental Policy*, 20, 561–571. https://doi.org/10.1007/s10098-017-1455-5

Road Safety Operation Center (RSOC) by Department of Disaster Prevention. (2023). *Thailand road safety master plan 2022–2027. Bangkok: Department of Disaster Prevention.* Retrieved September 18, 2024. https://roadsafety.disaster.go.th/roadsafety/download/7377?id=21555

Sababhi, S., Aldala'in, S., Al Taani, A., Al Rawashdeh, S., Al Barari, T., Aladwan, Z., & Abd Manan, T. S. (2024). Safety on Jordan's highways: A GIS-based approach to identifying road accident hotspots. *GeoJournal*, 89(3), 105. https://doi.org/10.1007/s10708-024-11115-5

Sae-Ngow, P., Kulpanich, N., Worachairungreung, M., Ngansakul, P., & Prasert, T. (2024). Geospatial analysis for identifying blackspots on national and rural highways in Thailand. *International Journal of Geoinformatics*, 20(4). https://doi.org/10.52939/ijg.v20i4.3147

Sirikup, N. (2016). *Factors determining Phuket's tourism economy (Master's thesis).* Sukhothai Thammathirat Open University, Thailand.

Sitthiyot, T. (2023). Income distribution in Thailand is scale-invariant. *PLoS ONE*, 18(7), e0288265. https://doi.org/10.1371/journal.pone.0288265

Tanaboriboon, Y., & Satiennam, T. (2005). *Traffic accidents in Thailand*. IATSS Research, 29(1), 88–100. https://doi.org/10.1016/S0386-1112(14)60122-9

Thailand Development Research Institute. (2017). *Road accidents – serious damage to the Thai economy. Bangkok.* Retrieved September 18, 2024, from https://tdri.or.th/2017/08/econ_traffic_accidents/

Tippayanate, N., Impool, T., Sujayanont, P., Muttitanon, W., Chemin, Y. H., & Som-Ard, J. (2024). Temporal analysis of road traffic accidents at major intersections in Khon Kaen Province, Thailand: A time series investigation from 2012 to 2021. *International Journal of Geoinformatics*, 20(7), 43–58. https://doi.org/10.52939/ijg.v20i7.3403

Vongurai, R. (2018). The influence of Thailand's image and foreign tourist satisfaction on foreign tourist loyalty for Thailand. *Thai Journal of East Asian Studies*, 22(2), 2-21.

Wu, P., Meng, X., & Song, L. (2021). Identification and spatiotemporal evolution analysis of high-risk crash spots in urban roads at the microzone-level: Using the space-time cube method. *Journal of Transportation Safety & Security*, 14(9), 1510–1530. https://doi.org/10.1080/19439962.2021.1938323

Article history: Received: 20.01.2025 Revised: 30.04.2025 Accepted: 27.05.2025 Available online: 30.06.2025