Road Traffic Accident Black Spot Determination by using Kernel Density Estimation Algorithm and Cluster Statistical Significant Evaluation

A Case Study in Hanoi, Vietnam

Khanh Giang LE, Vietnam, Pei LIU, and Liang-Tay LIN, Taiwan

Key words: Traffic Accident (TA), Black Spots (BS), Geographic Information System (GIS), Kernel Density Estimation (KDE), Local Moran's I.

SUMMARY

Determining road collision black spot locations plays an important role in reducing significantly the number of traffic accidents. The article presents a new procedure that identifies road traffic accident black spot locations by using GIS-based kernel density estimation algorithm, evaluates statistical significance of resulting collision clusters, and then arranging them in accordance with their significance. Road traffic accident data in three years (2015-2017) in Hanoi, Vietnam used to analyze, test, and validate this approach. The results of the paper show that the approach was effective and exact in identifying road traffic accident black spot in Hanoi, Vietnam, simultaneously these hot spots were ranked according to their level of dangerousness. These outcomes will not only enable traffic authorities to understand comprehensively the causes behind each collision, but also to help them manage and deal with hazardous areas according to the prior order in case of limited budget and allocate traffic safety resources appropriately.

1. INTRODUCTION

Road traffic accidents (RTA) are one of the important issues over the world. According to the reports of World Health Organization (WHO), there are more than 1.24 million deaths and about 50 million people injured as results of RTA every year in the world (WHO, 2013). To decrease significantly the number of crashes, it is crucial to understand where and when traffic accidents happen frequently. The locations, where are identified by a high accident occurrence compared with the other locations, are known as black spots. The past studies showed that the occurrences of RTA are infrequently random in space and time. In fact, these locations identified by several key factors such as geometric design, traffic volume, or weather conditions, etc. (Chainey and Ratcliffe, 2013).

WHO reported that there were over a third of deaths owing to RTA in low and middle-income nations among vehicles, cyclists, and pedestrians (WHO, 2013). Vietnam is a developing country, thus RTA issue also is one of the most concerns of transportation authorities. The

annual social expenditure of RTA in Hanoi, is the capital of Vietnam, in term of medical treatment, deaths, and property damage occupy 2.9% GDP (5-12 billion USD) (Mai, 2018).
In 2017, there were 20,000 traffic crashes, about 8,200 deaths and 17,000 injured on Vietnam's road networks (Giang, 2018). Currently, non-spatial modelling has been used in Vietnam to identify RTA hot spots, namely: Accident Frequency Method (AFM) (classification by level of injury) over one year period (MOT, 2012). This is the oldest and simplest method to identify dangerous locations. However, this method has many limitations such as lacking of visualizing, connecting between space and time, ranking of hot spot's priority, does not take into consideration traffic volume, which has a direct relationship with crash frequency. Therefore, the results have bias toward high-volume locations and suffers from the RTM bias (Li, 2006). Currently, there has not any study dealing with collision mapping in Vietnam.
Geographic Information System (GIS) is a very powerful tool for analyzing traffic safety. GIS can visualize the locations of accidents and store its attributes. Thus, it is easy to find the reasons behind each collision. Spatial data usage plays an important role on traffic safety analysis. GIS enables us to collect, store, manipulate, query, analyze, and visualize the spatial data (Lloyd, 2010; Satria and Castro, 2016).
Spatial analysis of RTA has been popularly applied to explore hot spots (Anderson, 2009). GIS has been applied as a management system for accident analysis by combination of spatial statistical methods (Shafabakhsh et al., 2017). In the recent years, the combination of GIS and statistical analysis is increasingly more used by many researchers for assessing the road accidents (Yalcin and Duzgun, 2015; Benedek et al., 2016). Kernel density estimation (KDE) is one of the most popular density-based methods and has been widely used for detecting dangerous road segments (Xie and Yan, 2013). However, KDE method has a drawback is that the uncertainty about the exact location of the traffic collision is showed by the search bandwidth of the kernel (Anderson, 2009). Thus, KDE only is better for visualization purpose than for determining TA black spot locations (Plug et al., 2011). The same issue was showed by (Xie and Yan, 2008), KDE method lacks an investigation of the statistical significance of the high-density locations. Recently, there are very few researches that investigate comprehensively statistical significance of KDE method. Thus, how to identify which clusters is statistical significance is really necessary.
Therefore, in our study, firstly, RTA black spot locations was determined by using GIS-based kernel density estimation algorithm, after that statistical significance of resulting collision clusters was evaluated, and then their order was arranged in accordance with their significance. Finally, to validate this approach, we compare the results with traffic accident reports during three years (2015-2017) in Hanoi, Vietnam. The purpose of this paper is to present an improved procedure of identifying RTA black spots. The remainders of the article are arranged as follows. Section two depicts proposed methodology. Section three illustrates analysis of the case study. Section four presents the check and validation of the results of the proposed methodology. Finally, conclusions and discussions are presented in section five.

2. METHODOLOGY

In this study, KDE method was utilized to identify traffic accident black spot locations. However, this method lacks an investigation of the statistical significance of the high-density locations (Xie and Yan, 2008). Therefore, this article proposed a new procedure aim to improve the effectiveness and accuracy of KDE method. Figure 1 presents the combination of KDE method with a statistical significance evaluation process of the resulting clusters.
Proposed methodology was carried out by the following steps:
Firstly, collision locations were geocoded on the digital road network. Secondly, KDE method was applied to calculate and create RTA density map. On the other hand, RTA locations may be reported at the same location. Therefore, integrate and collect events tools were used to integrate and collect crashes that occurred at the same location. This step created a collect events map. However, it is necessary to test random distribution of RTAs in a section. If the RTAs in a section are distributed randomly, this process stops. On the other hand, if the RTAs in a section are non-random distribution, it is necessary to determine bandwidth in which autocorrelation or clustering phenomena is maximized. In order to do this, we applied Incremental Global Moran's I and this process was repeated many times. However, we need to find out what a starting distance at which any given point has at least one neighbor. After getting the optimal bandwidth, Local Moran's I was applied to generate a hotspots map. This optimal bandwidth will be threshold distance input. Finally, RTA hotspots priority map was produced as a result of the combination between the RTA density map and the hotspots map.
Section 2.1 and 2.2 will explain more detail about two methods that were applied in this study includes Kernel Density Estimation and Anselin Local Moran's I.

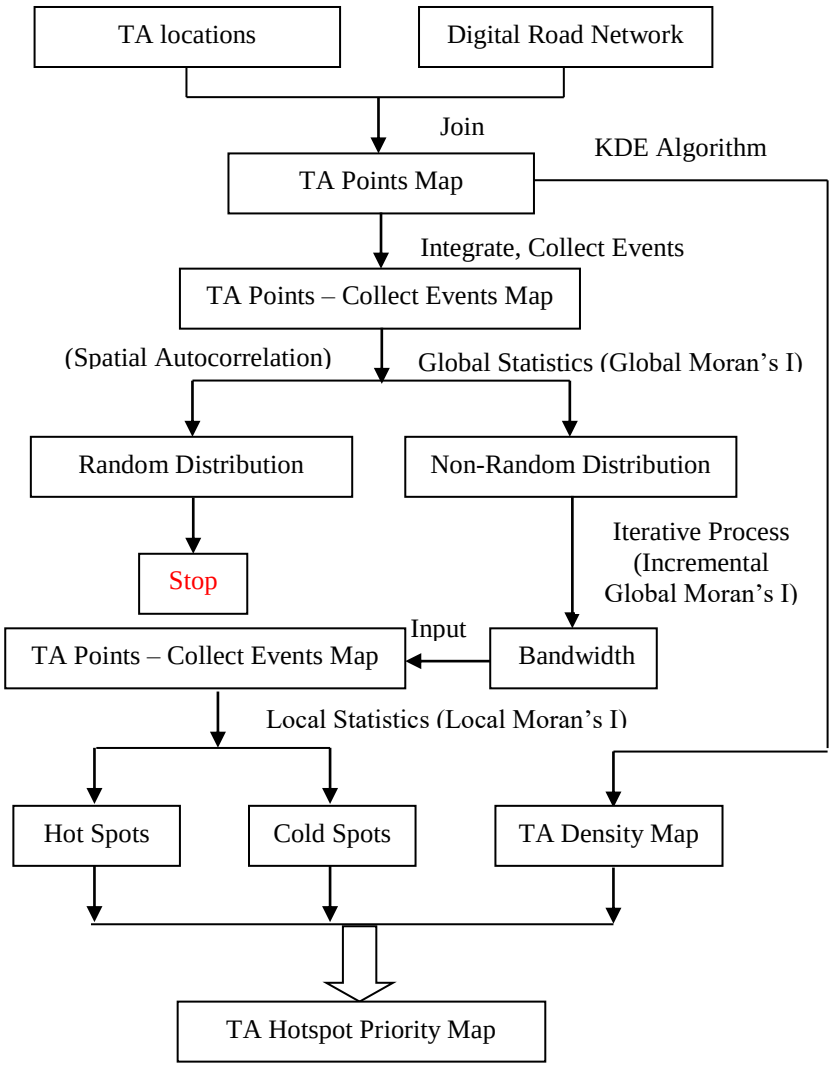

Fig. 1 The flowchart presents the process of RTA back spot determination and statistical significance evaluation of the resulting clusters.

2.1 Kernel Density Estimation (KDE)

There are several spatial analysis tools that enable us to comprehensively understand the geographical changing of point models. KDE is one of the most effective methods to determine the spatial models of RTA (Blazquez and Celis, 2013; Satria and Castro, 2016). The density of events is calculated within a definite research radius in the study areas to create a smoothed surface. A kernel function is utilized to assign a weight to the area surrounding the events proportional to its distance to the point event. From there, the value is highest at the point event location centre and decrease smoothly to a value of zero at the radius of the research circle (see Fig. 2). At the end, a smoothed continuous density surface is generated by

adding the individual kernels in the research area (Anderson, 2009; Rahimi and Shad, 2017). The intensity at a specific location is calculated by Eq. (1):

$$f(s) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right) \quad (1)$$

where f(s) is the density estimate at the location s, n is the number of observations, h is the bandwidth or kernel size, K is the kernel function, and d_i is the distance between the location s and the location of the i^{th} observation.

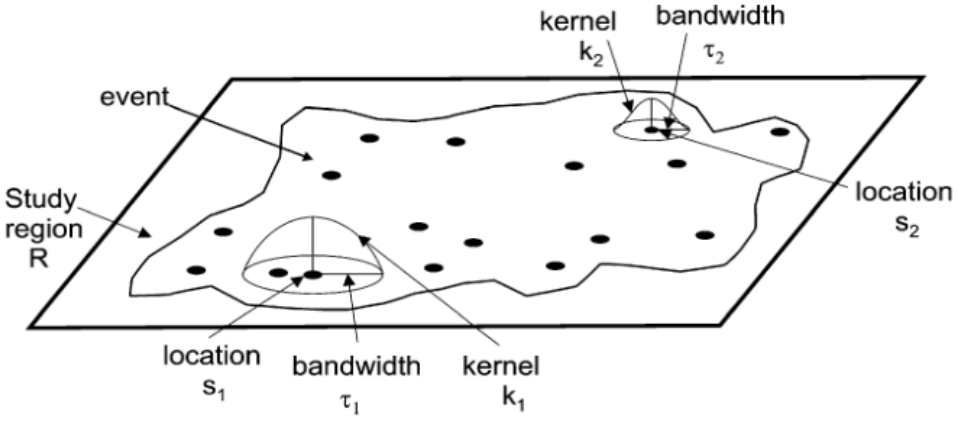

Fig. 2 Diagram of how the quadratic kernel density method works and is the basis for the density method used for this study (source: Bailey and Gatrell, 1995).

2.2 Anselin Local Moran's I

The Cluster and Outlier Analysis tool identifies spatial clusters of features with high or low values. The tool also identifies spatial outliers. To do this, the tool calculates a local Moran's I value, a z-score, a pseudo p-value, and a code representing the cluster type for each statistically significant feature. The z-scores and pseudo p-values represent the statistical significance of the computed index values.
The local Moran's I (Anselin, 1995) is one of the most widely used Local Indicators of Spatial Association (LISA) statistics (Satria and Castro, 2016). It measures the statistical correlation between attributes at each location in a study area and the values (usually the statistic mean) in the neighboring locations. It also tests the significance of this similarity. Formally, the local Moran's I can be expressed as Eq. (2):

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

where $w_{i,j}$ is a measure of the spatial weight between regions i and j, $\bar{X}$ is the mean value, and $x_{i,j}$ is the value of the variable at locations i and j, and:

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n} \left(x_j - \bar{X}\right)^2}{n-1} \quad (3)$$

with n equating to the total number of features.
The z_{Ii} -score for the statistics are computed as:

$$z_{Ii} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \quad (4)$$

where:

$$E[I_i] = -\frac{\sum_{j=1, j\neq i}^{n} w_{i,j}}{n-1} \quad (5)$$

$$V[I_i] = E[I_i^2] - E[I_i]^2 \quad (6)$$

In general, there are four types of correlation among neighbouring values: high-high (H-H), low-low (L-L), high-low (H-L), and low-high (L-H). (H-H) and (L-L) indicate that there is a positive autocorrelation, while (H-L) and (L-H) show that there is a negative autocorrelation (O'Sullivan and Unwin, 2010). The (H-H) areas are relevant for hazardous location detection and show locations where a high number of crashes are surrounded by high values (Xie and Yan, 2013).

3. ANALYSIS OF THE CASE STUDY

3.1. Data and Area Study

This study was carried out in Hanoi, Vietnam. Two different databases were used for this study. First, a road network map was provided in a shape file format, which includes specifications of roads such as road length, road width, road type, and speed limits. Second, a traffic accident database in three years (2015-2017) was provided by the Transport Police Department in Hanoi. Such a time span is sufficient because there are many records and the characteristics of the TA remains unchanged relatively (Elvik, 2008). There are 1,132 crashes were recorded on Hanoi's roads. The collision database was provided in an Excel file and contained significant accident parameters such as the date and time of a crash, crash location, accident types, age and sex of drivers, the number of the injured, etc.

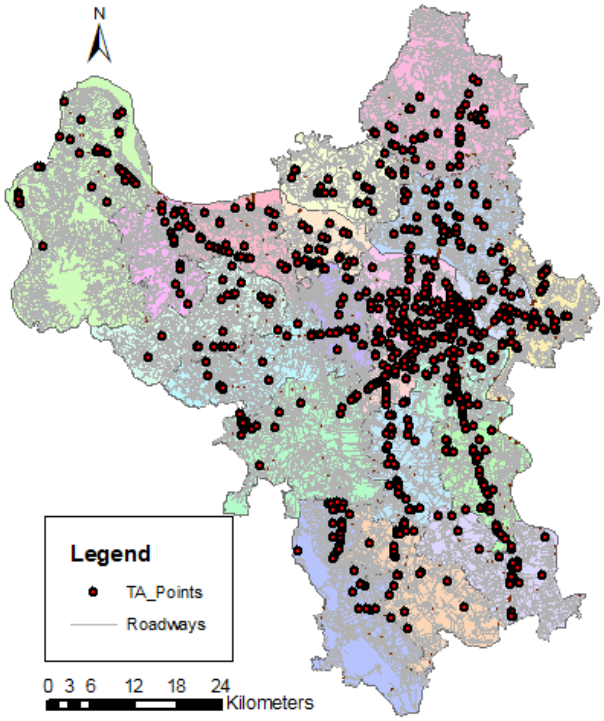

Fig. 3. Study area with distribution of all collisions in Hanoi (2015-2017).

3.2. Analysis Results

3.2.1. Kernel Density Estimation (KDE)

The output of KDE method is presented in a raster format consisting of a grid of cells. The two main parameters that influence the KDE are cell size and bandwidth. The choice of bandwidth is quite subjective (Anderson, 2009). The past studies used this value changing from 20 to 1,000 m (Xie and Yan, 2013). In our research, we tried to pratice it ten times including 100 m, 200 m, …, 1000 m in order to find the optimal bandwidth for our research. Finally, we considered 1000 m-bandwidth value because it enable us visualize RTA back spot locations easily. However, it is not always a good idea to choose a large bandwidth, as the RTA black spot locations will not be accurate. This is true as the mention of (Anderson, 2009) is that the uncertainty about the exact location of the traffic collision is showed by the search bandwidth of the kernel. Fig. 4. shows RTA black spot locations in two different bandwidth values are 500 m and 1000 m.

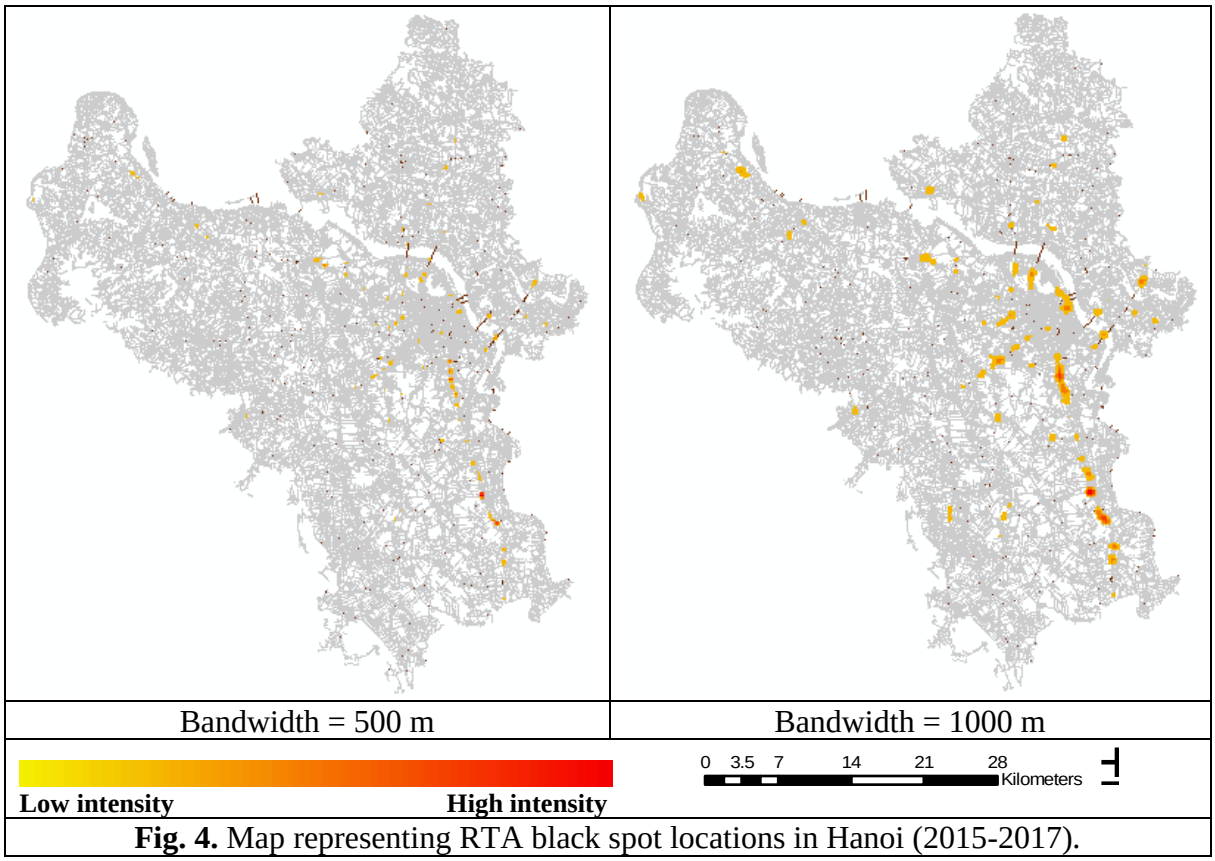

Fig. 4. Map representing RTA black spot locations in Hanoi (2015-2017).

With the positions of RTA in Fig. 3, it is impossible to find out RTA black spot locations. However, KDE method enables us visualize RTA black spots easily. Fig. 4 shows that red colored areas are RTA black spots in Hanoi (2015-2017), which mainly concentrate on NH-1A section such as Van Dien station, Cho Tia station, Quang Trung – Nguyen Trai intersection, Ha Dong, etc. However, the main advantage of the KDE method as opposed to classical statistic clustering methods is that the uncertainty about the exact position of the RTA is showed by the bandwidth of the kernel – this means something like spreading the risk of an accident (Anderson, 2009). Therefore, it is necessary to investigate statistical significance of the resulting clusters of RTA and find out the most hazardous location.

3.2.2. Statistical Significance Evaluation Process

At this point the common application of the KDE method usualy ends. The clusters which form the local maxima of the kernel function are determined. Sometimes as arbitrary level of significance is identified (Erdogan et al., 2008). However, we tried to identify the statistical significance of a cluster more objectively. Our process was stating with the null hypothesis: "The RTA in a section are distributed randomly". Statistical testing of the null hypothesis is based on a Spatial Autocorrelation tool in ArcGIS software 10.2 that is Global Statistics – Global Moran's I.

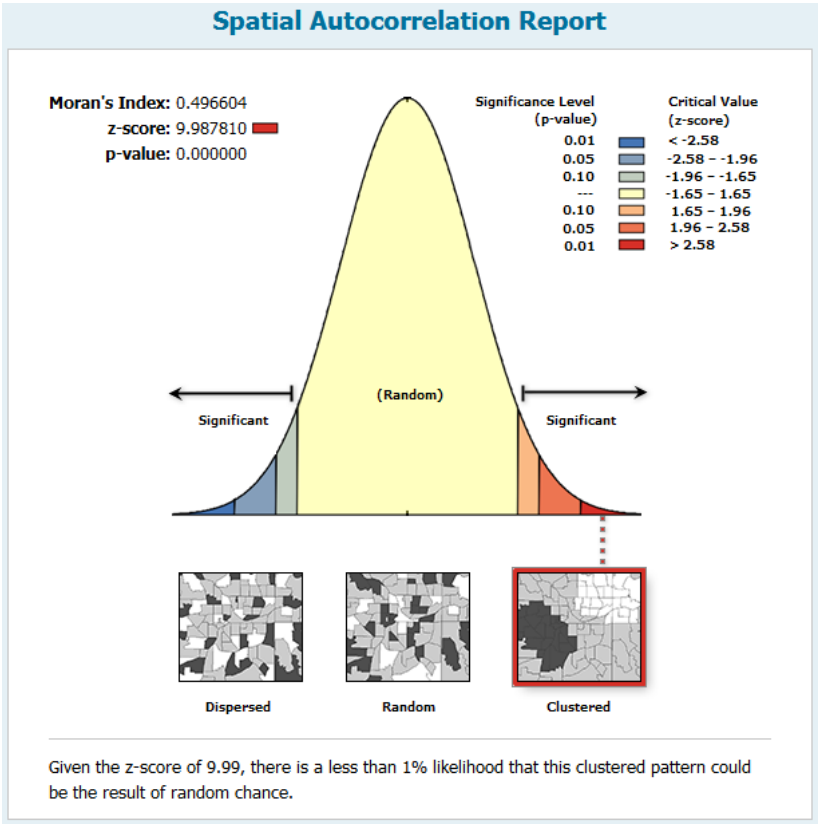

Fig. 5. Spatial Autocorrelation Report.

From Fig. 5, we can conclude that there is less than 1% likelihood that this clustered pattern could be the result of random chance (z-score of 9.99). Therefore, the next step is to identify bandwidth in which clustering phenomena is maximized. In order to do this, we applied Incremental Global Moran's I and this process was repeated many times. However, we need to find out what a starting distance at which any given point has at least one neighbor. We use Calculate Distance Band from Neighbor Count to calculate, then we have a result is 500 m. Then, we use incremental spatial autocorrelation to calculate and the result is showed as Fig. 6 and Table 1.

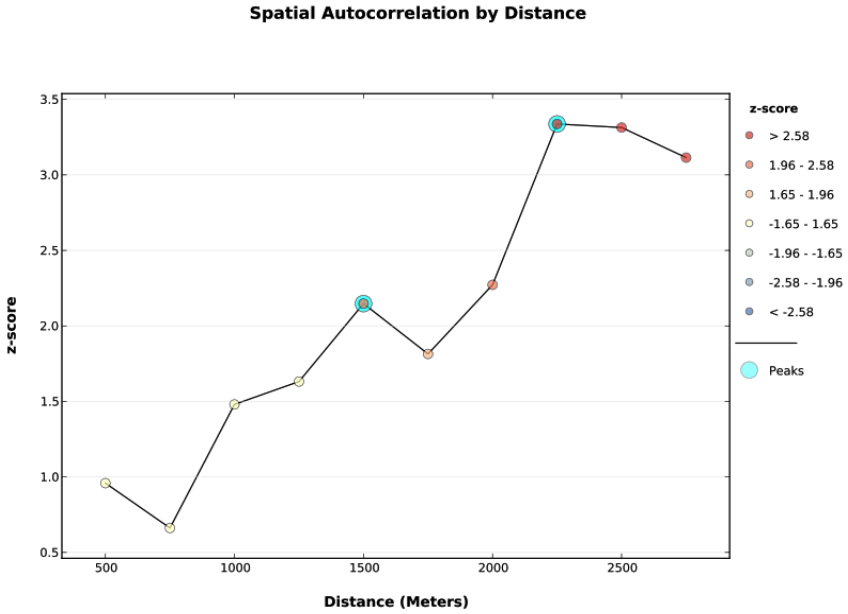

Fig. 6. Spatial Autocorrelation by Distance.

Table 1. Global Moran's I Summary by Distance.

Distance	Moran's Index	Expected Index	Variance	z-score	p-value
500.00*	0.026614	-0.001616	0.000867	0.958860	0.337629
750.00*	0.018387	-0.001372	0.000892	0.661623	0.508213
1000.00*	0.039438	-0.001307	0.000758	1.480188	0.138823
1250.00*	0.041200	-0.001233	0.000676	1.631558	0.102773
1500.00*	0.049820	-0.001202	0.000564	2.147713	0.031737
1750.00*	0.038418	-0.001182	0.000476	1.814229	0.069643
2000.00*	0.044918	-0.001168	0.000411	2.272086	0.023081
2250.00*	0.060999	-0.001156	0.000347	3.337184	0.000846
2500.00*	0.054846	-0.001152	0.000286	3.313633	0.000921
2750.00*	0.048476	-0.001147	0.000254	3.114572	0.001842

First Peak (Distance, Value): 1500.00, 2.147713

Max Peak (Distance, Value): 2250.00, 3.337184

Distance measured in Meters

* At least one distance increment resulted in features with no neighbors which may invalidate the significance of the corresponding results.

Fig. 6 shows that the Moran's I spatial autocorrelation was run at a variety of distances and for each of those it got a z-score which is the level of statistical significance. It deviated from our assumption of randomness and when we compare these z-score across the various increments of distance, we find that some of them are higher than others. Thus, we can see here is that there is fact that a couple of Peaks where z-score gets very high which is an indication that it is at those distances where the clustering is maximized. We are more likely to find natural clustering within the data. In addition, Table 1 shows that the maximum peak is

at 2250 m at which we can find maximum clustering and that is the number that we need in order to process forward.
In the next step, we applied the cluster and outlier analysis (Ansellin Local Moran's I) to generate a map of hotspots (Fig. 7). Fig. 7 shows that all the gray points are points that did not show any significant clustering with z-scores are low, so there is nothing really happening. The red points show areas of clusters where we have features with similarly high values near each other so in this case what that means is that we have got RTA point's high priority near each other and those clusters are statistically significant meaning that they are very far from random arrangement. In contrast, the green points represent areas where they have similar low values clustered near each other so those points are low priority. However, in this case, these points did not appear. Besides, the orange and the yellow points are outliers that are points in which case we find a high value or high RTA surrounded by low RTA and conversely for the yellow points. In this case, the red points were mainly occurred on NH-1A such as Van Dien station, Cho Tia station; Thang Long Boulevard - Me Tri intersection and Pham Van Dong road.

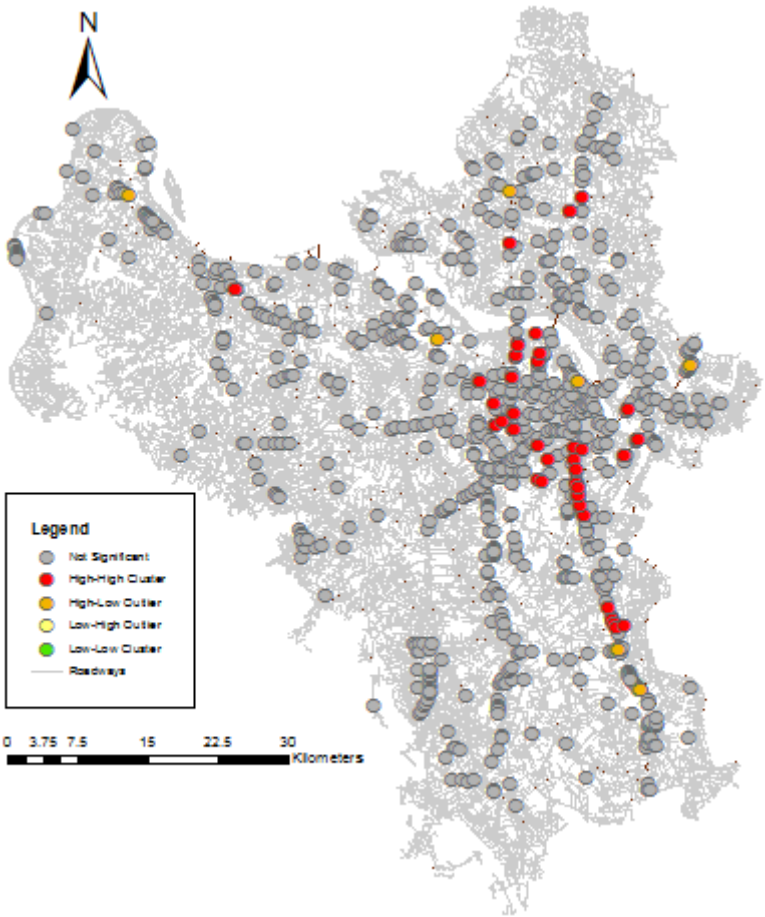

Fig. 7. Map representing RTA Hot spots, Cold spots with statistical significance meaning.

4. THE VALIDATION OF THE RESULTS OF THE PROPOSED METHODOLOGY

The results of the proposed methodology showed that this approach is appropriate for overcoming drawbacks of KDE method. Figure 8 illustrates road traffic accident hotspost priority map. In general, there are four types of correlation among neighbouring values: high-high (H-H), low-low (L-L), high-low (H-L), and low-high (L-H). (H-H) and (L-L) indicate that there is a positive autocorrelation, while (H-L) and (L-H) show that there is a negative autocorrelation. The (H-H) areas are relevant for hazardous location detection and show locations where a high number of crashes are surrounded by high values. In this case, the red points (circled in red) are (H-H) clusters where RTA occurred frequently and these locations were mainly occurred on NH-1A such as Van Dien station, Cho Tia station; Thang Long Boulevard - Me Tri intersection and Pham Van Dong road.

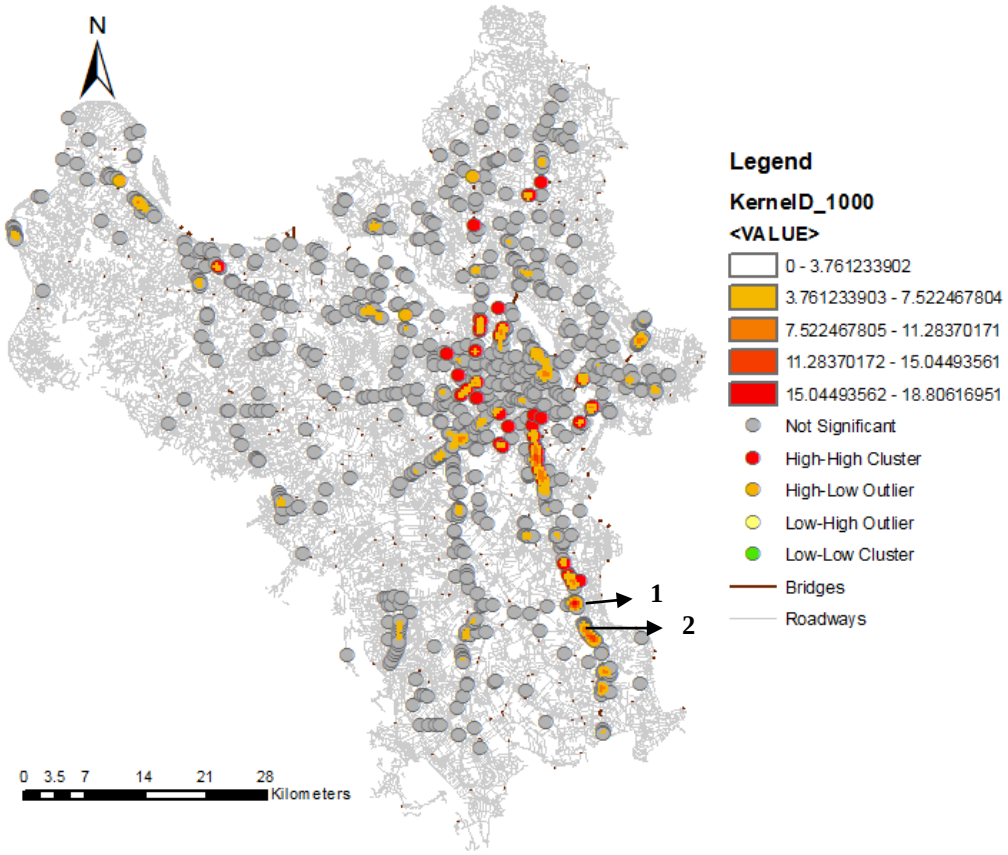

Fig. 8. Road traffic accident Hotspot priority Map

In addition, this approach investiagted the statistical significance of the high-density loactions. For instance, location 1 (Fig. 8) was identified as a high density point of RTA through applying KDE method. However, after investigating the statistical significance of the high-density locations, this location was identified as a (H-L) outlier point. It means this location is a high RTA surrounded by low RTA. Location 2 (Fig. 8) was identified as a high density zone of RTA through applying KDE method. But, after investigating the statistical significance of

the high-density locations, this location was determined as a not significant point (grey color) (Fig. 7). The results of the proposed methodology are appropriate to the observations from the reality and the reference data. This proposed methodology enables traffic authorities understand the situations more clear and comprehensively.

5. CONCLUSION

The paper proposed a new procedure that determines road traffic accident black spot locations by using GIS-based kernel density estimation algorithm, evaluates statistical significance of resulting collision clusters, and then arranges them in accordance with their significance. The results of the paper show that the approach was effective and exact in identifying road traffic accident black spot in Hanoi, Vietnam. These outcomes will not only enable traffic authorities to understand comprehensively the causes behind each collision, but also to help them manage and deal with hazardous areas according to the prior order in case of limited budget and allocate traffic safety resources appropriately.

The integration of KDE method and statistical significance evaluation of the resulting clusters of RTA help to overcome the drawbacks of KDE method. From there, the determination of RTA black spot locations will be improved with high accuracy. The results of the paper show that RTA black spots mainly occurred in NH-1A namely Van Dien station, Cho Tia Station, and at Nguyen Trai - Quang Trung intersection, Thang Long Boulevard - Me Tri intersection and Pham Van Dong road. This is also the first study about this issue in Vietnam, so the contribution of the article will help the traffic authorities easily solve this problem not only in Hanoi, but also can apply for other cities.

However, within the scope of the paper, there is a limitation is that does not take traffic volume in identifying RTA hot spots. Therefore, in the forthcoming studies, the authors will solve this issue. In addition, the authors will deploy this application online, which not only helps the traffic authorities, police patrol to update emergence information easily but also provide the citizen a black spot map in an updated, accurate, and visual way.

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BIOGRAPHICAL NOTES

Khanh Giang Le
Doctoral Candidate, Ph.D program of Civil and Hydraulic Engineering (2017 – Now).
Institution: College of Construction and Development, Feng Chia University, Taiwan.
Master Degree: Birmingham City University, United Kingdom (2013 – 2014)
Bachelor Degree: University of Transport and Communications, Hanoi, Vietnam (2001-2006)
He is a lecturer at Geodetic Division, Civil Engineering Faculty, the University of Transport and Communications, Hanoi, Vietnam (2006 – Now).
He is interested in applying GIS, GPS, spatial statistics, and geospatial analysis in transportation sector and urban studies.

Associate Professor **Pei LIU**
He is an Associate Professor of College of Construction and Development, Feng Chia University, Taichung, Taiwan.
He got his PhD degree in Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, America. He is an expert in Highway Engineering, Artificial Intelligence Methods, Numerical Methods, and Pavement Engineering.

Professor **Liang-Tay LIN**
He is Dean of College of Construction and Development, Feng Chia University, Taichung, Taiwan.
He got his PhD degree in Department of Civil Engineering, National Taiwan University, Taiwan. He is President of Chinese Institute of Transportation, Taiwan. He was Director General of Transportation Bureau, Taichung City Government. He is Director of innovation centre for Intelligent Transportation and Logistics. He is an expert in Traffic Engineering, Traffic Control, Traffic Flow Theory, and Urban Traffic Management.

CONTACTS

Khanh Giang LE
Doctoral Candidate, Ph.D program of Civil and Hydraulic Engineering.
College of Construction and Development, Feng Chia University.
Taichung
Taiwan
Tel. + 886 984267484
Email: khanhgiang298@gmail.com