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To cite this article: Raghad Zeki Abdul Majeed and Dr Hussein A. Ewadh 2020 *IOP Conf. Ser.: Mater. Sci. Eng.* **671** 012092

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Spatial Analyses of Traffic Conflicts to Assess Safety at Signalised Intersections

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Abstract. Safety improvements at intersections play an important role in reducing the number and severity of crashes in roadway networks, as such locations are associated with high numbers of crashes. This paper presents an approach to assessing traffic safety at intersections by using GIS software tools to achieve spatial analyses of traffic conflicts data to enable the identification and ranking of intersections by risk instead of using crash data. Traffic conflict data were collected for nine four-legged signalized intersections in Baghdad city, Iraq through site-based observations in 2017, and archived crash data for three years obtained to conduct a comparison. Kernel density estimation was used as a spatial analysis tool in ArcGIS software to estimate conflict intensity at each location, and an Intersection Prediction Conflict Index (IPCI) used to represent the ratio of the proportion of conflicts events occurring within the identified hazard locations (hotspots within intersections) to the area covered. The results showed that the developed approach, based on the spatial properties of traffic conflict events, is efficient and reliable in terms of identifying potential hot spots and ranking sites as compared with observed crash frequency. This approach can thus be used as a tool to support effective decision making about improvements in safety at signalised intersections.

1.Introduction

Due to the limitations or unavailability of crash data, road safety analysts can strongly benefit from reliable analysis methods that utilise observable non-crash traffic events [1]. The Traffic Conflict Technique (TCT) is one form of non-crash-based analyses that can be used to measure and assess traffic safety conditions. Assessing traffic conflict as a Surrogate Safety Measure (SSM) has the advantages compared to crash-based analysis of being both pro-active and, in some conditions, more time-efficient, informative, and accurate [2]. In addition, examining traffic conflicts can directly record the occurrence of unsafe events (frequencies, where they occur, and their severity), not only offering a faster way to measure safety but also developing a more characteristic method of estimating the expected frequency and occurrence of crashes.

The use of real data and Arc GIS software tools is now considered an effective method of conducting spatial analyses of traffic crashes, including spatial analyses of point objects representing locations of crash occurrences clustered in specific areas, given the existence of particular environmental features such as vertical and horizontal curves on roadway segments. The kernel density method (Kernel Density Estimation (KDE)) as used in traffic safety applications represents the density of incidents in a certain neighbourhood-around those incidents. KDE thus enables the extraction and visualisation of event density within a specific area or within a road network [3]. Spatial analysis based on KDE thus gives decision makers an innovative overview of the problems within a



location and makes them more aware of dangerous areas, allowing them to adopt treatments before crashes occur. However, most previous studies are based on previous crash data subject to spatial analysis to predict hotspot areas.

The main objective of this study is thus to conduct spatial analyses for traffic conflict data to develop an Intersection Prediction Conflict Index (IPCI) that can act as a safety measure, based on spatial analyses of two surrogate safety indicators (evasive actions-based traffic conflict and temporal proximity-based traffic conflict). Further, this paper offers a first attempt at developing a method to measure safety at signalised intersections based on spatial density estimation of traffic conflict data by using tools within Arc GIS software to profile potential crash hotspots.

2. Traffic conflict definition

According to operational definitions of traffic conflict, it is possible to group them into two types: evasive actions-based traffic conflict and temporal (and/or spatial) proximity-based traffic conflict. Parker and Zegeer defined evasive actions-based traffic conflict as "... an event involving two or more road users, in which the action of one user causes the other user to make an evasive maneuver to avoid a collision" [4]. Hence, determining conflict according to that definition requires considerable judgment with regard to the conflict situation. Further, this definition infers that conflicts and crashes would automatically be of similar natures without the presence and the success of evasive action. In a proximity-based traffic conflict, the critical events are recognised depending on temporal (and/or spatial) proximity, creating "...an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged" [5]. The most common temporal proximity indicator family is Time-To-Collision (TTC) [6]. Specifically, a conflict is defined to be serious (severe) if the TTC value is equal to or less than threshold of 1.5 sec. However, the threshold values have varied in other studies from 1.0 to 5.0 sec.

3. Traffic conflict as a surrogate measure of safety

SSM aims to complement crash history analysis or to serve as an alternative in cases with no crash history. The expression "surrogate" represents measures that do not depend on historical crash data, but which depend on unsafe events (non-crash events), thus acting as a complement or an alternative to crash record-based analyses [7, 8]. Many factors and different techniques have been proposed for use as surrogate safety measures, such as volume, speed, delay, accepted gaps, headways, and deceleration-to-safety time. One widely used surrogate measure for traffic safety is the TCT which is focused on observing traffic conflicts [9, 10]. The basic theory behind the use of conflict to study road traffic safety is the assumption that a relationship exists between the severity and the frequency of different events in traffic [11].

4. Spatial analysis of traffic safety

Common approaches to identifying high-risk locations are not robust enough to reflect the underlying conditions of unsafe events that increase the probability of crashes, as they neglect the spatial properties of those events [3]. Hotspot mapping has become a popular analytical technique used by road safety analysts, visually identifying where crash numbers tend to be highest; such crash danger mappings could be useful to planners and engineers in terms of decision making for developing road traffic safety, yet to significantly reduce the number of crashes, it is necessary to understand where traffic crashes occur (i.e., high-risk locations) and why. A review of past studies shows that traffic crashes rarely occur randomly in space-time and that they tend mostly to cluster in specific areas. This depends on several factors, including measure of exposure (usually measured by traffic volume), and environmental characteristics such as weather (snow, rain, fog, and wind) and geometry of design (sharp turns, steep slopes) [12].

Point Pattern Analysis (PPA) represents a spatial analysis of point events; this method can be classified into two broad categories [13, 14]: measures investigating first-order (density-based methods) effects of a spatial process, and measures investigating second-order (distance-based methods) effects of a spatial process. The first category concentrates on the fundamental

characteristics of point events and measures the variation in the mean values of the process. Kernel density and quadrant count analysis are examples of such measures used to estimate the level of density for events. The second category of these measures deals with spatial dependency, with nearest neighbour statistics, the K function, and Moran's I offering examples of these measures. Of these two groups of measures, kernel density is one of the most popular methods for analysis, with the first report using Kernel Density Estimation (KDE) for safety analyses being achieved by Banos and Huguenin-Richard [15], who distributed crash data for pedestrians by applying KDE. Numerous researchers have now recognised spatial clusters of unsafe events (crashes, crimes, etc.) by using KDE [16-18].

In Turkey, Erdogan et al. studied the risk locations of crashes to reveal safety deficient areas on the highways in the city of Afyon, [19]. Repeatability and KDE analysis were performed to investigate high-risk crash locations, and the results of both methods identified much the same sites as high-risk locations, with most of them located at junction points, crossroads, and access roads to the towns and villages.

5. Study sites

For the purpose of the current study, a group of nine four-legged signalised intersections in an urban area of the Baghdad were used. Figure 1 shows the locations and names of the study intersections.

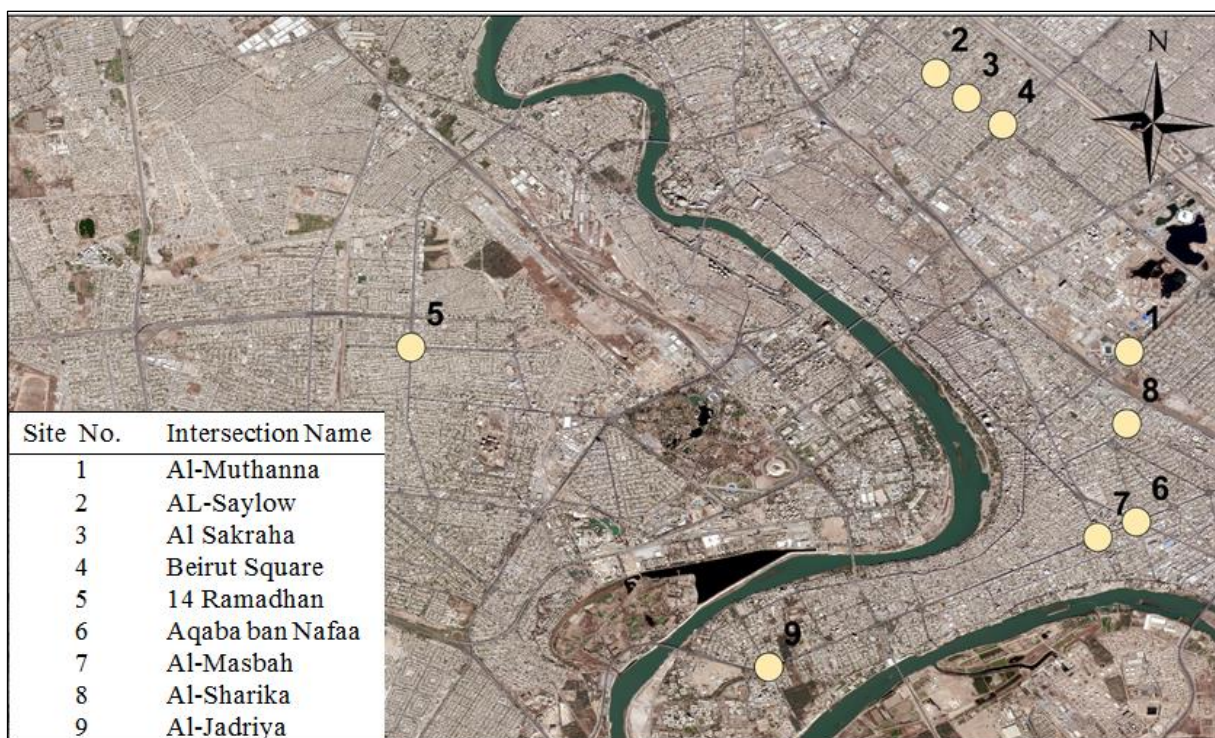


Figure.1 Map of selected sites

6. Data collection

6.1 Geometric data

The geometric data for this study was collected from the field for each site for use in conjunction with maps obtained in a scale of 1/500 from the Survey Department of the Design Directorate of the Mayorality of Baghdad. These maps are plotted according to the metric geographic coordinates provided by the Mayorality of Baghdad, and them very valuable for matching with the satellite imagery of Baghdad available in the Arc GIS-Arc-map document repository. Figure 2 shows an example of the base map for the Aqaba ban Nafaa intersection (site No.6).

The area of each intersection was divided into a grid of cells of 3m by 3m in order to more accurately identify the conflict points; each conflict noted from video recording was assigned its

position on the map survey of a site using Arc Map software, generating an x and y coordinate for each conflict point.

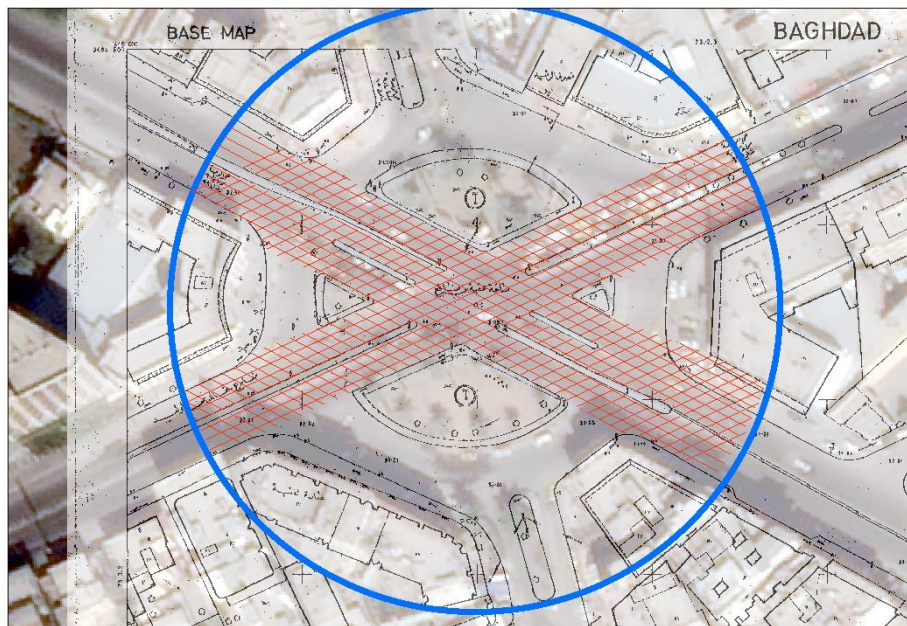


Figure2. Base map for site No. 6 with satellite image of Baghdad city

6.2 Crash data

Crash data were collected for three years from 2015 to 2017 inclusive for the nine sites. According to the crash data, 143 crashes occurred in the nine sites during these three years. Crash data in this study represented crashes between vehicles only, however.

6.3 Traffic conflict data

Conflict data were collected with the help of video recording equipment. In this study, conflict data was observed for 20 minutes per hour from 16 hours of video recordings; the total duration of conflict observation used in this study was thus 5 hours and 20 minutes for each intersection. These periods fulfilled the requirements reported by Glauz and Migletz that the minimum number of hours needed to estimate mean hourly count for major conflict data for signalised intersection should not be less than 3 hours and 25 minutes per each site [20]. Two surrogate safety indicators of conflict measures were collected: total traffic conflict frequency, based on evasive actions and serious conflict frequency based on temporal proximity. Traffic conflict frequency was identified based on the definition introduced by Parker and Zegeer, while serious conflict frequency was identified based on the definitions introduced by Amundsen and Hyden, using 1.5 sec as the threshold value for TTC. Further, in this study, Hourly Traffic Conflict (HTC) was used to represent the total conflict frequency, based on evasive actions at a site divided by observation hours. Similarly, Hourly Serious Conflict (HSC) represents the number of serious conflicts frequency (temporal proximity-based traffic conflicts with TTC less than or equal to 1.5 sec) at each site, divided by observation hours.

In order to deal with the clustering technique at intersections, 665 points for HTC and 285 points for HSC were identified as conflict points (spatial locations of predicted trajectories for two or more vehicles, known as Potential Points Of Collision (PPOC)). Each PPOC observed from the video recordings was assigned a position according to its geographic location within the intersection area using Arc-map software. Table 1 presents the number of PPOCs of the two measures of conflicts for each site; attribute data for each PPOC consists of location and hourly frequency for each site.

Table1. Number of PPOC for HTC and HSC

Site No.	PPOC-HTC	PPOC-HSC
1	77	33
2	73	31
3	71	29
4	75	35
5	95	31
6	76	30
7	62	31
8	66	28
9	70	37

7. Density-based method for spatial analysis of traffic conflict

The spatial analysis included a set of methods to describe and model the spatial data. This research used ArcGIS 10.4.1 software as a tool for such spatial analyses and to identify the density level of non-crash events.

Spatial analyses based on the density of data were conducted to estimate how traffic conflict intensity varied across the area of intersections. Kernel density estimation (KDE) was the spatial-analysis tool in ArcGIS used for that purpose. The kernel density around each point at which the indicator is observed refers to a circular area (the Kernel) of defined bandwidth. According to some appropriate function, this takes the value of the indicator at that point and spreads it into a surface of density estimates by summing all values of indicators at all places, taking in account those at which no happenings were recorded for the variable [21]. In KDE, identifying high-density areas aids in the classifying of areas as significantly different from others. Hence, the critical places identified and targeted can be studied and investigated for any purpose. In this study, the density values depicted the magnitude or intensity of conflict frequency and severity separately in nine intersections. The high-density values thus represented those locations which are hotspots for potential crashes due to unsafe and critical events, allowing authorities to study and investigate these. KDE is used extensively in analyses of unsafe events such as crimes and crashes [22], as the main benefit of KDE lies in its recognition of the risk spread of an event [18]. The spread of danger can be defined as the zone or area around a defined cluster in which there is an increased probability for an event to happen based on spatial dependency.

In this study, the estimated results were obtained according to kernel density analyses for HTC and HSC to develop a quantitative measure of risk level reflecting the magnitude of the potential crashes that could occur due to unsafe events in those sites based on traffic conflicts. Thus, areas (at intersections) with a larger values indicate that there is a higher chance of crashes happening there than those with lower values. Risk level for intersection areas was classified into five different levels using an equal interval classification method. Thus, the entire set of estimated grid cells (ordered with respect to their estimated values) was divided into five groups ranging from very low to very high according to kernel density analyses. Those in the top-most level (i.e., level 5), representing the most disaster-prone intersections were selected as hotspots, as shown in Table 2.

Bandwidth is important to estimating the most suitable density levels [13, 21], as selecting bandwidth affects the output of hotspots. Typically, a tight bandwidth interval will lead to a finer mesh density estimate with all peaks and valleys detected, while a larger bandwidth interval will lead to a smoother distribution and the appearance of hotspot areas in a larger form, which may affect the result.

Table2. Classification of kernel density levels of areas of intersections

Density level	Type of area within site	Colour For each Level
1	Very low: not disaster -prone	
2	Low: barely disaster-prone	
3	Average: not very disaster-prone	
4	High: disaster-prone	
5	Very high: disaster -prone	

In this study, an iterative approach was applied to selecting appropriate bandwidth, by testing the results of KDE in which the bandwidth was 5, 10, 15, and 20 m. The results from the iterative approach showed that the bandwidth of 20 m overestimated clustering of traffic conflicts, while the 5 m bandwidth showed an excessively sharp density for clustering of conflicts. Thus, a bandwidth of 10 meter in KDE was found to give an acceptable result for all sites, being more accurately than the 15 and 20 m selections and less sharp in terms of density level than the 5 m bandwidth.

7.1 Results of Kernel Density Estimation of the study sites

The results of KDE for traffic conflicts for site No 1 for two measures of conflicts (HTC and HSC) are been depicted in Figures 3 and 4 respectively. Similar KDE results for traffic conflicts for other study sites (site 2 to site 9) are illustrated in Appendix A. The results are presented in the form of maps (raster), with the estimated densities placed into coloured categories as laid out in Table 2; thus, the most unsafe areas can be seen clearly in red. The spatial analyses for conflict data by kernel density revealed the following:

- 1-Most of the very high density level for risk conflict (very high: disaster-prone) are located at an axis of a major street, with the highest intensity located at the ends of legs of intersections (entrances and exits of intersection), where higher levels of traffic interactions occur that generate more safety problems.
- 2-Most of the very high density levels for risk conflict (very high: disaster-prone) are located near those lanes used for left-turn and U-turn movements or in the portions of intersections used for merging rightward movements with traffic exiting from an intersection.
3. Kernel density analysis showed convergent results in terms of identifying high-risk areas for both measures of conflicts (HTC and HSC). However, the high unsafe-prone zones produced by analyses of HSC are more concentrated in terms of location of high-risk areas.
- 4- The percentage of similarity in results between the two measures of conflicts for identification of very high risk disaster-prone zones is about 77 %.



Figure 3. Kernel Density Estimation of HSC in site No.1 (Al Muthana Int.)

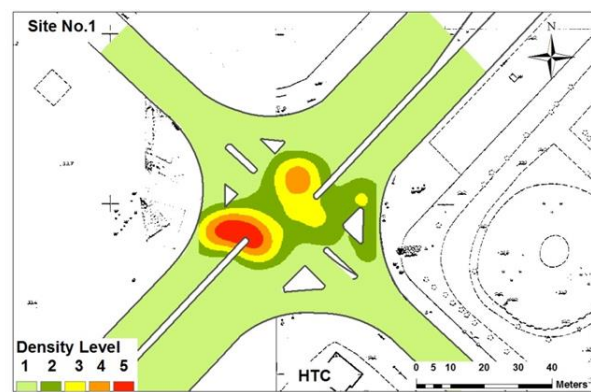


Figure 4. Kernel Density Estimation of HTC in site No.1 (Al Muthana Int.)

8. Developing the Intersection Prediction Conflict Index (IPCI)

In order to investigate the prediction accuracy of hotspot maps, several studies have used a Prediction of Accuracy Index (PAI) based on spatial analyses of point events. The larger PAI values denote a greater number of future events occurring in hotspots that are smaller than the study area [23]. Initially, this method was developed for crime mapping [24], and it was only later used in the analysis of traffic safety [25]. PAI is a ratio of the proportion of events occurring within the identified hotspot (hit rate) to the proportion of area covered by it, as follows:

$$PAI = \left(\frac{\frac{n}{N} \times 100}{\frac{m}{M} \times 100} \right) \quad (1)$$

where n is the number of events in the hotspots, N is the total number of events, m is the area in the hotspot or area covered, and M is the total area covered. Larger index values denote a greater number of future events occurring in hotspots smaller than the study area.

This study uses IPCI as an abbreviation to indicate **Intersection Prediction Conflict Index** instead of PAI because only the intersection sites are studied; the concept above is applied solely at the level of the intersection. IPCI thus concentrates on predictive accuracy for the areas that most likely to benefit from safety improvement.

One of the reasons for normalising the proportion of events happening within the identified hotspot by area percentage is that a higher ratio of proportion of events happening within an identified hotspot hit rate value may not always necessarily show better recognition of unsafe zones without such normalisation. For example, a whole region may be identified as hotspots (Area percentage of 100), which would create a hit rate of 100, making the IPCI 100. With normalisation by area percentage, the IPCI index becomes 1, which is more sensible.

The IPCI index measure represents the ability to locate the potential for a high number of potential crashes in a small area by using non-crash events. A convincing example could be 10% of the crashes occurring in hotspots according to KDE representing 50% of the total area; similarly, it could be 10% of crashes in 80% of the area; the IPCI values would be 0.2 and 0.125 for these scenarios, respectively. Comparison would thus lead to selection of the site in the first case, with IPCI 0.2.

IPCI is useful in the identification of the most hazardous locations within intersections and allows a focus on safety problems. In addition, reviewing the hotspots map of a site identified as an at-risk site based on high values of IPCI can allow visual detection of a more accurate location of the problem. This could allow road agencies to allocate resources effectively by mobilising them in smaller areas to address high crash potentials. Table 3 presents the IPCI values for the nine sites in this study according to both HTC and HSC measures, with values calculated according to equation (1) for each site using predictive hotspots mapping based on analysing traffic conflict events with the kernel density tools in Arc GIS software.

Table3. IPCI of the HTC and HSC for study sites

Site No	IPCI-HTC ^a	IPCI-HSC ^b
1	13.91	30.51
2	9.41	25.50
3	11.27	27.56
4	11.74	28.78
5	15.71	37.04
6	12.54	30.10
7	14.30	35.71
8	10.88	27.78
9	10.121	27.56

^a IPCI-HTC: Intersection Prediction Conflict Index for Hourly Traffic Conflict

^b IPCI-HSC: Intersection Prediction Conflict Index for Hourly Serious Conflict

The results of IPCI show that for the two surrogate safety indicators of traffic conflicts, the 14th Ramadhan intersection (site No. 5) has the highest value of IPCI while AL-Saylow intersection (site No.2) has the lowest value. Seven out of the nine sites have the same order based on values of IPCI for HTC and HSC.

8.1 Validity of IPCI in measuring and assessing traffic safety.

In this step, the values of IPCI based on spatial analyses of traffic conflicts measures (for two surrogate safety indicators of traffic conflicts) were compared with the observed crash frequency measures for three years in order to identify the sites most likely to profit from safety improvement. The statistical tests used were as follows:

1- The Pearson correlation coefficient (r) between the values of IPCI-HTC and IPCI-HSC was identified by conflict-based on the special analysis method, and the crash frequency for the study site,

calculated as

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}} \quad (2)$$

$$t = \frac{r}{\sqrt{\frac{1-r^2}{n-2}}} \quad (3)$$

where r is the Pearson correlation coefficient, n is the number of samples, x , y is the data of two compared sets of events (crashes and IPCI values); and t is the t-statistic. The value of the t-statistic can thus be compared to a critical t-value at the 95-percent level of significance.

2- The rank-based mean absolute error (MAE) value is used to compare the ranks derived from the two methods [26]. The MAE quantifies how close one set of ranks (the ranks based on a value of IPCI) to the other set of ranks (the ranks of crash frequency). A lower MAE value indicates that the two sets have less relative error. The MAE is calculated as

$$MAE(rank) = \frac{1}{n} \sum |\text{Rank}(x) - \text{Rank}(y)| \quad (4)$$

where n is the number of locations, $\text{Rank}(x)$ is the rank of location on the basis of subjective measure (IPCI for HTC or HSC) and $\text{Rank}(y)$ is the rank of location on the basis of observed crash frequency, as a reference measure.

8.2 Test results

Table 4 shows the calculated measures and the derived ranks for the intersections, and Table 5 shows the results of the correlation tests and comparative analyses between the two methods. It was found that the IPCI-THC and IPCI-HSC had strong relationships with the crash frequency method (correlation coefficients of 0.824 and 0.861 respectively) and that these coefficients were statistically significant based on the t-statistic.

Table4. Safety Measures and Simple Ranks of Study Sites

Site No.	Measurement of safety			Rank sites		
	CF ^c	IPCI- HTC	IPCI- HSC	CF ^c	IPCI-HTC	IPCI-HSC
1	17	13.9	30.51	3	3	3
2	12	9.4	25.60	9	9	9
3	13	11.27	27.70	8	6	7
4	16	11.74	28.00	5	5	5
5	21	15.7	37.03	1	1	1
6	17	12.54	30.09	3	4	4
7	18	14.25	35.76	2	2	2
8	15	10.88	27.90	6	7	6
9	14	10.121	27.56	7	8	8

^cCF: crash frequency

Furthermore, comparisons on the basis of the MAE values revealed that the IPCI-HSC method (IPCI values based on spatial analyses for hourly serious conflicts) performed better than the IPCI-HTC (IPCI values based on spatial analyses for hourly total conflicts) with respect to crash frequency for the study sites, showing less relative error..

Table5. Correlation coefficients and MAE values for study sites

Statistic	Compared	CF	IPCI-HTC	IPCI-HSC
r	All	1	0.824	0.861
t-statistic(r)			3.85 ^d	4.48 ^d
Rank-based MAE	All		0.555	0.333
	Top 3		0	0

^d significant at 95% confidence interval level.

9. Conclusions and recommendations

Road crashes analysis, particularly analysis of the spatial patterns of road crashes, requires further attention. This study aims to highlight the possible use of unsafe events in traffic processing to fill the gap in the analyses and to measure safety for sites where there is a shortage of crash data by paying particular attention to the spatial clustering of unsafe events in traffic that may lead to crashes.

Understanding where traffic crashes may occur at signalised intersections is one of the most significant questions faced by traffic engineers, and spatial analyses of unsafe events using kernel density can indicate geometric design deficiencies of signalised intersections, which must be considered one of the most important results of this research.

Identifying hotspots zones using KDE technique with physical surveys of study sites illustrated that the unsafe zones showed some differences between sites depending on the distribution of traffic conflicts on legs of intersections. The very high unsafe-prone areas at all nine sites were commonly located at ends of legs of major streets of the intersections, generally concentrated in or near to the left and U-turn lanes where more interaction between vehicles occurs.

The IPCI-based method (spatial analyses of conflicts) was quite well matched with the observed crash frequency method (correlation coefficient of 0.824 for IPCI-HTC and 0.861 for IPCI-HSC respectively). Further, IPCI-HSC (based on spatial analyses for serious conflicts) performed better than IPCI-HTC (based on spatial analyses for hourly conflicts) in terms of MAE values.

With respect to the conformity of the two surrogate safety indicators used in this study and the crash-based method for the period 2015 to 2017, a fair and sensible level of agreement arose between the two methods used.

Comparison of the simple rankings indicates that the two methods result in similar lists of rank positions. The findings suggest that further investigation is required to achieve more definite conclusions, however, as the samples used in this study are small. Although a study with more intersections is desirable, the study results do already imply that the developed method (IPCI based on spatial analyses of conflicts) could serve as a viable way of measuring safety performance of signalised intersections in urban areas, however.

The outputs of this study showed that a quantitative approach based on unsafe events in traffic process (conflict-based method) to detecting traffic safety problems at study sites offers useful value as an alternative means of safety assessment that can be used as a tool to support effective decision making.

10. Appendix A

Maps of Kernel density estimation of HTC and HSC for the Study Sites.



Figure A1. Kernel density estimation of HTC for study sites (from site 2 to 9 respectively).

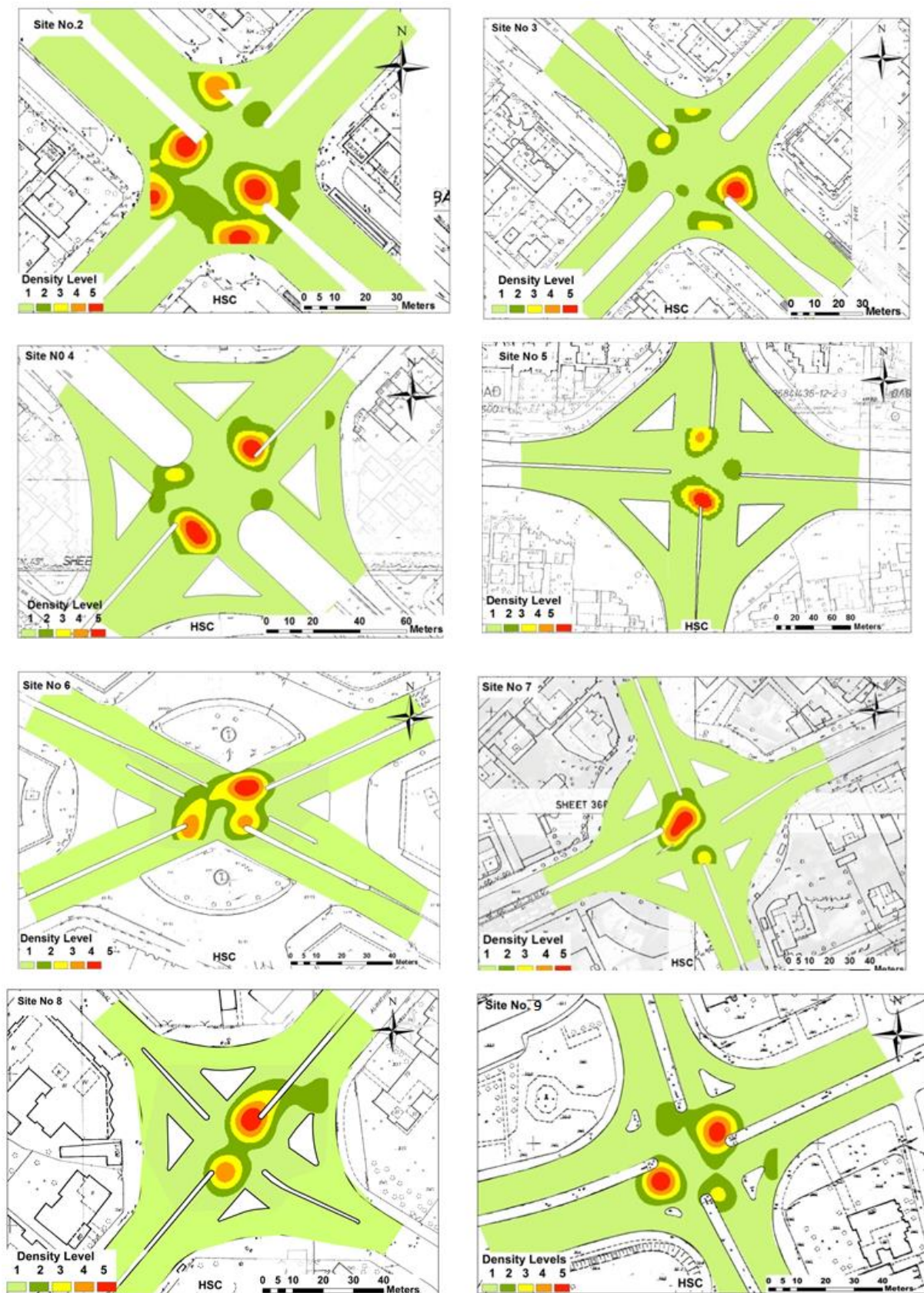


Figure A2. Kernel density estimation of HSC for study sites (from site 2 to 9 respectively).

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