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# MAPPING ROAD ACCIDENT HOTSPOTS ON MALAYSIAN INTER URBAN EXPRESSWAYS: AN ANALYSIS ON SEVERITY LEVEL

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## Abstract

Road accidents can have a profound and often life-altering impact on the victims involved. Reducing severity due to road accidents is crucial even when the absolute numbers are relatively low. The problem at hand revolves around the need to ascertain the degree of accident severity at locations identified as hotspots, thus requiring focused interventions to improve road safety. This study aims to identify road accidents hotspots of an inter-urban expressway in Malaysia, and to determine the level of accident severity at locations identified as hotspots. This involves visualizing and analyzing the spatial distribution of road accident data to identify the hotspot locations of road accidents along the expressway. The study employed ArcGIS as a platform for data visualization and analysis. The evaluation of accident hotspots by accident severity level was conducted using Kernel Density Estimation (KDE). Learning from each incident and implementing changes can help prevent future accidents. Targeted safety measures and interventions to mitigate the risks associated with specific locations is crucial in reducing the likelihood and severity of accidents.

***Keywords***: road accident, hotspot, mapping, expressway, ArcGIS, KDE

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# INTRODUCTION

Road accidents are a significant issue in Malaysia, causing numerous deaths and injuries each year. Statistics showed that the number of road accidents in Malaysia has increased over a period of 10 years. According to the Department of Statistics Malaysia (2019), road traffic accidents ranked among the top five leading causes of death in Malaysia. The country's road safety situation has improved since then, but it remains a concern. In 2021, the number of road accidents in Malaysia was around 370 thousand, indicating a decrease compared to the previous year (Statista, 2023). The consequences from road accidents can vary widely depending on the severity of the accident, the type of injuries sustained, and the overall health and resilience of the individuals affected. Major key impacts involve the loss of human life, emotional and psychological disturbance, economic consequences, traumatic and some others.

Mapping road accident data is essential as it provides valuable insights that can contribute to improved road safety, urban planning, and public policy. By mapping accidents over geographical areas, patterns and trends can be analyzed. Mapping road traffic crash hotspots using Geographic Information System (GIS)-based methods is a common approach to identify high-risk locations for road accidents. GIS software is a useful tool for determining hotspots, as it can visualize accident locations (mapping) and run spatial analysis (Aldala'in, 2023). These locations, known as hotspots, can be referred to as hazardous road locations, high-risk locations, accident-prone locations, black spots, hot spots, hot zones, black zones, sites with promise, and priority investigation locations (Al-Aamri et al., 2021). Nogueira et al. (2023) applied various methods in GIS to obtain robust conclusions. Understanding where accidents occur most frequently helps in developing strategies to address specific challenges in those regions. One of the most widely used methods in GIS-based crash analysis is Kernel Density Estimation (KDE), which generates a continuous density surface from point-based accident data. KDE is particularly effective in identifying accident-prone zones (hotspots) by smoothing crash frequencies over space, thus allowing researchers to detect high-concentration areas along highways and urban corridors. In Malaysia, KDE has been applied to analyze accident distributions along the North–South Expressway and selected federal routes, revealing spatial clusters near interchanges, toll plazas, and high-traffic junctions (Manap et al., 2021; Shariff et al., 2018; Zahran et al., 2019). These findings align with international studies in countries such as Nigeria, Oman and Vietnam, where KDE has been used to map crash intensities and examine seasonal and demographic variations in accident occurrence (Afolayan et al., 2022; Alhajri et al., 2024 and Le et al., 2020).

As for the Malaysian expressways, although some of them have been given five-rating star through Malaysian Road Assessment Programme, accident statistics may vary from time to time (Nusa et al., 2025; Zahran et al., 2021). Monitoring the accident risk is crucial in order to maintain the status of expressways with good rating, as well as to improve road safety of Malaysian expressways in general. Expressways in Malaysia often experience high traffic volumes due to their role in connecting major cities and regions. The increased traffic can contribute to a higher likelihood of road accidents and studies demonstrated that expressway crashes are more strongly associated with high-speed segments and entry–exit ramps, while urban hotspots correlate with pedestrian activity and signalized intersections (Hisam et al., 2022; Amri et al., 2021). Such comparisons underscore the importance of context-specific spatial modeling when designing safety countermeasures.

Road accidents on expressways can result in fatalities, injuries, and damage to property. Fatalities are a significant concern, and efforts are made to reduce the number of lives lost on the roads. Examining spatial hotspots of accidents enables more effective implementation of remediation measures in these areas, potentially preventing future fatalities (Halim et al., 2017; Masron et al., 2018). Prioritizing prevention efforts can be further enhanced by comparing hotspots for all vehicle crashes to those specifically associated with fatal accidents. Even on straight expressways, understanding accident patterns is crucial for proactive safety measures, infrastructure improvements, and the overall goal of preventing accidents and promoting safer road environments.

Accident patterns can guide traffic engineering solutions on straight highways. To address this limitation, many studies incorporate spatial autocorrelation techniques such as Moran's I and Getis-Ord Gi* statistics. Moran's I evaluates global spatial autocorrelation to determine whether accidents are randomly distributed or spatially clustered, while Getis-Ord Gi* identifies statistically significant local hotspots and cold spots. In Malaysian regional analyses, these methods have been used to compare accident clustering across states such as Selangor, Johor, and Penang, demonstrating significant spatial concentration in highly urbanized and industrialized districts (Manap et al., 2019; Halim et al., 2017). Similarly, research in Pakistan and the United States has applied Moran's I and Gi* to validate hotspot locations along urban road networks and interstate highways, confirming persistent high-risk zones that warrant engineering interventions (Kamh et al., 2024; Zahran et al., 2019).

Another popular technique used in studying accident hotspot patterns is KDE. It is a valuable tool for visualizing road accidents across the spatial domain (Srikanth & Srikanth, 2020). It offers insights into the spatial distribution of accidents and helps identify areas with higher or lower accident density. KDE uses statistical techniques in estimating the probability density function. Many studies use planar KDE for hot spot analysis such as the study of road and highway accident hotspots (Anderson, 2009; Erdogan et al., 2008). A point analysis method utilizing kernel density estimators has been employed by Waldon et al. (2018) and Chen et al. (2018) in the occurrence of hotspots in road traffic accidents. Hence, this study aims to utilise Kernel Density Estimation (KDE) to identify spatial accident hotspots along the expressway and analyse their association with location-specific factors. By highlighting areas with a higher concentration of accidents, the study provides evidence-based insights to assist relevant authorities in implementing targeted safety interventions and optimising the allocation of traffic management and enforcement resources.

## RESEARCH METHODOLOGY

### Study Area

This study focuses on an inter-urban expressway in Klang Valley, which is Shah Alam Expressway (also known as E5). This expressway is the third east–west-oriented expressway after the Federal Highway and New Klang Valley Expressway and it is part of the Kuala Lumpur Middle Ring Road 2 Scheme from Sunway Interchange to Sri Petaling Interchange. As a bustling expressway, it links the primary industrial and residential zones within the Klang Valley and has been a popular travelling mode due to its high accessibility to a wide range of highway networks within the Klang Valley.

### Study Flow

The general approach of this study underwent four steps. The flow of study process is presented in Figure 1. The process begins with data collection, followed by data preparation, data visualization, and ends with data analysis.

#### *Data collection*

The first step for the study is data collection. This study involves secondary data acquired from the highway authority, KESAS Sdn. Bhd. The daily road accident data for Shah Alam Expressway of five consecutive years from 2013 to 2017 was investigated. The accident dataset encompasses several information such as the accident location, date and time of accident occurrence, type of vehicles involved, collision type, causal factors, weather condition, and the severity type resulted from the accident.

#### *Data preparation*

The second step in this study involves data preparation. In this step, the accident dataset was organized into Microsoft Excel spreadsheet, and missing data were observed and discarded. Missing data are the absence of data that arise for various reasons, such as incomplete data collection or technical issues during data recording. Addressing missing data is crucial in statistical analysis and research, as it can impact the accuracy and reliability of findings. The locations of the road accidents in the dataset were recorded in the form of KM marker (Jalil et al., 2023). Preparation of data from KM marker to longitude and latitude coordinates was done with the help of Google Earth Pro. This was done by pinpointing each KM marker on the map of study area. At this point, the longitude and latitude coordinates were observed and recorded.

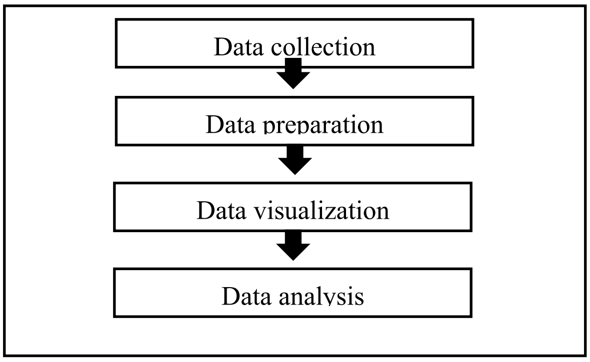


**Figure 1.** Process of study flow

***Data visualization***
The third step in the study flow involves data visualization. This study utilized Geographic Information System (GIS) application, namely ArcGIS for data visualization and analysis. For data visualization, the process is done by employing heat map symbology within ArcGIS.

***Data Analysis***
The final step in the study process is the data analysis using Kernel Density Estimation (KDE), In KDE, the crucial factor in determining the optimal density surface is the selection of both the cell size and bandwidth. The decision on bandwidth significantly influences the identification of hotspots and subsequently affects the overall results. The selection of suitable values for these parameters is both critical and subjective. The general equation for density estimation of KDE is given in equation (1).

$$f(s) = \frac{1}{nh} \sum_{i=1}^{n} \frac{K(s - s_i)}{h} \tag{1}$$

In this context, $f(s)$ is the density estimate at location $s$, $n$ denotes the total number of locations, $h$ signifies the smoothing parameter known as the bandwidth, $K$ stands for the kernel function, and $(s - s_i)$ represents the distance between the location of $i$th observation and the location of $s$.

## ANALYSIS AND DISCUSSION

### Data description

Accidents can happen anywhere on the expressway whether on monotonous straight road, curves, or intersections. Shah Alam expressway is an expressway that connects the east and west of the Klang Valley. The eastbound route spans from Pandamaran to Sri Petaling, whereas the westbound route traverses in the opposite direction. The expressway, which is straight and extends over a considerable distance, covers a total length of 34.5 kilometres and includes 15 interchanges along its route. Figure 2 illustrates the yearly breakdown of total accidents at Shah Alam expressway. From 2013 to 2017, the expressway has recorded a total of 2,823 road accidents. The peak occurred in 2013, with 728 reported accidents along both east and west bounds of the expressway. Subsequent to that, in 2014 and 2015, there was a decrease of approximately 30% compared to the year 2013. However, there was a relative increase in 2016 and 2017 with 570 and 536 cases respectively.

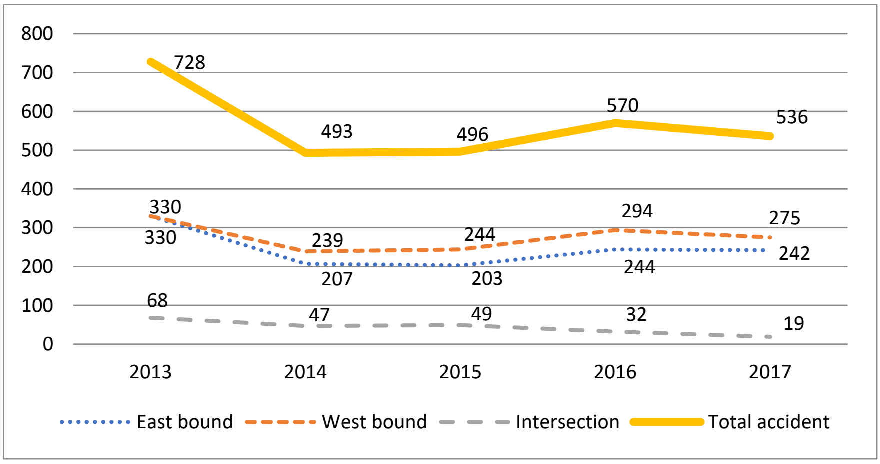


**Figure 2.** Number of accidents by expressway's route

From Figure 2, it is observed that the eastbound route followed a comparable trend to the overall road accident pattern, and similarly, the westbound route exhibited a quite similar trend to the total road accidents. Nevertheless, intersections displayed a distinct trend compared to the overall road accidents during the five-year period. In summary, a relatively similar pattern can be observed between the eastbound and westbound directions, but this does not hold true for intersections.

Figure 3 displays the breakdown of number of accidents according to the level of accident severity at each route. This breakdown is represented yearly, from 2013 to 2017. It is observed that most accidents that occurred at Shah Alam expressway did not involve any injury to road users. A total of 1748 accidents was recorded for non-injury in five years. Although no injuries are sustained by individuals involved, there is still damage to vehicles or property. These accidents are considered less severe in terms of human impact but still involve financial costs for repairs. The impact of road accidents varies significantly depending on the severity of injuries incurred. From 2013 to 2017, there were a total of 161 accidents associated with severe injuries and 816 accidents related to light injuries. The physical impact from severe injuries and light injuries can lead to long-term consequences and disabilities or can also cause minor harm. Regardless of whether there are severe or light injuries, there may still be psychological effects such as stress, anxiety, or a fear of driving. In other context, fatal injuries have a profound impact on families and communities. The loss of a loved one is emotionally devastating, and it can have long-lasting effects on the mental and emotional well-being of those affected. The data on road accidents along the Shah Alam Expressway indicates a total of 98 fatal accidents over the five-year period from 2013 to 2017. This number is the lowest among the other severity levels. However, it leaves the most devastating impact on family members and communities.

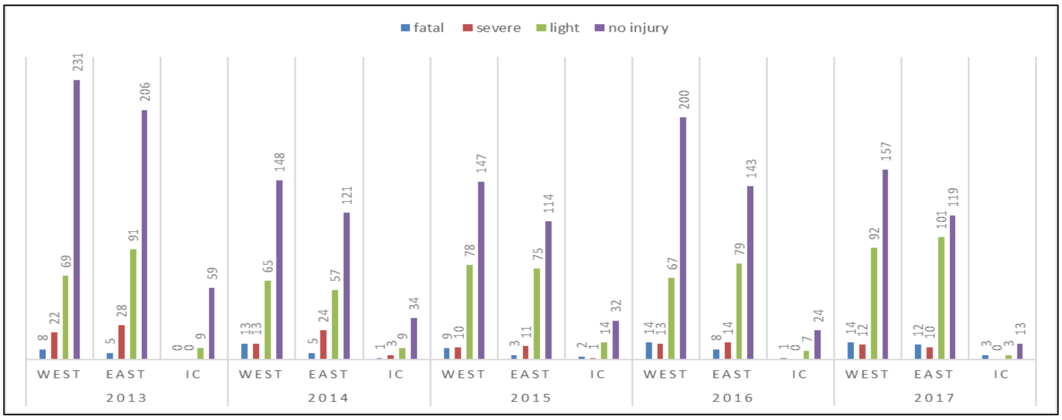


**Figure 3.** Accident severity level by route

**Mapping of overall accident data**

The first step taken in the mapping process is to identify the overall accident pattern for Shah Alam expressway regardless of accident severity. This is done by filtering the accident dataset into west bound and east bound. A heatmap in ArcGIS is used for visualizing the data. It is a spatial data visualization technique that uses a continuous colour gradient to represent the density or intensity of a phenomenon across a geographic area. When applied to road accident data, a heatmap reveals the spatial distribution of accidents and highlight areas with higher concentrations of incidents. The intensity of the heat at a specific location reflects the concentration of accidents. Hotspots, where accidents are more frequent, appear as areas with more concentrated and intense heat on the map. Figure 4a and Figure 4b represent the heatmaps of overall accidents from 2013 to 2017 along the west bound and east bound respectively. Based on the colour gradient in each heat map, higher accident densities are represented with yellow, while lower densities are represented with blue. From Figure 4a, two locations with the highest concentration and intensity are found for west bound. These are locations where accidents occurred more frequent, known as hotspots. For east bound, it is found that three locations along the expressway having the highest concentration and intensity as shown in Figure 4b. Scrutinizing the hotspots indicates that all the hotspots are nearing the toll plazas in both directions. This result is consistent with Jing et al., 2019, Xing et al., 2023.

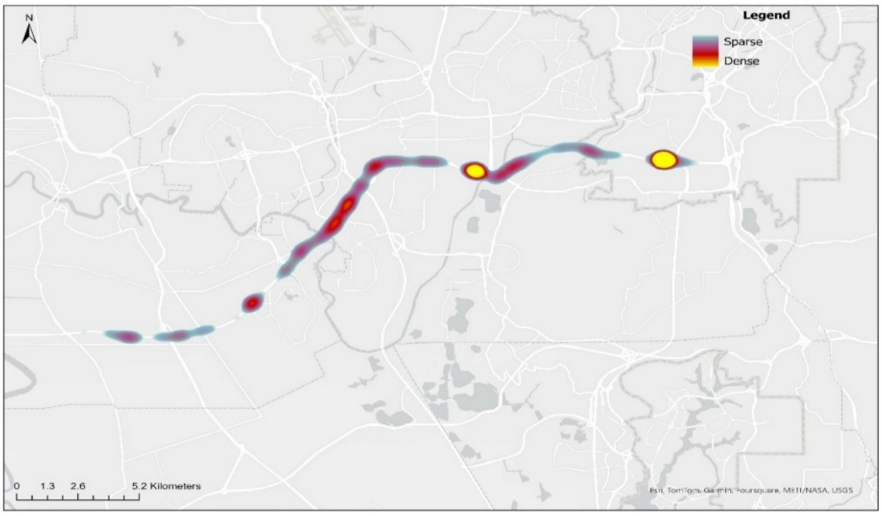


**Figure 4a.** Heatmap of overall accident count for west bound


**Figure 4b.** Heatmap of overall accident count for east bound

## Mapping of overall accident count using KDE

Mapping using KDE involves creating a visual representation of the spatial distribution and intensity of road accident, and its process results in a continuous surface representing the estimated density of road accidents across the study area. This surface is generated based on the concentration of accidents, with areas of higher density depicted by more intense colours. For this study, a default cell size and bandwidth have been employed for estimating the kernel density. In this context, ArcGIS selects the optimal values for the cell size and bandwidth using internal heuristics that consider the spatial dispersion and number of input points (Zheng et al., 2024). This ensures computational efficiency and avoids arbitrary parameter selection. Figure 5a represents the spatial distribution of road accidents along Shah Alam expressway for west bound, while Figure 5b represents the spatial distribution of the accidents for east bound. The results from KDE indicate the same accident hotspots as seen in the heatmaps, where two accident hotspots are found for west bound and three hotspots for east bound are observed. The hotspots for west bound are located at KM49.0–KM49.4 and KM40.5–KM40.9, while the hotspots for east bound are located at KM40.5–KM40.9, followed by KM47.5–KM47.9 and KM27.0–KM27.5. Note that the locations are arranged according to colour intensity across the hotspots. Note that the number and locations of identified hotspots are consistent with the earlier mapping technique.

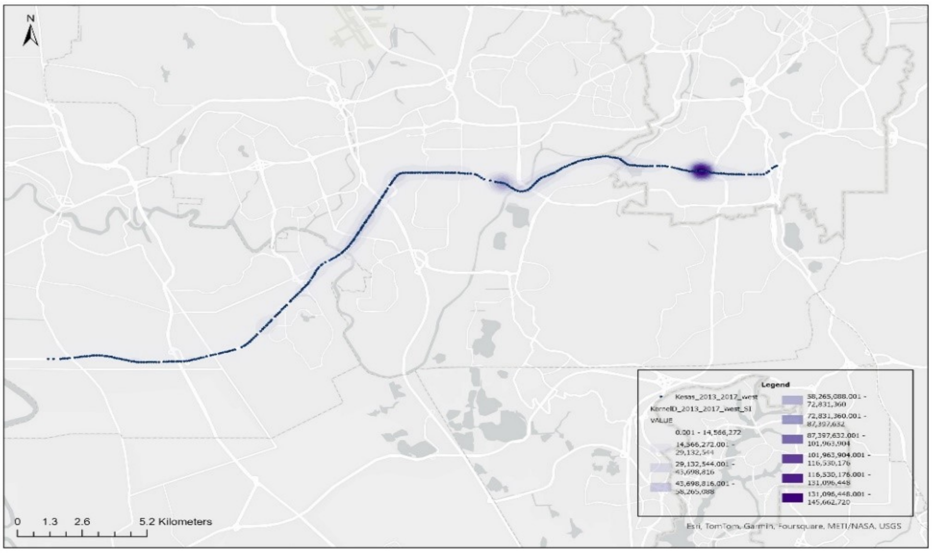


**Figure 5a.** Accident distribution for west bound using KDE

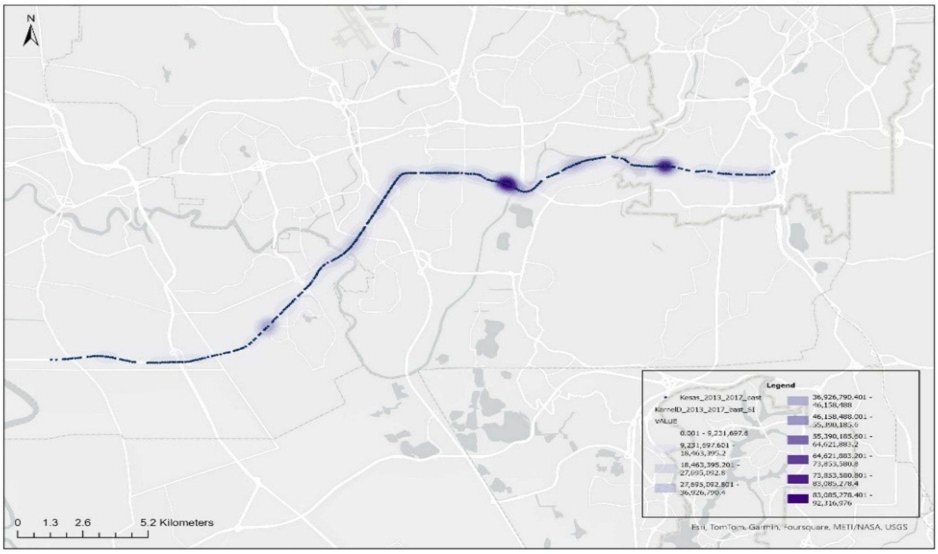


**Figure 5b.** Accident distribution for west bound using KDE

To test whether there is an association between the number of accidents and traffic directions, a Chi-square test at $\alpha = 0.05$ was done. Table 1 summarises the accident counts at each segment and its calculated expected frequencies.

Test Statistic, $\chi^2 = \sum \frac{(O-E)^2}{E}$

where (2)

$O$ = observed frequency

$E$ = expected frequency

**Table 1:** Frequency Table & Expected Frequencies

| Segment (KM) | West | East | Row Total |
|---|---|---|---|
| 27.0–27.4 | 42 (56.81)<br>***3.86*** | 70 (55.19)<br>***3.97*** | 112 |
| 40.5–40.9 | 65 (75.57)<br>***1.47*** | 84 (73.43)<br>***1.51*** | 149 |
| 47.5–47.9 | 9 (40.07)<br>***24.12*** | 70 (38.93)<br>***24.83*** | 79 |
| 49.0–49.4 | 129 (74.55)<br>***41.55*** | 15 (72.45)<br>***42.73*** | 147 |
| **Column Total** | **247** | **240** | **487** |

*Note: in brackets (expected frequencies), in italic (Chi-Square values)*

The Expected Frequencies were calculated as follows:

Example calculation for KM27.0 – KM27.4 (West): $E = \frac{112 \times 247}{487} = 56.81$

Example calculation for KM27.0 – KM27.4 (East): $E = \frac{112 \times 240}{487} = 55.19$

Note that all the expected counts > 5, so the Chi-square assumption is satisfied.

From Table 1, the total Chi Square value was calculated to be $\chi^2 = 144.04$ and at degrees of freedom=3, the critical value is $\chi^2_{0.05,3} = 7.815$. Since, $\chi^2_{calculated} > \chi^2_{critical}$ = (144.04 > 7.815), which is significantly greater than the critical value of 7.815 at α = 0.05, the null hypothesis of independence is rejected. In conclusion, there is a statistically significant association between accident counts and traffic direction (East vs West). This indicates that the distribution of accidents differs significantly between Eastbound and Westbound directions, suggesting that traffic direction may influence accident occurrence at the observed locations. This could indicate location-specific safety issues or geometric road differences that may require further investigation.

**Mapping accidents severity on KDE**

Accident severity is a crucial metric in assessing the overall impact of incidents, and it is commonly used in the perspective of various domains, including road safety. This section aims to identify whether the hotspot locations as found in the previous section, exhibit a tendency for more severe accidents, while neighbouring areas may witness incidents of a milder nature.

In this process, accident severity level has been selected to be parameters for visualization. Different color-coded markers as well as the sizes of markers in symbology have been chosen for different accident severities, representing the number of accidents at KM markers on the expressway. The layer of severity levels in ArcGIS was overlayed with the kernel density layer in ArcGIS. By overlaying the kernel density layer with severity layer, the spatial patterns, relationships, and context surrounding the density of accidents can be explored. The results from this process are shown in Figure 6a for west bound and Figure 6b for east bound. It is seen that at the hotspot location of KM40.5–KM40.9 for west bound, accidents occurrence involved severe and minor injuries, and no fatal accident is observed. On the other hand, there is also no fatal accident at KM49.0–KM49.4 while other severities involved. However, it is observed that there is one fatal accident in close proximity to the hotspot location. The possibility of a road accident can occur in proximity to a specific location depends on various factors. It may be influenced by the dynamic interactions of drivers, road conditions, and the environment. For east bound, a single fatal accident is observed between KM40.5 and KM40.9, with other forms of severity resulting from road accidents at all hotspot locations.

 

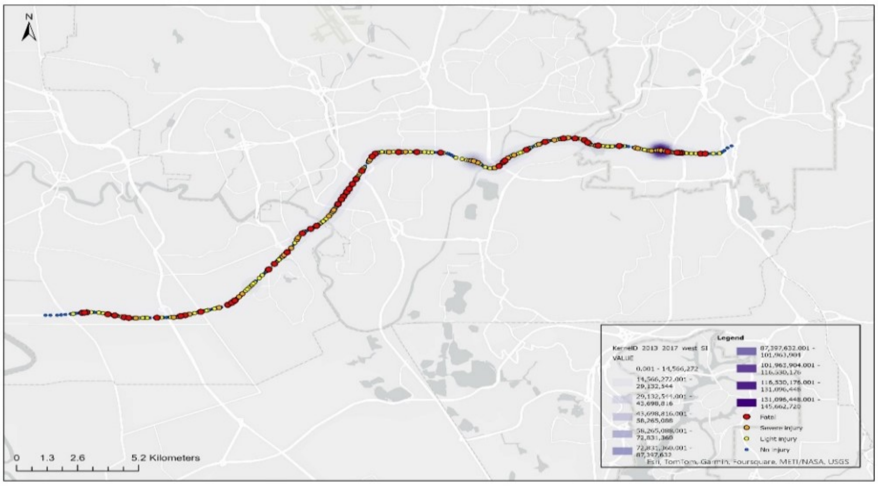


**Figure 6a.** Layer combination of KDE and severity level for west bound

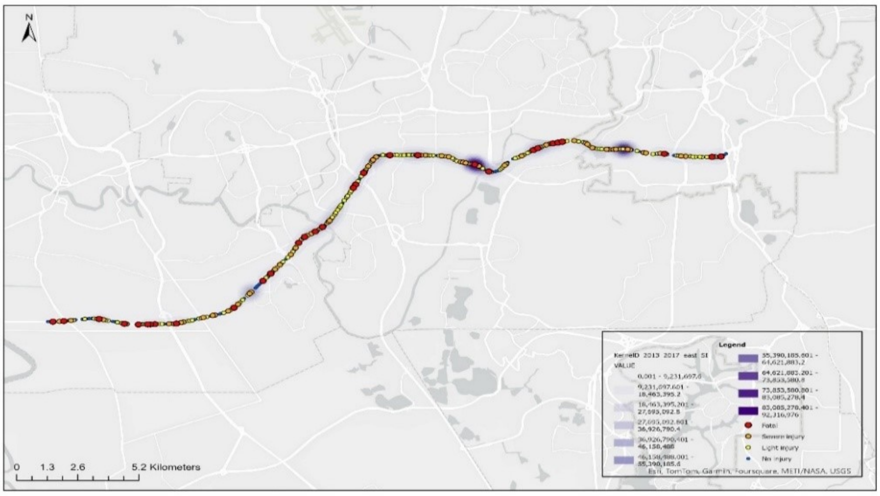


**Figure 6b.** Layer combination of KDE and severity level for east bound

The test was also run for severity cases and shows that there is no statistically significant association between accident severity counts and location (West vs East) at the 5% significance level. However, due to the small number of severity cases within individual kilometre segments, the Chi-square assumptions are not fully satisfied. Therefore, the association between severity occurrence and location should be interpreted cautiously, and alternative exact tests or aggregated segments may provide more reliable inference.

## CONCLUSION

Visualizing road accidents using maps is a powerful way to analyze and communicate spatial patterns of the data. Both the heat map and KDE help in visualizing the distribution of road accident data across the study area. This study successfully identified spatial accident hotspots along the study corridor between 2013 and 2017, revealing two hotspot segments along the westbound direction and three along the eastbound direction. The analysis highlights that KM49.0–KM49.4 and KM40.5–KM40.9 represent critical accident-prone segments in the westbound direction, while KM40.5–KM40.9, KM47.5–KM47.9, and KM27.0–KM27.4 were identified as key hotspots in the eastbound direction. Among these, KM40.5–KM40.9 is of particular concern as it consistently recorded high accident occurrences in both travel directions, indicating the need for immediate attention from highway operators and local authorities.

Although fatal accidents were relatively limited within the identified hotspots, the presence of severe and minor injury accidents indicates that these segments pose notable safety risks. The occurrence of a fatal accident in close proximity to the hotspot area further underscores the importance of proactive safety interventions. Road accident occurrences are influenced by a complex interaction of driver behaviour, roadway characteristics, traffic flow conditions, and environmental factors. Therefore, hotspot identification provides an important evidence-based approach for understanding spatial risk patterns along highway corridors.

The findings also offer valuable insights for transportation planners, highway authorities, and local governments to prioritise safety improvements at critical locations. Targeted interventions such as improved road geometry, enhanced signage and lighting, traffic calming measures, and better enforcement strategies can be strategically implemented at the identified hotspots. Integrating accident hotspot analysis into road safety planning can also support more efficient allocation of resources and guide future infrastructure upgrades. In the context of sustainable transportation planning, continuous monitoring of accident patterns using spatial analysis techniques is essential for strengthening road safety management. Future studies may further integrate traffic volume data, roadway design characteristics, and behavioural factors to better understand the underlying causes of accidents. Such efforts will contribute to more comprehensive and proactive road safety planning, ultimately supporting safer and more resilient transportation systems.

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