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A study on identifying and analyzing road traffic incident hotspots on National Highway 1A, Thanh Hoa province, Vietnam, employing Statistical and GIS Techniques

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ABSTRACT

The study focuses on the prevalence of road traffic accidents in Vietnam, particularly along national highways, which are frequent and severe. Specifically, it examines National Highway 1A passing through Thanh Hoa province, utilizing statistics and geographic information systems (GIS) to identify high-risk areas. Data from road traffic incidents spanning from 2020÷2023 were used to analyze spatial autocorrelation, kernel density estimation (KDE), and Getis-Ord Gi hotspot analysis. Spatial autocorrelation assessed the autocorrelation of incidents, while KDE visualized hotspot clusters. Meanwhile, Getis-Ord Gi* hotspot analysis determined the statistical significance of incident hotspot locations. The analysis revealed a higher concentration of hotspots in the northern section of the national highway compared to the southern section. Notably, the section passing through Thanh Hoa city center, Hau Loc, and Hoang Hoa districts exhibited very high traffic density. Hotspots identified through Getis-Ord Gi* statistics aligned with those detected using KDE. Furthermore, several hotspots were concentrated at bends in the national highway, often lacking warning signs despite high traffic density. The study's findings serve as valuable references for authorities, enabling them to implement timely intervention measures such as infrastructure improvements or enhanced law enforcement to address issues and provide warnings regarding road traffic incident risks.*

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1. Introduction

Road transportation plays a pivotal role in every nation's socio-economic development and international integration. However, road traffic incidents (RTIs) are at risk, significantly impacting human health and property. According to a report by the World Health Organization (2015), RTIs are most prevalent in low- and middle-income countries, where the number of deaths resulting from these incidents is three times higher than in high-income countries (Abdullah et al., 2021). In Vietnam, congestion resulting from traffic incidents is commonplace in major cities (Truong, 2023). Vietnam also exhibits a high death rate due to RTIs, with approximately 2.34 deaths per 100,000 people (Peden, 2004). Several factors contribute to RTIs, including subjective human factors such as poor awareness of road traffic safety laws, speeding, driving under the influence of stimulants, and disregarding traffic signals (Oliver et al., 2021).

Furthermore, other influencing factors contribute to Vietnam's road traffic incidents (RTIs). These include incomplete transport infrastructure, resulting in numerous blackspots, lax operation, management, and supervision of transport activities, and the uneven quality of vehicles participating in traffic (Tran et al., 2016).

To mitigate the risk of incidents, it is imperative to have warnings regarding incident hotspot locations (Khatun et al., 2024). According to Mhetre & Thube (2023), hotspots are considered as the number of severe injury collisions occurring within a defined length segment (500 m) in 3 years or if the number of deaths is equal to or greater than 10. In other words, a cluster of crashes with high levels of injuries is called hotspots. Conversely, if there is a cluster of low-injury crashes, it is called coldspots. Researchers have employed various traditional methods to identify hotspots, such as the incident rate method (Carson & Powers, 2004), equivalent property damage index (Campbell & Knapp, 2005), and the Empirical Bayes method (EB) (Hauer et al., 2002). Among these, the most effective method is the EB method (Manepalli et al., 2011).

Nonetheless, the Empirical Bayes (EB) method has limitations, notably the requirement for training and proficiency in statistical analysis. Numerous other techniques utilizing Geographic Information Systems (GIS) to identify hotspots have emerged, enabling the identification of areas at high risk of incidents (Aguero-Valverde & Jovanis, 2006).

Spatial statistics analysis of incident hotspots is crucial in understanding the spatial patterns of road traffic incidents. Moran's I statistic is a commonly used technique for testing autocorrelation. This method assesses whether a set of incidents in an area is clustered, dispersed, or randomly distributed by comparing the values of a variable at one location with those at all other locations of that variable. However, for detailed identification of significant hotspot or cold spot clusters, it is essential to utilize the Getis-Ord Gi* statistical analysis (Nie et al., 2015).

Kernel density estimation (KDE) is a non-parametric method well-suited for identifying incident hotspots (Plug et al., 2011; Prasannakumar et al., 2011). The KDE algorithm delineates the range encompassing the risk of an incident, visually indicating areas where incidents are likely to occur based on spatial relationships. Moreover, the KDE analysis generates a raster layer wherein pixels are allocated values corresponding to the intensity characteristic of the entire area, facilitating comparison and classification (Anderson, 2009).

However, KDE has limitations as it does not furnish statistical significance of hotspots (Xie and Yan, 2013; Yao et al., 2016), nor does it offer criteria for prioritizing incident hotspots (Plug et al., 2011). To address this shortfall, some studies have employed Getis-Ord Gi* statistical to identify critical locations where accidents occur (Manap et al., 2019; Ord and Getis, 1995). The output of Getis-Ord Gi*statistical analysis comprises a z-score and p-value for each incident location, aiding in determining whether the cluster is statistically significant.

This study aims to integrate spatial autocorrelation analysis, kernel density estimation, and hotspot incident analysis utilizing GIS to identify and assess the severity of traffic incident hotspots. Moran's I index is employed to detect incident clusters, while kernel density estimation visually represents incidents in the study area through color coding and corresponding density values. Furthermore, the Getis-Ord Gi* statistic is utilized to determine the statistical significance of these density values.

2. Materials and methodology

2.1. Study area

National Highway 1A serves as a crucial link between the Northeast and Southeast regions of Thanh Hoa province, spanning coordinates between $19^{0}18'45''$ - $20^{0}08'00''$ North latitude and $105^{0}04'30''$ - $105^{0}05'45''$ East longitude. This highway traverses through 5 districts, one city, and one town within the province. With a total length of 98 kilometers, National Highway 1A features a level III road classification (asphalt road) and comprises four lanes (refer to Figure 1).

2.2. Data

Figure 2 illustrates the distribution of incident locations in 4 years (2020÷2023) on National Highway 1A in Thanh Hoa province.

There are two different datasets used for this study, including:

- Map of Thanh Hoa Road network and administrative boundaries digitized from Google Earth in shapefile form. Road attribute data includes length, width, road type, speed limit, etc., collected from reports provided by Thanh Hoa

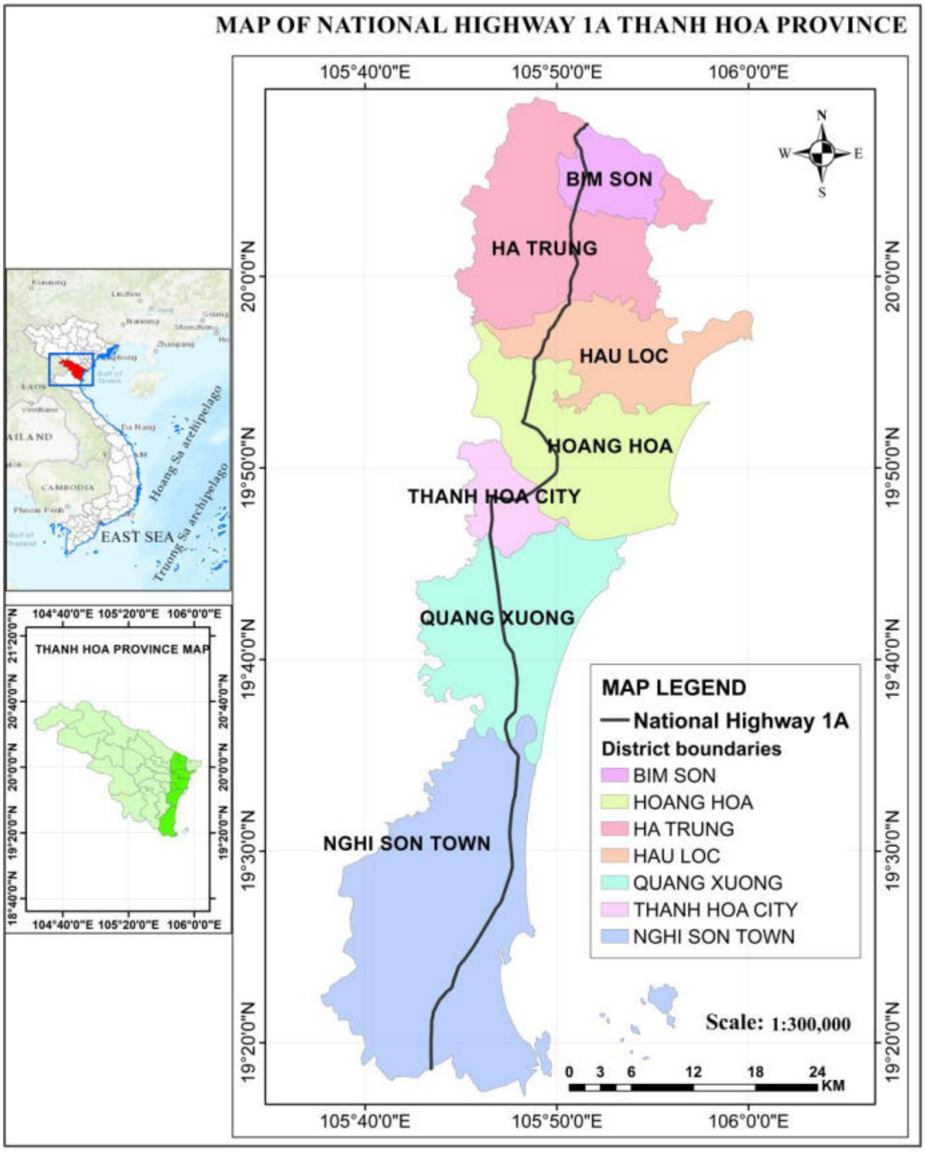

Figure 1. Study area - National Highway 1A passing through Thanh Hoa province.

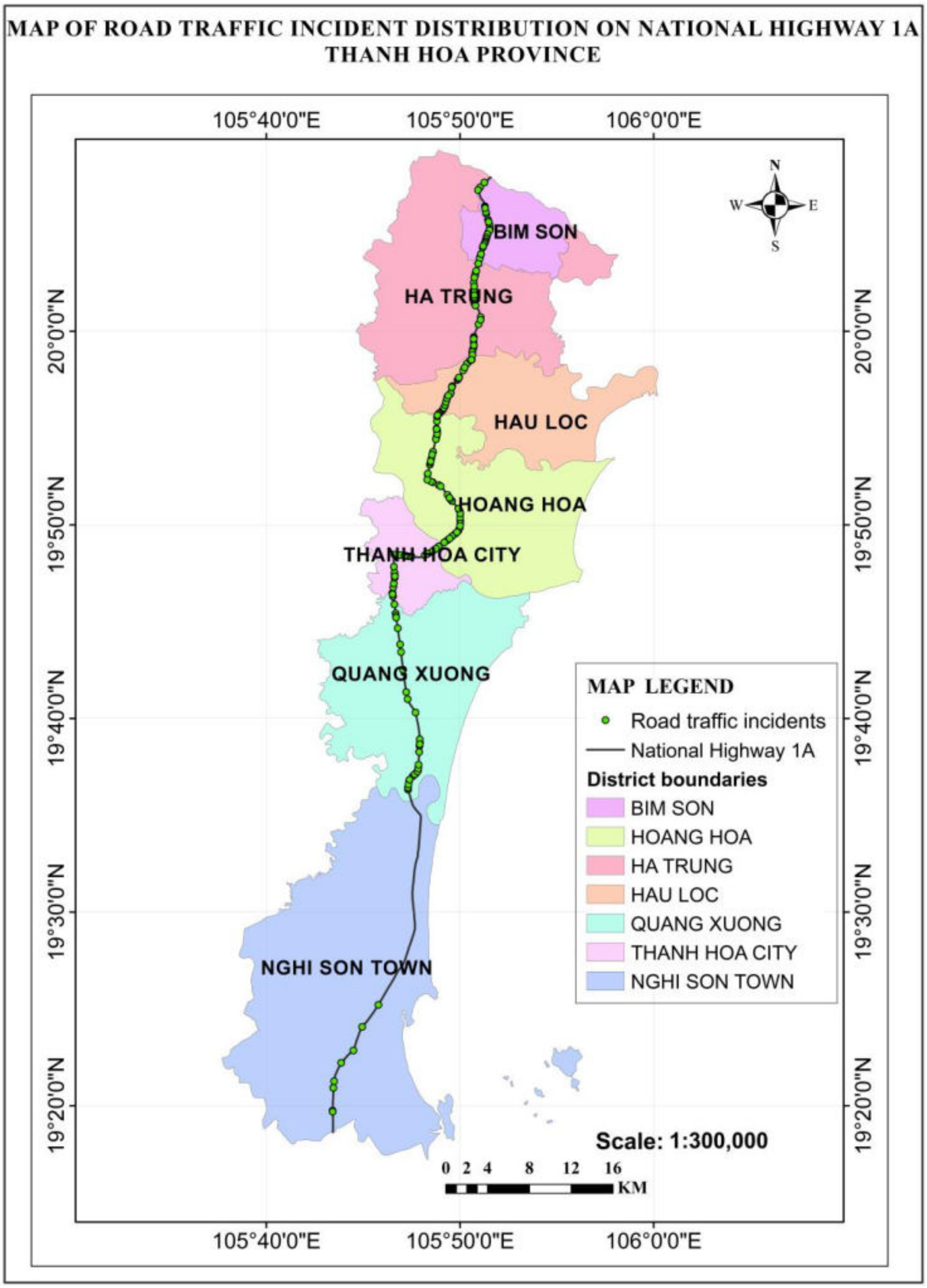

Figure 2. Map of road traffic incident distribution on National Highway 1A in Thanh Hoa province from 2020÷2023.

Department of Natural Resources and Environment.

- Road traffic incident dataset for four years from 2020÷2023 on National Highway 1A passing through Thanh Hoa province provided by the Transportation Police Department. This dataset includes essential information such as the date, time, and location of the incident, type of incident and vehicle, number of deaths, number of injuries, etc. These datasets were combined and processed using ArcGIS 10.8 software. The process changes raw data into input data for the GIS system includes (1) Clean and filtering data to remove incomplete data; (2) Convert coordinates; (3) Add coordinate data to determine the actual location of the accident on the map; (4) Enter attribute information; (5) The join and link method in ArcGIS 10.8 was then used to link the road data with the road accident data.

2.3. Methodology

2.3.1. Research Framework

After collecting data and building a thematic database of road traffic incidents in National Highway 1A in Thanh Hoa province for four consecutive years and a geographical database (including road network and administrative boundaries), analysis results were obtained by running the hotspot analysis tool in ArcGIS software. The study proposes a process for analyzing incident hotspots using spatial autocorrelation techniques, kernel density estimation, and Getis-Ord Gi* spatial statistics, as shown in Figure 3.

2.3.2. Data analysis

**Moran's index statistics of spatial autocorrelation*

Statistically significant analysis of hotspots is a measure of spatial autocorrelation by observing incidents' distribution patterns. The test will decide to stop when there is a random distribution and vice versa. The spatial autocorrelation technique simultaneously examines the incident's location and properties (Afolayan et al., 2022). Values of determined Moran's I ranging from -1÷1 Are considered statistically significant (Liu et al., 2019). If the Moran index value is close to 1, the data contain spatial autocorrelation and cluster patterns; If the Moran index value is close to -1, the data is not continuous and scattered. While an absolute zero index value indicates no spatial autocorrelation (Nejadrekabi et al., 2022). Based on the weight matrix, the Moran statistic is calculated using equation (1) as below (Lee and Wong, 2001).

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

In which: z_i, z_j are the deviation from the average value; $w_{i,j}$ is the spatial weight between feature i and j; n is the number of features, S_0 is the sum of all spatial weights and is calculated as follows:

$$S_0=\sum_{i-1}^{n}\sum_{j=1}^{n} w_{i,j} \qquad (2)$$

The z_i score is calculated as follows:

$$z_i = \frac{I-E[I]}{\sqrt{V[I]}} \qquad (3)$$

With:

$$E[I]= -1/(n-1) \qquad (4)$$

$$V[I] = E[I^2] - E[I]^2 \qquad (5)$$

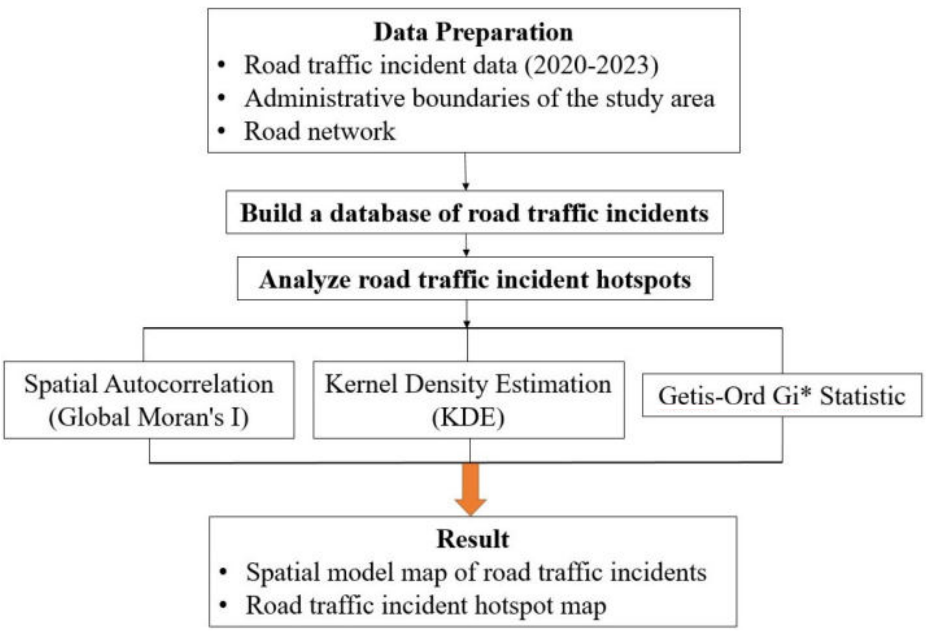

Figure 3. Road traffic incident hotspot analysis process.

** Kernel density estimation*

The kernel density estimating method estimates the density of incident in an area by flattening the surface. This method is widely applied to analyze incident hotspots (Jientrakul et al., 2022; Su et al., 2019; Le et al., 2020). The analysis is implemented by applying the kernel function to each point and summing the results as the formula (Lakshmi et al., 2019).

$$\lambda(s)=\sum_{i=1}^{n}\frac{1}{\pi r^2}k\left(\frac{d_{is}}{r}\right) \tag{6}$$

Where $\lambda(s)$ is the density at location s, r is the bandwidth of KDE, and k is the weight of point i with distance d_{is} to location s.

** Getis-Ord Gi* statistics:*

Mapping incident clusters in the study area based on hotspot analysis - Getis-ord Gi*. The output of this method includes Gizscores and Gipvalues that indicate whether high-value or low-value objects tend toward clusters (Le et al., 2022). The z-score and *p*-value obtained from spatial autocorrelation analysis indicate the incident locations with high values -hotspots and low values coldspots. However, to be designated as a hotspot, the incident location needs to have a higher value, with surrounding incident characteristics also having high values. The Getis-ord Gi* statistic was calculated to identify such hotspots according to formula 7:

$$G_i^*=\frac{\sum_{j=1}^{n}w_i x_j-\bar{X}\sum_{j=1}^{n}w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n}w_{i,j}^2-\left(\sum_{j=1}^{n}w_{i,j}\right)^2\right]}{n-1}}} \tag{7}$$

There: x_j is the attribute value of object j, wi,j is the spatial weight between objects i and j, and n is the total number of objects.

With:

$$\bar{X}=\frac{\sum_{j=1}^{n}x_j}{n} \tag{8}$$

$$S=\sqrt{\frac{\sum_{j=1}^{n}x_j^2}{n}-(\bar{X})^2} \tag{9}$$

The correlation between significance level *p*, confidence, and *z*-sore is shown in Table 1.

Table 1. Correlation between p significance level, confidence level, and z score.(Cheng et al., 2019)

z Score	Reliability	Level of significance *p*
<-1.65 or >1.65	90%	<0.10
<-1.96 or >1.96	95%	<0.05
<-2.58 or >2.58	99%	<0.01

A positive *z*-score value (>1.96) is statistically significant (*p*=0.05), indicating that the observations are hotspot spatial clusters, and a negative *z*-score (<-1.96) is statistically significant (*p* = 0.01) otherwise is the cold spot. In the case of *z*-score > 1.96 and *p*-value <0.05, the observations are spatial clusters, and Gi* is statistically significant at the 95% confidence level. On the contrary, the observations are random in the case of p-value of 0.05 (Le et al.,2022).

3. Results

3.1. Global spatial autocorrelation analysis (Spatial Autocorrelation Moran's I)

From Figure 4 and the correlation in Table 2, Moran's I is 0.183853 (> 0.00), which shows that traffic incidents positively correlate with spatial distribution. The *p*-value is 0.029047 (<0.05), indicating that the probability of random

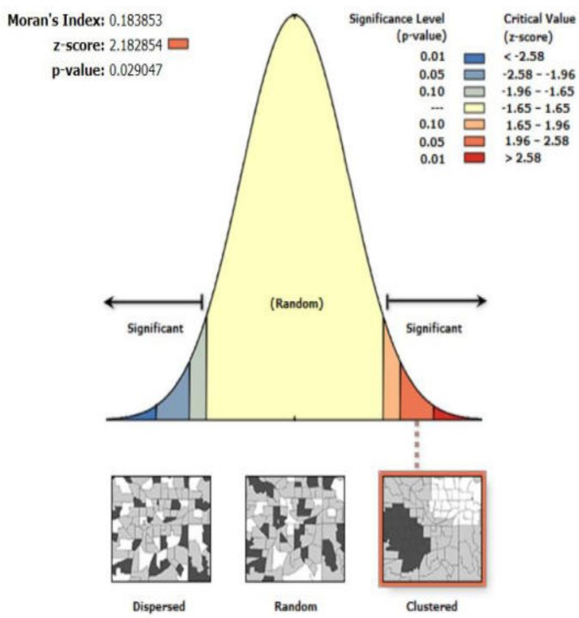

Figure 4. Spatial autocorrelation report of incident data from 2020÷2023 on 1A National Highway, Thanh Hoa province.

distribution of traffic incidents is less than 5%. In contrast, the spatial clustering state in Figure 4 has a more than 95% probability. Furthermore, the value z=2.182854 is higher than 1.96, which proves that the spatial aggregation trend of accident incidents distributed according to the global Moran is significant, which means there is a concentrated pattern with traffic incidents.

3.2. Kernel density estimation

A map of traffic incident locations was created, as shown in Figure 2, after geocoding and combining traffic incident locations with the road network map. Then, the KDE method was applied to develop an incident density map while considering the Severity Index (SI). SI should be regarded as identifying hotspots appropriate to Vietnam's conditions (Le et al., 2022). After analyzing KDE, it becomes easy to visualize traffic incident hotspots.

Figure 5 shows incident hotspots on National Highway 1A passing through Thanh Hoa province (2020÷2023), mainly in Hau Loc and Hoang Hoa districts. However, the results of applying the KDE method lack an assessment of the statistical significance of the above-identified hotspots. Therefore, it is necessary to investigate the statistical significance of hotspots using Getis-Ord Gi* statistics to determine the most severe incident locations with corresponding statistical significance according to the dangerous level.

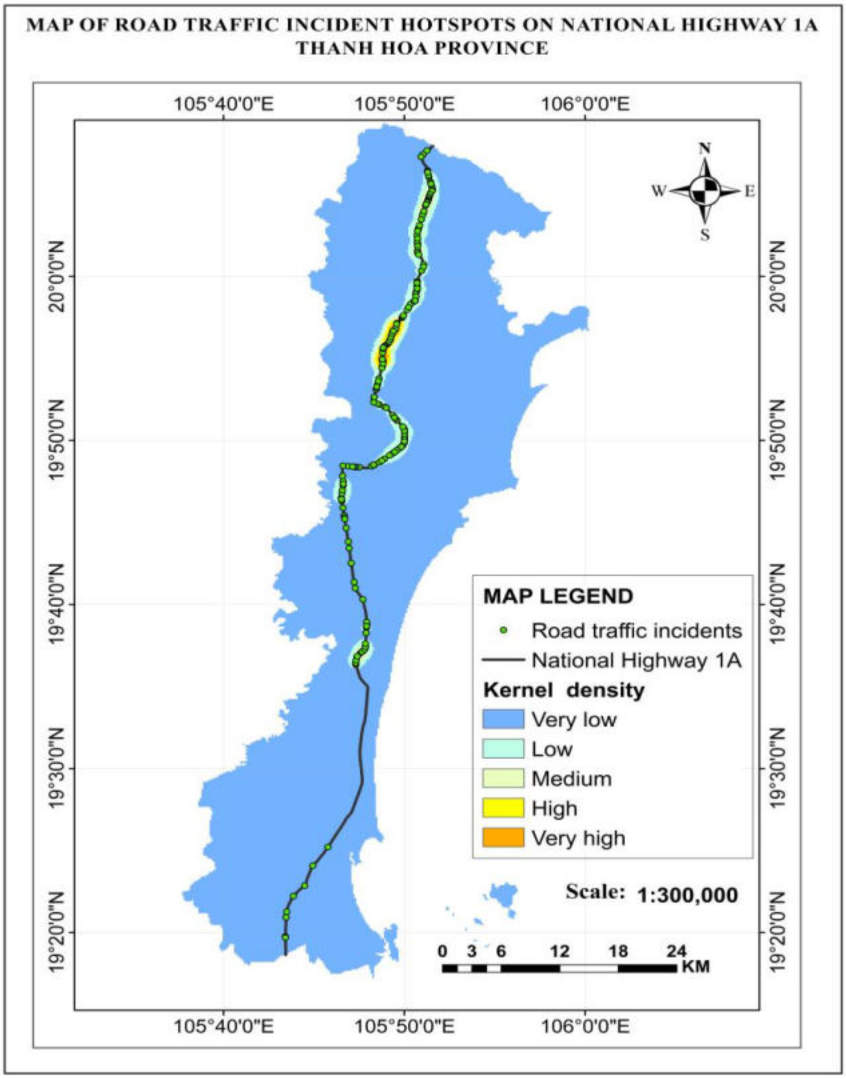

Figure 5. Map of Kernel density of road traffic incidents from 2020÷2023 on National Highway 1A in Thanh Hoa province.

3.3. Getis-Ord Gi statistics*

According to spatial autocorrelation analysis, the bandwidth of 3000 m, Getis-Ord Gi* analysis results in incident severity is shown in Figure 7. From 2020÷2023, on National Highway 1A through Thanh Hoa, there were 12 hotspots of road traffic incidents, with 6 points marked in red for a 99% statistical confidence level and 6 points marked in pink for a 95% statistical confidence level. This score is a high severity index and a high *z*-score value.

4. Discussion

Moran's I analysis revealed a statistically significant clustering pattern of road traffic incident data along National Highway 1A traversing Thanh Hoa province. The Getis-Ord Gi* analysis also detected traffic incident hotspots with a significance level of 0.05. These hotspots are predominantly situated along National Highway 1A, passing through Hau Loc and Hoang Hoa districts (see Figure 6).

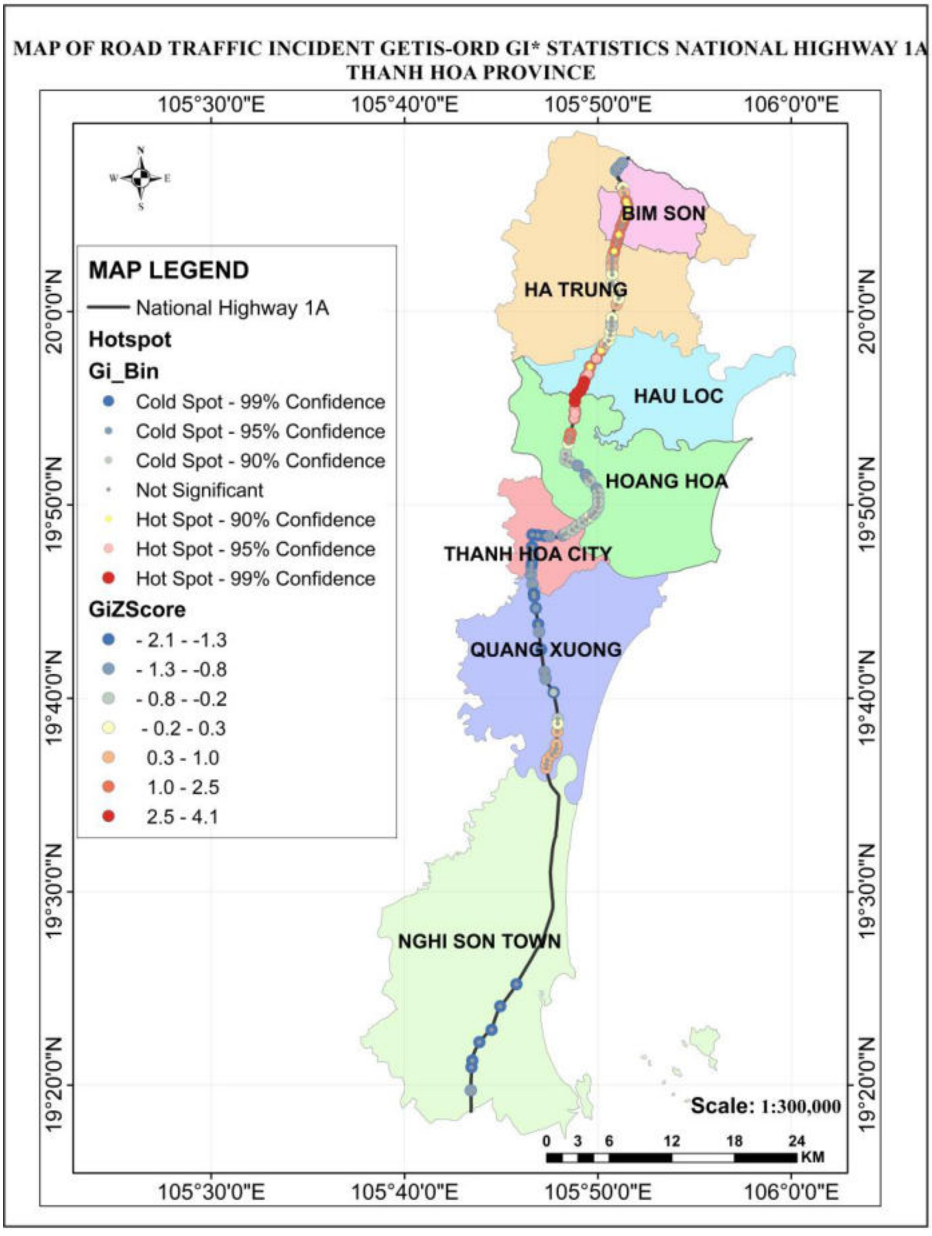

Figure 6. Getis-Ord Gi statistical map of road traffic incidents (2020÷2023) on National Highway 1A, Thanh Hoa province.*

The choice of bandwidth significantly influences the results of kernel density estimation. Through the application of an incremental spatial autocorrelation tool, the study determined a bandwidth of 3000 meters, deemed appropriate for the spatial pattern of incidents occurring on National Highway 1A in Thanh Hoa province. If the bandwidth is too large, the output results may fail to elucidate the detailed density of the study area, whereas if it's too small, the hotspots may become even more fragmented, hindering the determination of incident density (Anderson, 2009; Lakshmi et al., 2019).

Upon comparison of the results from the Getis-Ord Gi* statistical analysis and the kernel density estimation analysis illustrated in Figure 7, it becomes evident that the hotspot regions identified by both methods exhibit similarity when overlaid. Both analytical techniques identify and emphasize similar areas where hotspots occur. Consequently, the amalgamation of multiple analytical methods yields consistent results, effectively pinpointing hotspots with high confidence.

The analysis results reveal a greater concentration of hotspots in the northern section

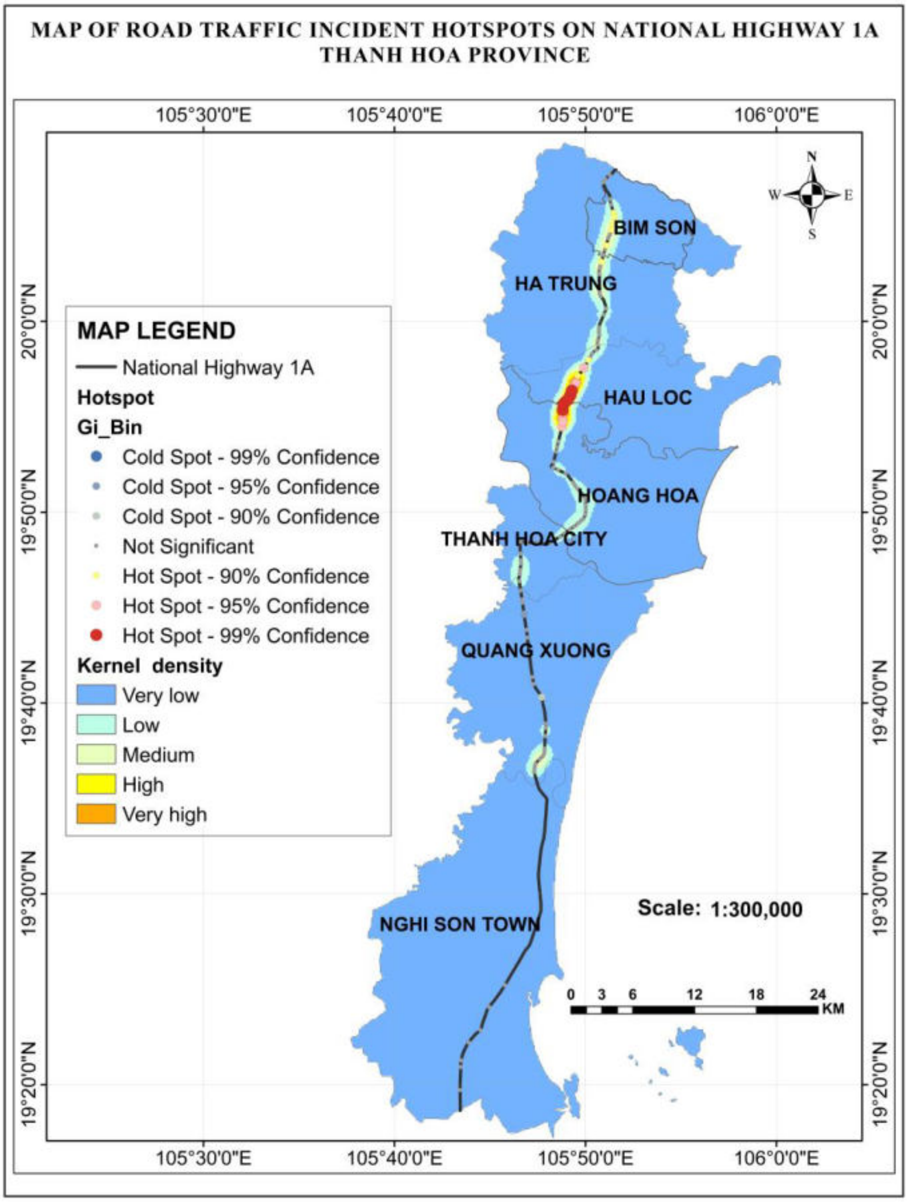

Figure 7. Map of road traffic incident hotspot analysis using Getis-Ord Gi and Kernel density estimation d on National Highway 1A in Thanh Hoa province.*

of the national highway compared to the southern section. Mainly, there is notably high traffic density in the stretch from Thanh Hoa city center through Hau Loc and Hoang Hoa districts. Hotspots identified by Getis-Ord Gi* statistics, namely points 46, 47, 48, 49, 50, 52, 54, 56, 57, 59, and 62, coincide with the hot zone identified through kernel density estimation (refer to Figure 8).

Points 47, 50, 52, 54, 56, 59, and 62 are concentrated at bends in the national highway. These locations lack traffic signs, and some road segments are undergoing upgrades, possibly contributing to traffic incidents.

5. Conclusion

The study utilized spatial autocorrelation techniques, kernel density estimation (KDE), and Getis-Ord Gi* statistical analysis to identify statistically significant road traffic incident hotspots. This analysis considered 332 traffic incidents from 2020÷2023 on National Highway 1A in Thanh Hoa province. KDE was used to visualize incident hotspots, while Getis-Ord Gi* demonstrated the statistical significance of these hotspots.

In cluster analysis, Moran's I index identified a confidence limit value above 95%, which is considered a hotspot. Results from KDE and Getis-Ord Gi* statistical analysis revealed seven hotspots, ranked by priority according to z-score values, in areas with a very high risk of incidents: locations 56, 57, 48, 59, 49, 62, and 47. Both analytical techniques identified and emphasized similar areas where hotspots occur. Combining these two methods in hotspot analysis provided consistent results, accurately identifying hotspots effectively and with high reliability.

Contributions of authors

Ha Thi Le, Thao Phuong Thi Vu - methodology, writing - original draft, review & editing; Thao Phuong Thi Do - review & editing.

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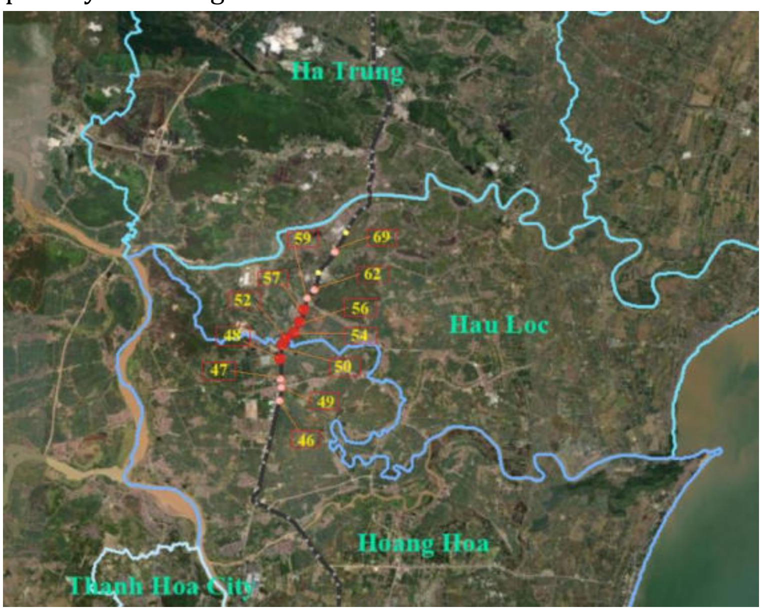

Figure 8. Location of road traffic incident hotspots on National Highway 1A in Thanh Hoa province.

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