Geographic Information System-based Analysis to Identify the Spatiotemporal Patterns of Road Accidents in Sri Racha, Chon Buri, Thailand

Narong Pleerux

Faculty of Geoinformatics, Burapha University, Chon Buri, Thailand

Received: 13 July 2019, Revised: 6 October 2019, Accepted: 22 October 2019

Abstract

The road accident rate has been growing in recent years; therefore, an analysis of the road accident hotspots is essential to reduce the number of accidents occurring in high-accident-density areas. Sri Racha district in Chon Buri province was selected as the study area for this research. The accident data of 2012-2017 was collected from the Road Accident Data Center (ThaiRSC). The spatiotemporal pattern of road accidents was clustered into various scales: accidents occurring on weekdays, weekends, daytime, nighttime and those involving fatality and injury. Spatial statistical methods, kernel density estimation (KDE), and Ripley's K-function in geographic information system (GIS) were applied to identify patterns and the distribution of road accidents. The findings showed that a high density of road accidents was found in three main areas: Sri Racha municipality, Laem Chabang City municipality and Bowin subdistrict. The spatial distribution of all types of road accidents was clustered at various distances. Several agencies can use the results for planning and managing road accident reduction strategies. Furthermore, GIS and spatial statistical methods are effective tools that are quite widely used for accident analysis.

Keywords: Kernel density estimation, Ripley's K-function, hotspot, spatial pattern, GIS
DOI 10.14456/cast.1477.6

1. Introduction

Road systems are important for transportation since they are cheap and rapid. However, it is associated with a high risk of accidents in comparison with other modes of transportation [1]. A lack of transportation infrastructure development has caused an increase in the number of road accidents [2]. Injuries, fatalities, and damaged properties are consequences of road accidents around the world [3-5], particularly in developing countries [6, 7]. Additionally, road accidents cause economic losses to victims, their families, and the nation [8]. Most road accidents result from human mistakes, such as inattentiveness of the drivers or pedestrians [9]. Hence, road accidents can be reduced through the analysis of the incident scenarios and spatial analysis [2, 8, 10].

The World Health Organization stated that 1.25 million people were killed in road accidents in 2013, with high fatality rates in low and middle income countries. In Thailand, the fatality rates of road accidents were estimated at 24,237 people, i.e. 36.2 per 100,000 [11].

*Corresponding author: Tel.: +66 82-231-3386 Fax: +66 38-102-379
E-mail: narong_p@buu.ac.th

According to statistics recorded by the Road Accident Data Center (ThaiRSC), 522 fatalities and 51,841 injuries were reported in Chon Buri province, the city with the second largest economy in Thailand, following Bangkok [12]. The effect of road accidents has been investigated for many years by studying the relationship between real-time traffic and road safety [13-15], detecting accident hotspots [16, 17], and analyzing the spatiotemporal pattern of road accidents [18, 19].

The geographic information system (GIS) is a powerful tool for spatiotemporal analysis. It has been used for analyzing and visualizing road accidents [20], identifying the spatial pattern and hotspot of accidents [21] and determining the density and distribution in the accident area [6, 15, 22]. Furthermore, the GIS facilitates researchers' understanding of the relationship between accidents and their contributing factors, such as accident data that include socioeconomic information, land use and travel information [16]. At present, GIS with spatial statistical techniques has been developed. Kernel density estimation (KDE) is one of the most popular methods used for analyzing the distribution and accident hotspot [21, 23-26]. Another method, the network kernel density estimation (NetKDE), was developed to evaluate the density of road accidents over a network space [5, 27-29]. Other methods of spatial point pattern analyses, such as Moran's I, Getis-Ord Gi* [30, 31] and Ripley's K- function [2, 19, 32, 33], have been presented.

Using ArcGIS 10.0, the density and distribution of road accidents were analyzed using KDE and Ripley's K-function within a particular period. The spatiotemporal analysis of road accidents can help transportation agencies improve road safety in Sri Racha district, Chon Buri province. The rest of the paper is organized as follows. Section 2 describes the study area, the data, and methods. Section 3 reveals the results and discussion of the analysis of road accident density and distribution and section 4 presents the conclusions.

2. Materials and Methods

2.1 Study area

Sri Racha district, Chon Buri province, located on the east coast of Thailand, was selected as the study area. According to the Department of Provincial Administration [34], Sri Racha has a population of approximately 51,197. Sri Racha district, an industrial zone comprising manufacturing and shipping industries, covers approximately 616.40 km^2. The district was supported by the port of Laem Chabang, the 20th largest port in the world. Furthermore, it contributes to the economic development of the eastern seaboard of Thailand. Rapid economic growth and development and an increase in the number of vehicles may lead to an increase in the number of road accidents, as shown in Figure 1.

2.2 Road accident database

The road accident data used in this study were acquired from the ThaiRSC. However, not all road accidents were recorded in the ThaiRSC database. ThaiRSC only recorded the data of the victims who petitioned for indemnification or payment in accordance with the Protection for Motor Vehicle Accident Victims Act, 1992. Figure 1 shows that 20,003 accidents occurred between 2012 and 2017 in Sri Racha. Details of these accidents such as date, time, road type and accident location were recorded and save as a GIS shape file. Spatiotemporal analyses were presented at various scales: weekdays (Monday-Friday), weekends (Saturday-Sunday), daytime (06.00-17.59), nighttime (18.00-05.59) and accidents involving fatality and injury. Later on, these six categories of spatiotemporal road accidents were combined to new four groups: fatality during daytime on weekdays, fatality

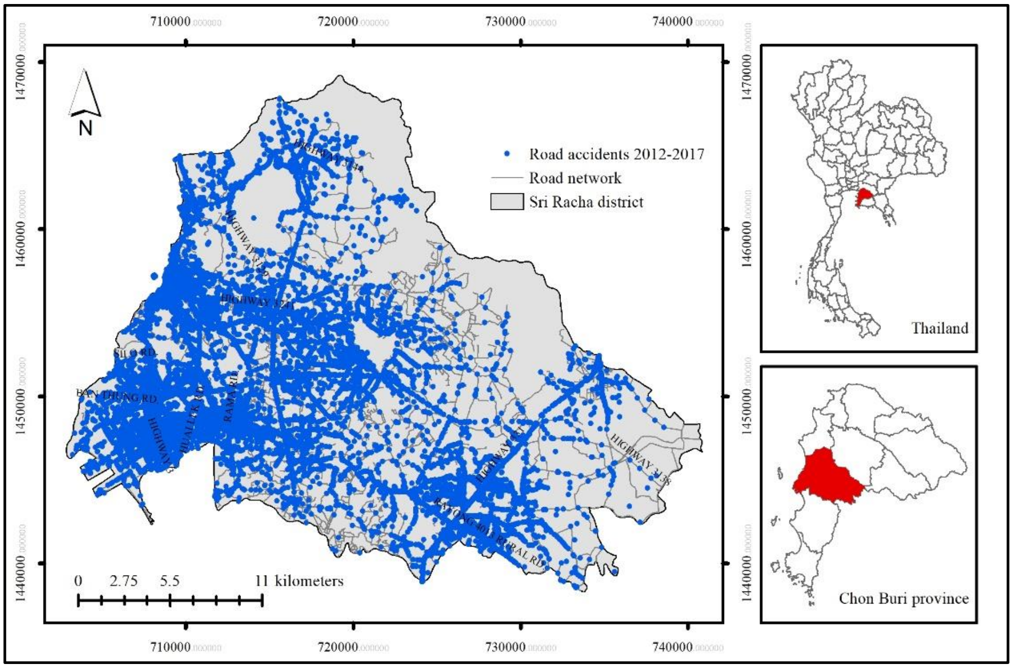


Figure 1. Study area, Sri Racha district, Chon Buri province, and spatial pattern of road accident points (2012-2017)

during nighttime on weekdays, fatality during daytime on weekends and fatality during nighttime on weekends.

2.3 KDE

KDE may be used to efficiently identify the point pattern of road accidents [22]. This method is used to create a density map based on a non-parametric approach. Furthermore, it distinguishes the areas by placing a plane-symmetry over each point. Afterwards, the distances between the center point and locations of accidents within the surface area are assessed. KDE repeats successive points and provides possibilities of using kernel functions for each observation. These kernels furnish density analysis of the distribution of accident points [35]. The density estimation function is as follows:

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

Where $f(x,y)$ represents the density estimate of the location (x, y), n refers to the number of observations, h is the bandwidth, K is the kernel function, and d_i indicates the distance between the location (x, y) and the location of the i^{th} observation ($i = 1, 2, 3, \ldots, n$).

The bandwidth shows a strong effect on density estimation. A large bandwidth will produce over smoothed density estimation and a small bandwidth creates inadequate smoothing [19]. The selection of the cell size is another parameter. In this study, a 300-m bandwidth and a 50-m cell size were applied for road accidents during 2012-2017 of all spatiotemporal scales using ArcGIS 10.0.

2.4 Ripley's K-function

Ripley's K-function is used to evaluate the spatial pattern of the point data and was successfully applied in spatial estimation of accidents [36]. The method summarizes spatial dependence over a range of distances. When the neighborhood size changes, it demonstrates the spatial clustering or dispersion of feature changes at a different distance [37]. In this regard, the K-function L(d) is employed as follows:

$$L(d) = \sqrt{\frac{A\sum_{i=j}^{n}\sum_{j=1,j\neq 1}^{n} k_{i,j}}{\pi n(n-1)}} \quad (2)$$

Where $L(d)$ is the difference between the observed and expected K-function values below a complete spatial randomness hypothesis (CPSR), d represents the distance, A represents the total area feature, n is equal to the total of features and $k_{i,j}$ is a weight.

ArcGIS 10.0, Ripley's K-function tool was used to estimate the road accident distribution in this study. This statistical test consolidates a normally used transformation (L(d)) with Monte-Carlo simulation to create a confidence envelope based on the results of the simulations [32]. At the specified distance of analysis, if the observed values are greater than the expected values and the upper confidence envelope is created from the simulation, the data are clustered in a statistically significant way. Similarly, if the observed values are lower than the expected values and the low confidence envelope, the data are dispersed in a statistically significant manner. However, if the observed values are within the lower and upper boundaries created by the confidence envelopes, the distribution does not randomly vary in a statistically significant manner [19, 32]. In this study, 99 permutations were run using the Ripley's K-function tool, and the corresponding results yield a 99% confidence level. The outcomes are presented using the unit m.

3. Results and Discussion

3.1 Number of road accidents

Figure 2 illustrates a distribution of hourly road accidents during 2012-2017 in Sri Racha, revealing 20,003 accidents points. During the time brackets of 20.00-20.59, 19.00-19.59, and 07.00-07.59, the number of accidents were 1,570 with 33 fatalities, 1,558 and 1,542. In addition, the highest number of fatalities, 48, was observed during 21.00-21.59. After midnight, the number of road accidents declined; the lowest number of accidents was recorded during 04.00-04.59 because people were sleeping at this time, resulting in less traffic. However, the number of accidents began to increase from 05.00 onwards, as people began their commutes to work at this time, particularly during 07.00-07.59. After 08.00, most people were at work, school and home; therefore, traffic reduced, resulting in a decline in the number of road accidents. During 16.00-20.59, the number of accidents was likely to increase because factory workers began to leave from or arrive at their workplaces, trucks travelled to Laem Chabang Port, and many people commuted during this time period.

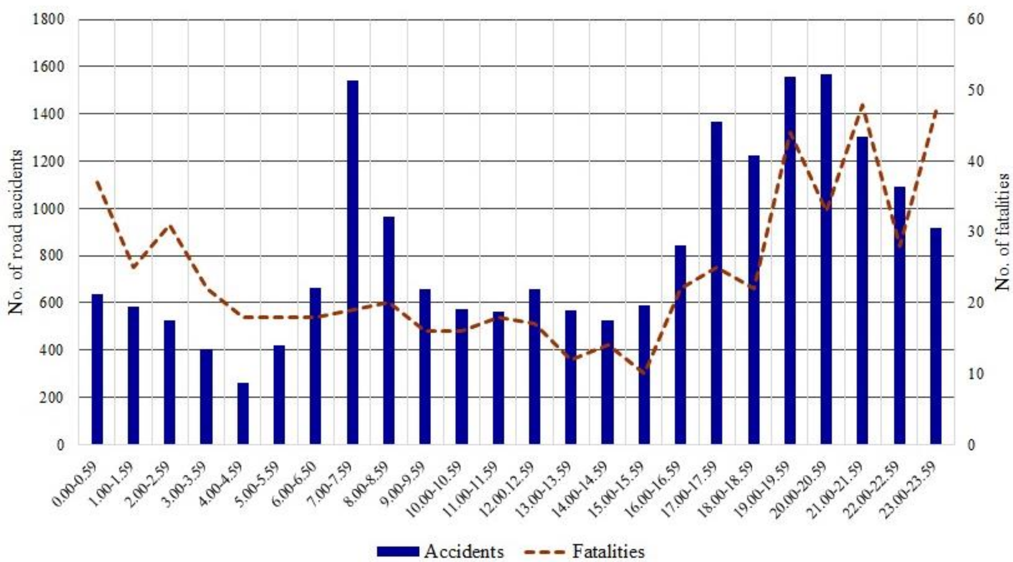


Figure 2. The number of road accidents and fatalities in 24 h

3.2 KDE

Road accidents during 2012-2017 were classified into six groups: (a) weekdays (n = 13,461), (b) weekends (n = 6,542), (c) daytime (n = 9,862), (d) nighttime (n = 10,141), (e) fatality (n = 580) and (f) injury (n = 19,423); fatality during daytime on weekdays (n = 135), fatality during nighttime on weekdays (n = 238), fatality during daytime on weekends (n = 68) and fatality during nighttime on weekends (n =139). Based on the KDE analysis, the bandwidth value was 300 m with a grid size of 50 m. Figure 3 illustrates three areas with high KDE value: Sri Racha municipality, Laem Chabang City municipality and Bowin subdistrict. These areas are considered to be the economic, industrial, and transportation center of Sri Racha district. Sri Racha municipality is located at the center of Sri Racha district and it is an important commercial area with shops, department stores, hotels, hospitals and government agencies. However, this area faces heavy traffic congestion, particularly on Saturdays and Sundays from the morning to the evening when tourists visited Sri Racha, Pattaya, and Koh Larn, which are the famous tourist centers in Chon Buri. Moreover, the highest KDE value was recorded at the clock tower intersection along highway No. 3 (Sukhumvit Road).

Laem Chabang municipality, which is located at the south of Sri Racha municipality, is the location of Laem Chabang Port, the main seaport used by the international sea freight and transportation industry. The presence of many shipping and logistics companies and a large population in this area lead to traffic congestion during daytime and nighttime. In particular, the highest KDE value of all the areas within Sri Racha was recorded at Highway No. 3 (Sukhumvit Road), in front of Laem Chabang Port.

The Bowin subdistrict is a large area with a very dense population. Owing to its proximity to many large industrial estates such as WHH Chon Buri Industrial Estate 1, Eastern Seaboard Industrial Estate, Rojana Industrial Estate, Bowin Industrial Estate, Hemaraj Eastern Seaboard Industrial Estate 2 and Amata City Industrial Estate Rayong, the area is congested owing to the transportation of goods, raw materials and workers throughout the day. As a result, frequent

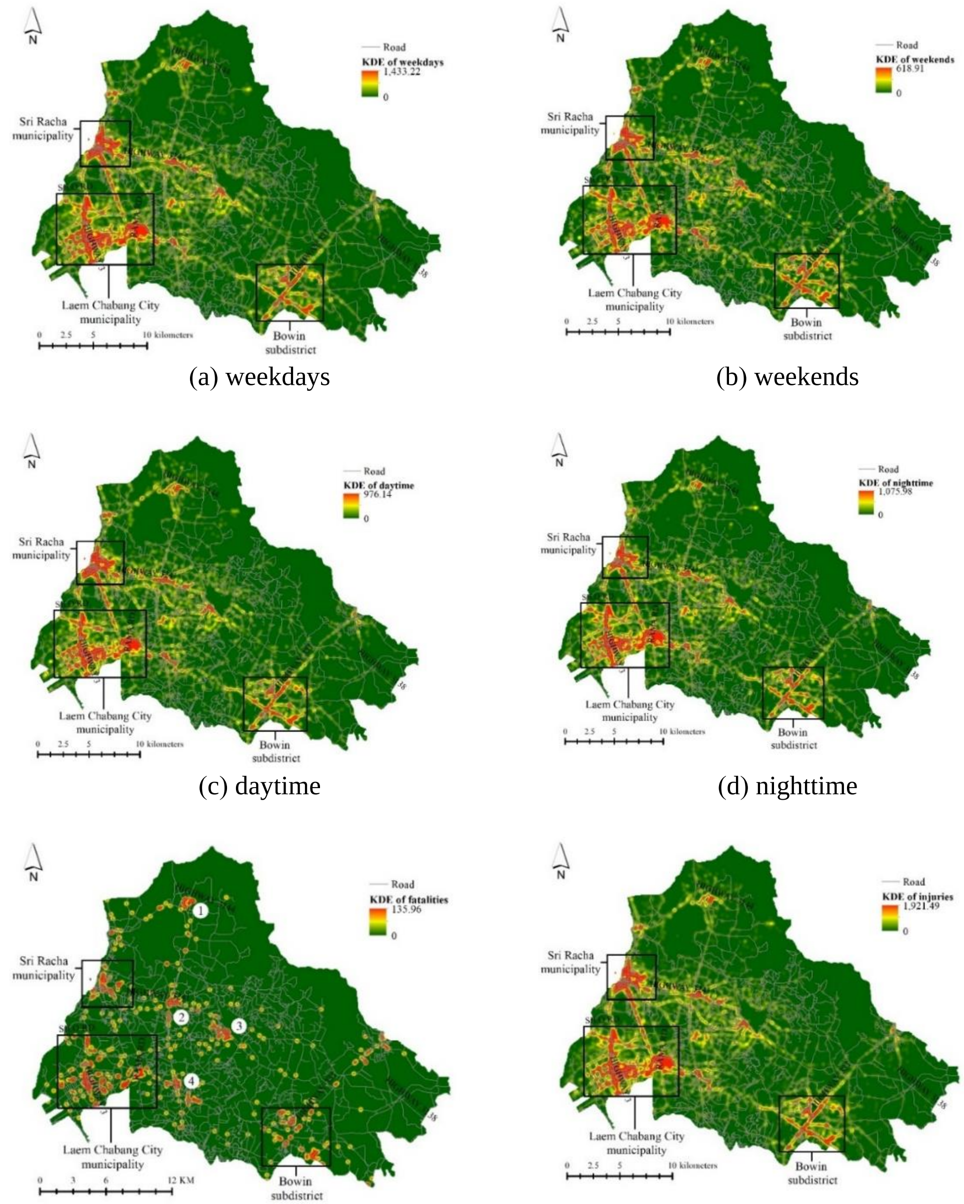
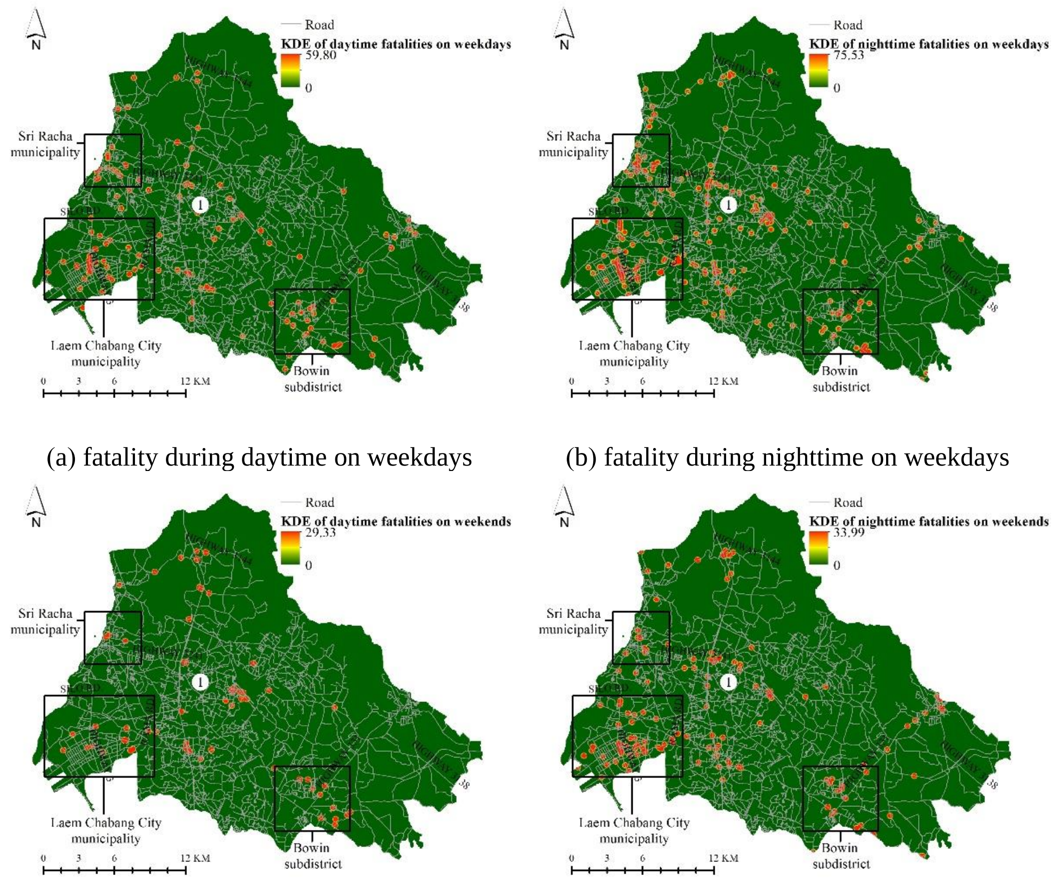


Figure 3. KDE of road accidents in Sri Racha district: (a) on weekdays, (b) weekends, (c) daytime, and (d) nighttime, (e) involving fatality and (f) injury

accidents occur at the intersection of Highway No. 331 in WHH Chon Buri Industrial Estate 1, recording the highest KDE value in this area.

Considering the KDE map of fatalities as shown in Figure 3(e), Sri Racha municipality, Laem Chabang City municipality and Bowin subdistrict have a high KDE value. In addition, other areas with a high KDE value are (1) Highway No. 3144 in the upper part of Sri Racha district, (2) the intersection between National Highway No. 7 (motorway road) and Highway No. 3241, (3) Highway No. 3241 at Nong Kham subdistrict near Nong Kho Reservoir and (4) National Highway No. 7 (motorway road) in the south of the district.

The number of fatalities during daytime, nighttime, weekdays and weekends were identified and it was found that the number of fatalities during nighttime was greater than during daytime on weekdays. Similarly, the highest number of fatalities was recorded during nighttime on weekends. Figure 4(a)-(d) illustrates the results based on KDE analysis in four spatiotemporal



(a) fatality during daytime on weekdays

(b) fatality during nighttime on weekdays

(c) fatality during daytime on weekends

(d) fatality during nighttime on weekends

Figure 4. KDE of (a) fatality during daytime on weekdays, (b) fatality during nighttime on weekdays, (c) fatality during daytime on weekends and (d) fatality during nighttime on weekends

scales; fatality during daytime on weekdays, fatality during nighttime on weekdays, fatality during daytime on weekends and fatality during nighttime on weekends. Sri Racha Municipality, Laem Chabang City Municipality and Bowin Subdistrict have a high KDE value. Apart from three aforementioned areas, some other areas have also been found to have high KDE, especially (1) the center of the district which is a large community with many housing estates and the location of Pinthong Industrial Estate 3. Therefore, during nighttime on weekdays (Figure 4(b)), there have been more fatalities than on weekends, particularly along National Highway No. 7 (motorway road) and Highway No. 3241 because many people and workers commuted during this time period and these routes.

3.3 Ripley's K-function

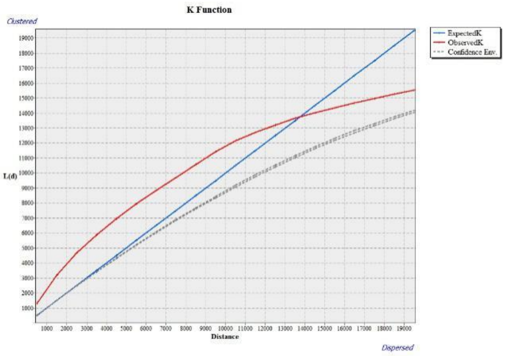
Ripley's K-function was used to analyze the distribution of road accidents at all scales, which include accidents that occurred on weekdays, weekends, daytime and nighttime and those that involve fatality or injury. The confidence envelope value was set to 99 times and the statistical significance at 0.01 level.

Figures 5(a)-(f), the road accidents in all groups showed a clear distribution pattern. When the observed K values were based on the expected K values and higher than the confidence envelope values, the road accidents were clustered and distributed in the distance range of less than 10,300-13,800 m. Clustered distributions of road accidents occurring on weekdays, weekends, daytime and nighttime and those involving a fatality or injury were at distances of less than 13,700, 13,400, 13,600, 13,500, 10,300 and 13,800 m, respectively.

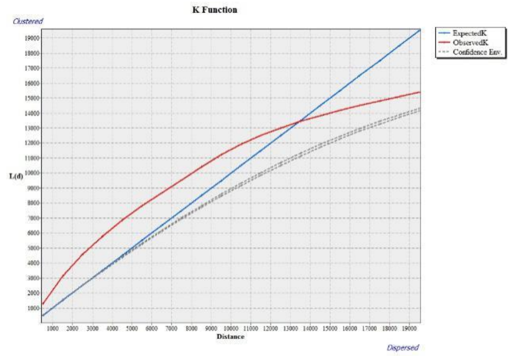
4. Conclusions

Road accidents are a major problem in many countries globally. One of the countries suffering the greatest impact of and damage caused by road accidents is Thailand. The characteristics, locations and periods of road accidents offer important information that can be used to solve and reduce the problems associated with road accidents. GIS tools have been employed to effectively study road accidents and in particular, the accident data that can be used to identify the location and time of the accident. This improves the accuracy and precision of studies. Sri Racha district in the Chon Buri province was chosen as the study area in this research because it is the economic center of transportation, industry and tourism. Furthermore, road accidents occur at an alarming rate within this area.

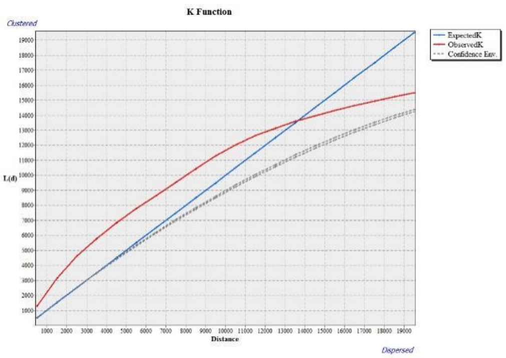
In this study, data were divided into ten spatiotemporal scales: accidents on weekdays, weekends, daytime and nighttime, accidents involving fatality and injury, fatality during daytime on weekdays and weekends and fatality during nighttime on weekdays and weekends. GIS was used for the analysis. First, KDE was used to analyze the density of the accidents. The corresponding results following three, important, high-density areas: Sri Racha municipality, Laem Chabang City municipality and Bowin subdistrict. Sri Racha municipality is the center of Sri Racha district; it is an important commercial area and has shops, hospitals, and government agencies. Laem Chabang City municipality is located at the Laem Chabang Port. Many shipping and logistics companies are located in the area. Bowin subdistrict is densely populated owing to its proximity to many large industrial estates. Second, Ripley's K-function was used to analyze the distribution of road accidents, revealing-the following three road accident distribution patterns: clustered, dispersed and random. The results demonstrated that the distribution pattern of each group was clustered in distances of less than 10.30-13.80 km.



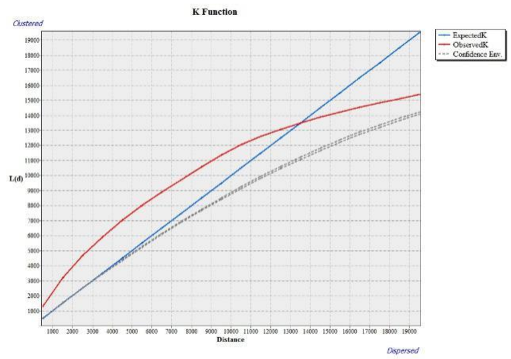
(a) weekdays



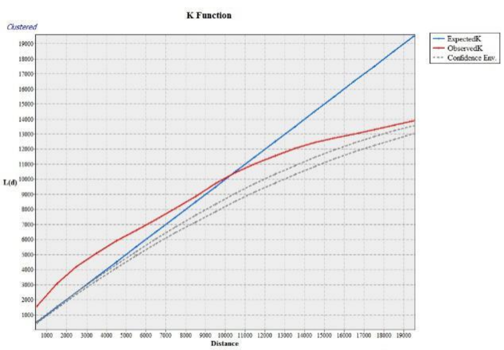
(b) weekends



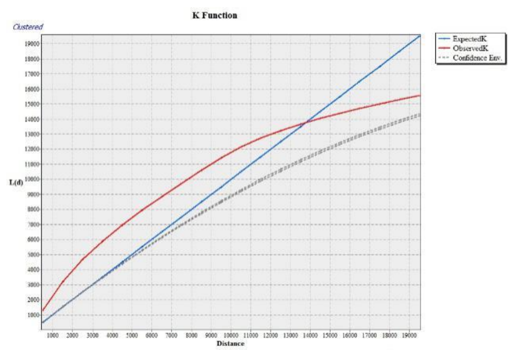
(c) daytime



(d) nighttime



(e) fatality



(f) injury

Figure 5. Ripley's K-function results for accidents: (a) occurring on weekdays, (b) weekends, (c) daytime and (d) nighttime, (e) involving fatality and (f) injury

The results of this research comprise important information that shows the trends, densities and distribution patterns of road accidents in the studied areas within each period of time. This information can be used for planning and setting measures to reduce road accidents. The accident information is categorized temporally as follows: accidents occurring on weekdays and weekends and during daytime and nighttime. Transport agencies and traffic police can use this information for monitoring accidents and increasing traffic safety during the aforementioned times.

The limitations of this research are as follows: first, the road accident data used for the study are only a part of insured accident data obtained from ThaiRSC, not all the accident data. Second, the published accident data lack important information such as the gender and age of the victims and causes of accidents. This important information could increase the integrity of this research. However, despite the aforementioned limitations, the finding of this research can be used to solve the problems associated with road accidents in Sri Racha district.

References

[1] Dereli, M.A. and Erdogan S., 2017. A new model for determining the traffic accident black spots using GIS-aided spatial statistical models. *Transport Research Part A*, 103, 106-107.

[2] Shafabakhsh, G., Famili, A. and Bahadori, M.S., 2017. GIS-based spatial analysis of urban traffic accidents: case study in Mashhad, Iran. *Journal of Traffic and Transport Engineering*, 4(3), 290-299.

[3] Anderson, T.K., 2009. Kernel density estimation and K-means clustering to profile road accident hotspots. *Accident Analysis and Prevention*, 41, 359-364.

[4] Indian Council of Medical Research (ICMR), 2009. Development of a feasibility module for road traffic injuries surveillance. *JCMR Bulletin*, 39(10-12), 41-50.

[5] Xie, Z. and Yan J., 2013. Detecting traffic accident clusters with network kernel density estimation and local spatial statistics: an integrated approach. *Journal of Transport Geography*, 31, 64-71.

[6] Satria, R. and Castro, M., 2016. GIS tools for analyzing accidents and road design: a review. *Transportation Research Procedia*, 18, 242-247.

[7] Soltani, A. and Askari, S., 2017. Exploring spatial autocorrelation of traffic crashes based on severity. *Injury*, 48, 637-647.

[8] Aghajania, M.A., Dezfoulian, R.S., Arjroodyb, A.R. and Rezaeid, M., 2017. Applying GIS to identify the spatial and temporal patterns of road accidents using spatial statistics (case study: Ilam province, Iran). *Transportation Research Procedia*, 25, 2126-2138.

[9] Prasannakumar, V., Vijitha, H., Charuthaa, R. and Geetha N., 2011. Spatio-temporal clustering of road accidents: GIS based analysis and assessment. *Procedia Social and Behavioral Sciences*, 21, 317-325.

[10] Rhee, K.A., Kim, J.K., Lee, Y.I. and Ulfarsson, G.F., 2016. Spatial regression analysis of traffic crashes in Seoul. *Accident Analysis and Prevention*, 91, 190-199.

[11] World Health Organization (WHO), 2018. *Road Traffic Deaths: Data by Country 2013*. [online] Available at: http://www.who.int/gho/road_safety/mortality/traffic_deaths_number/en/

[12] Road Accident Data Center (ThaiRSC), 2018. *Statistic of Injuries and Deaths All Provinces 2017*. [online] Available at: http://www.thairsc.com/

[13] Xu, C., Tarko, A.P., Wang, W. and Lui, P., 2013. Predicting crash likelihood and severity on freeways with real-time loop detector data. *Accident Analysis and Prevention*, 57, 30-39.

[14] Yu, R. and Abdel-Aty, M., 2014. Using hierarchical bayesian binary probit models to analyze crash injury severity on high speed facilities with real-time traffic data. *Accident Analysis and Prevention*, 62, 161-167.

[15] Zheng, Z., Ahn, S. and Monsere, C.M., 2010. Impact of traffic oscillations on freeway crash occurrences. *Accident Analysis and Prevention*, 42, 626-636.

[16] Li, L., Zhu, L. and Sui, D.Z., 2007. A GIS-based bayesian approach for analyzing spatial-temporal patterns of intra-city motor vehicle crashes. *Journal of Transport Geography*, 15, 274-285.

[17] Harirforoush, H. and Bellalite, L., 2019. A new integrated GIS-based analysis to detect hotspots: a case study of the city of Sherbrooke. *Accident Analysis and Prevention*, 130, 62-74.

[18] Yu, H., Liu, P., Chen, J. and Wang, H., 2014. Comparative Analysis of the spatial analysis methods for hotspot identification. *Accident Analysis and Prevention*, 66, 80-88.

[19] Ouni, F. and Belloumi, M., 2018. Spatio-temporal pattern of vulnerable road user's collisions hot spots and related risk factors for injury severity in Tunisia. *Transportation Research Part F*, 56, 477-495.

[20] Deepthi, J.K. and Ganeshkumar, B., 2010. Identification of accident hot spots: a GIS based implementation for Kannur district, Kerala. *International Journal of Geomatics and Geoscience*, 1(1), 51-59.

[21] Benedek, J., Ciobanub, S.M. and Man, T.C., 2016. Hotspots and social background of urban traffic crashes: A case study in Cluj-Napoca (Romania). *Accident Analysis and Prevention*, 87, 117-126.

[22] Mohaymany, A.S., Shahri, M. and Mirbagheri, B., 2013. GIS-based method for detecting high-crash-risk road segments using network kernel density estimation. *Journal Geo-Spatial Information Science*, 16(2), 113-119.

[23] Pulugurtha, S.S., Krishnakumar, V.K. and Nambisan, S.S., 2007. New methods to identify and rank high pedestrian crash zones: An illustration. *Accident Analysis and Prevention*, 39, 800-811.

[24] Plug, C., Xia, J.C. and Caulfield, C., 2011. Spatial and temporal visualisation techniques for crash analysis. *Accident Analysis and Prevention*, 43, 1937-1946.

[25] Bíl, M., Andrásik, R. and Janoska, Z., 2013. Identification of hazardous road locations of traffic accidents by means of kernel density estimation and cluster significance evaluation. *Accident Analysis and Prevention*, 55, 265-273.

[26] Hashimoto, S., Yoshiki, S., Saeki, R., Mimura, Y., Ando, R. and Nanba, S., 2016. Development and application of traffic accident density estimation models using dernel density estimation. *Journal of Traffic and Transportation Engineering*, 3(3), 262-270.

[27] Xie, Z. and Yan, J., 2008. Kernel density estimation of traffic accidents in a network space. *Computers, Environment and Urban Systems*, 32, 396-406.

[28] Matkan, A.A., Mohaymany, A.S., Mirbagheri, B., Shahri, M. and Mirzaie, M., 2012, Detecting the accident hazardious segments along Arakkhomein rural road using network kernel density estimation. *Proceeding of the International Geomatics Conference and Exhibition on Mapping and Spatial Information*, Tehran, Iran, May 7-9, 2012, 1-10.

[29] Delso, J., Martín, B. and Ortega, E., 2018. A new procedure using network analysis and kernel density estimations to evaluate the effect of urban configurations on pedestrian mobility. The case study of Vitoria-Gasteiz. *Journal of Transport Geography*, 67, 61-72.

[30] Ord, J.K. and Getis, A., 1995. Local spatial autocorrelation statistics: Distributional Issues and an Application. *Geographical Analysis*, 27(4), 286-306.

[31] Soltani, A. and Askari, S., 2017. Exploring spatial autocorrelation of traffic crashes based on severity. *Injury*, 48, 637-647.

[32] Thacher, D., Milne, S.B. and Park, R., 2017. Applying GIS and statistical analysis to assess the correlation of human behaviour and ephemeral architectural features among Palaeo-Eskimo sites on southern Baffin island, Nunavut. *Journal of Archaeological Science: Reports*, 14, 21-30.
[33] Keskina, F., Yenilmezb, F., Çolakc, M., Yavuzerc, I. and Düzgün, H.S., 2011. Analysis of traffic incidents in METU campus. *Procedia Social and Behavioral Sciences*, 19, 61-70.
[34] Department of Provincial Administration, 2018. *Statistic of Population and Residents in 2017*. [online] Available at: http://stat.dopa.go.th
[35] Fotheringham, A.S., Brunsdon, C. and Charlton, M., 2000. *Quantitative Geography: Perspectives on Spatial Data Analysis*. First ed. Sage: Thousand Oaks.
[36] Dixon, P.M., 2002. Ripley's K Function. In: El-Shaarawi A. H., Piegorsch W. W., ed. *Encyclopedia of Environmetrics*, pp.1796-1803.
[37] ESRI, 2019. Multi-distance spatial cluster analysis (Ripley's K-function). [online] Available at: http://desktop.arcgis.com