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Identifying Street Hotspots Using a Network Kernel Density Estimation

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Throughout history, police have dedicated their attention to locations with a high incidence of crime and/or disorder. These efforts have become more systematic since the introduction of hotspot policing in the 1990s. A large body of research conducted over the last three decades has shown that focusing police resources on areas characterised by high concentration of crime (hotspots) may have positive preventive effects. If crime hotspots inaccurately reflect the spatial patterning of crime, (intense) criminal activity may not attract police attention. The progress of the crime mapping discipline, spurred by the development of information technology (e.g. GIS) and spatial statistics, enabled crime analysts to identify hotspots more accurately than before. When identifying hotspots, crime analysts use spatial statistical methods which are based on the assumption of a 2D homogeneous Euclidean space. However, in an urban setting, the street network may significantly affect the patterning of crime. Crime may be concentrated along the streets, thus forming linear hotspots. When such linear distribution is analysed, the assumption of homogeneity of the 2D space, which is inherent in "traditional" spatial statistical methods, could lead to a false conclusion. In order to avoid that from happening, these methods should be extended to a network space. This paper explains the specifics of spatial analysis in a network environment and its relevance to the crime analysis practice. Finally, the network extension of one of the most popular methods of hotspot identification, i.e. the kernel density estimation (KDE) method, was applied in the present paper. Having compared the network and planar KDE outputs, the authors concluded that the network-based KDE allowed a more accurate identification of linear hotspots, resulting in a more effective deployment of resources.

Keywords: crime mapping, hotspot policing, spatial analysis, GIS, traffic accidents

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1 Introduction

Urban settings greatly affect the spatial patterning of crime. They determine the places people visit in the course of their day-to-day activities, the routes they take when moving between them and the interactions that they experience as they do so (Birks & Davis, 2017: 900). One of the most distinctive urban features is the street network. Street segments, which are more accessible and/or likely to lie in people's everyday paths, will be expected to be more familiar to everyone and, consequently, more likely to be targeted by offenders (Summers & Johnson, 2017: 399). Because of the presence of a larger number of people, the owners will tend to locate their commercial properties along the streets, thus further increasing the number of potential crime targets (Beavon, Brantingham, & Brantingham, 1994: 119).

Locations and movements of potential victims, offenders and guardians are largely constrained by the structure of the street network. By dictating where, when and in which contexts potential victims, offenders and guardians interact with one another, the street network substantially influences the spatial distribution of crime (Birks & Davies, 2017; Summers & Johnson, 2017). As a result, many crimes will be concentrated on or near the street network. For example, Weisburd, Bushway, Lum and Yang (2004) examined street segments in the city of Seattle between 1989 and 2002 and found that 50% of crime incidents over the 14-year period occurred at between 4 and 5% of street segments. The existence of spatial concentration of crime on street segments was confirmed by subsequent research conducted not only in Seattle (Weisburd, Groff, & Yang, 2012; Weisburd, Morris, & Groff, 2009), but also in other cities in the USA (Weisburd, 2015), Canada

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(Andresen, Curman, & Linning, 2017; Boivin & Melo, 2019), Latin America (Chainey, Pettuchi, Rojas, Ramirez, Monteiro, & Valdez, 2019; Melo, Matias, & Andresen, 2015) and Europe (Favarin, 2018; Steenbeek & Weisburd, 2015; Vandeviver & Steenbeek, 2019).

Crime concentration along a street will form a linear distribution (Milić, 2015; Milojković & Petrović, 2019). To identify this type of distribution, crime analysts may use "traditional" spatial statistical methods which are based on the assumption of a 2D homogeneous Euclidean space. However, when the spatial pattern of crimes which usually occur on street network is analysed, the assumption of homogeneity of the 2D space could lead to a false conclusion (Okabe, Satoh, & Sugihara, 2009; Xie & Yan, 2008). To become suitable for analysing the linear distribution, these methods should be extended to the network space, which will ensure an unbiased identification of potential "linear" hotspots. Unfortunately, the limitations of the planar spatial statistical methods are often disregarded in police practice. This paper explains the specifics of the spatial analysis in a network setting, its relevance to the crime analysis practice and the extension to the network space of one of the most popular methods for hotspot identification, i.e. the kernel density estimation (KDE) method. The aim of the study presented in this paper was to apply both the planar KDE and the network-based KDE (hereafter the NKDE) methods to the linear distribution and to compare their outputs in order to assess how accurately they reflect the spatial patterning of (linear) incidents. Based on the comparison of these outputs, a conclusion is made on the extent to which crime analysis may benefit from introducing the NKDE in its practice.

2 The Need for a Network Spatial Analysis in Crime Mapping

Urban facilities, such as residential and commercial buildings, are situated on the streets, goods are transported along the street networks and the main protagonists of crime events are either on or near the street network during their day-to-day activities. Therefore, the spatial distribution of various police calls for service is inherently linked to the street network. From the point of view of police organisations, crimes and traffic incidents are the most prominent events that trigger a police response on the streets. Consequently, the street network is an important area of police deployment (e.g. police patrols), where the street layout often influences the way police resources are deployed (e.g. configuration of the patrol area, police response time, etc.).

Beginning with the Minneapolis Hot Spots Patrol Experiment (Sherman & Weisburd 1995), a series of studies has shown that crime prevention, which focuses on specific "micro" places with a greater number of crimes or a higher risk of victimisation in comparison with the surrounding areas, produces significant crime prevention gains (Braga, Turchan, Papachristos, & Hureau, 2019). These micro places, commonly referred to as "hotspots" of crime, are specific locations ranging from individual addresses or buildings, clusters of street addresses or groupings of street blocks to single street segments (Weisburd, Bruinsma, & Bernasco, 2009). Acting as "behaviour settings" and capable of capturing the rhythms of everyday life in cities better than larger spatial units (e.g. neighbourhood), street segments have become increasingly popular as analysis units in place-based criminology (Weisburd, 2015).

According to Weisburd (2015: 26), more than 80% of crime incidents were associated with street segments. This applies not only to property crime (Beavon et al., 1994; Lu, 2006), but also to violent crime (Summers & Johnson, 2017). Police resources are deployed to high-risk street segments in order to deter potential offenders (e.g. increased patrols) and/or modify situational characteristics of places usually under the framework of problem-oriented policing (Goldstein, 1990).

High-risk street segments (hotspots) must be identified in order to come to the forefront of police attention. There is a number of hotspot identification methods and techniques in contemporary crime mapping practice (Eck, Chainey, Cameron, Leitner, & Wilson, 2005). Basically, these methods are aimed at establishing whether crime distribution is spatially clustered and, if so, at identifying them. Most of these methods are based on the assumption that crime events are distributed in an infinitely homogenous and isotropic space, and use the Euclidean distance for denoting the distance between them (Tompson, Partridge, & Shepherd, 2009; Yamada & Thill 2010). However, many spatial point events associated with human activities take place in urban environments, where homogeneity and uniformity are highly distorted by the restriction of movement imposed by the street network. For example, street crimes and car accidents tend to happen only on street networks; hence it is unrealistic to expect that hotspots would be found outside the street network. In view of the benefits of hotspot policing, crime analysts are very interested in identifying linear (street) segments where these events are concentrated, i.e. network hotspots, in order to ensure an effective deployment of resources and initiate remedial measures.

Traditionally, the spatial distribution of events that occur either on or alongside a network is analysed by using the *planar spatial analysis methods,* which are based on the assumption of the 2D homogeneous Euclidean space. This might lead to biased conclusions because the Euclidean distance is an inappropriate measure in networks. Locations may be very close to one another in a planar space, however, this is not the case in a network space. The point distribution that forms a random pattern on a network may be interpreted as a clustering pattern on a plane merely because the network itself is a clustered subset of the planar study region (Okabe & Sugihara, 2012: 5; Yamada & Thill, 2007: 271). In the network analysis, the proximity of events is not the only criterion for the establishment of clustering. Indeed, connectivity is another criterion that should be considered. Consequently, clustering techniques based on proximity may reveal different potential common causes for network events than clustering techniques based on connectivity (Steenberghen, Dufays, Thomas, & Flahaut, 2004: 170). In order to ensure a more realistic distance measurement, some planar spatial statistics methods use an alternative measurement, i.e. the Manhattan distance, which is based on a grid street layout and is measured by combining two straight lines connected at a right angle. In a gridded network, the Manhattan distance appears to be a worthy substitute for the Euclidean distance, however, as noted by Tompson et al. (2009: 80), the Manhattan distance may still underestimate the distance between two points even on a gridded network and could fall short of the total network distance between the points. Nevertheless, when the measurement of the street/network distance is not possible, the Manhattan distance is a better measurement than the Euclidean distance (Chainey & Ratcliffe, 2005: 301; Rossmo, Laverty, & Moore, 2005: 111). The Euclidean or straight-line distance is always the shortest distance between two locations. The network distance is almost always the longest and the most accurate. Empirical examinations show that the difference between Euclidean distances and their corresponding network distances exceeds 20% when Euclidean distances are shorter than 400 metres (Okabe & Sugihara, 2012). As a result, the network or shortest-path distance should be used instead of the Euclidean distance in network spatial analysis.

3 Network Spatial Analysis

Spatial analysis along networks, or *network spatial analysis*, entails statistical and computational methods for analysing events occurring on and alongside networks (Okabe & Sugihara, 2012). Network spatial analysis is a relatively new concept in the spatial statistics field. Until the early 1990s, there was little interest in researching the statistical analysis of on- network events. The situation has changed drastically due to the GIS advances, progress in computational geometry and a greater availability of the digital representation of network data, together with a growing recognition among scientists of the limitations of spatial methods based on the 2D Euclidean space (Okabe, Yomono, & Kitamura, 1995: 153). Researchers from different fields set out to extend the traditional (planar) point pattern analysis methods to a network-constrained environment or to formulate new methods. Major progress was made within two decades. These efforts mainly focused on extending planar spatial statistics to networks. For example, Okabe and Yamada (2001) extended the planar K-function method and formulated the network K-function method, which is used for testing the hypothesis that points are uniformly and independently distributed over a network, as well as the network cross K-function method, which is used for testing the hypothesis that two different distributions are independently distributed over a network. Comparing the outputs of the planar K-function and the network K-function, Yamada and Thill (2004) concluded that the planar K-function analysis has a significant chance of over-detecting clustered patterns. When analysing the crime pattern of vehicle thefts, Lu and Chen (2007) reached a similar conclusion – the planar K-function is likely to produce false positives when detecting clusters. The existence of false positives or false negatives, according to these authors, largely depends on the nature of the urban street networks and the distribution of urban activities. Yamada and Thill (2007, 2010) introduced network extensions of the local Moran's I statistic, and the local Getis and Ord G statistic in the case of phenomena, which are represented by attribute values of individual network links. Steenberghen et al. (2004) used the linear local Moran's I and the planar KDE for identifying road crash hot zones. Black (1992), and Black and Thomas (1998) applied the Moran's I to assess the network autocorrelation in order to estimate the influence of values associated with interconnected links. Okabe et al. (1995) made an extension of the nearest-neighbour distance method defined on a plane to a method defined on a network. Shiode (2008) extended the conventional (planar) quadrat method and proposed a network-based quadrat method. The network-based units are used instead of planar quadrants in order to achieve greater accuracy in the aggregation of points on the network. Borruso (2005) proposed a KDE extension, called the Network Density Estimation (NDE), which is based on network distances. By comparing the KDE and the NDE, Borruso (2008: 399) concluded that although differences between the results are not very high, the NDE seems to be more proficient in highlighting "linear" clusters oriented along a street network. Xie and Yan (2008, 2013) developed a network-based kernel density estimation to estimate the density distribution of traffic accidents in a network space. The network space is represented by basic linear units of equal network length, termed *lixels* (linear pixels). According to their test results, the NKDE is more appropriate than the standard planar KDE for the density estimation of traffic accidents, since the latter includes the space beyond the event context (network space) and is likely to overestimate the density values. Okabe et al. (2009) proposed a network-constrained KDE method and developed a plug-in tool for using this method in the GIS. Nie, Wang, Du, Ren and Tian (2015) introduced a two-step integrated method, called the NKDE-GLINCS, in order to identify high-risk locations on road segments. Firstly, they applied the network-constrained kernel density estimation (NKDE) and then used the calculated density as the input value for the network constrained Getis-Ord Gi*.

4 Network Kernel Density Estimation

The planar KDE is a well-known tool for discrete events in point-pattern analyses. It is widely used by academics and practitioners as a spatial smoothing technique in many fields, such as economics (Haichao, Yan, Chengliang, &, Fei, 2018), demography (Vasan, Baker, & Alcantara, 2018), criminology (Chainey, Tompson, & Uhlig, 2008), ecology (Zanón-Martínez, Kelly, Mesa-Cruz, Sarasola, DeHart, & Travaini, 2016), epidemiology (Bithell, 1990), urban studies (Porta et al., 2012), etc. As for the field of crime analysis and hotspot identification, this is the most suitable technique for visualising crime data, while , as noted by Chainey et al. (2008), its predictive "strength" outperforms other methods.

The popularity of the KDE in crime analysis results from several factors. Firstly, it is easy to generate, as most GIS software allow their users to create KDE maps with a few mouse clicks. Secondly, it is easy to interpret. Thirdly, since the KDE is not reliant on administrative boundaries, it overcomes the modifiable areal unit problem (MAUP). Fourthly, it is visually appealing. Unlike some other hotspot analysis techniques (e.g. STAC, nearest neighbour hierarchical clustering, K-means clustering, etc.), where ellipses and/or convex hulls are drawn around the cluster(s) of crime incidents, the KDE offers a more realistic and accurate hotspot representation, which is often odd-shaped and irregular (Paulsen & Robinson, 2004: 326).

In the planar KDE, the space is characterised as a 2D homogeneous Euclidian space and the entire 2D plane of the study area is taken as the context. As a result, all network events falling into the "search window" are considered, including those that may be near one another, but are not connected on the network (Figure 1). Since the planar KDE takes into account the proximity, rather than the connectivity of events, its output may suggest a causal relationship between two close, albeit unconnected events (Steenberghen et al., 2004: 176). Therefore, when the planar KDE is extended to the NKDE, the network distance, calculated as the shortest-path distance in a network, should be used instead of the Euclidian distance, and applied to both the search bandwidth and the kernel functions' weighting (Xie & Yan, 2008). At the same time, circular bandwidth is replaced by a division of the road network into fixed length units, called *lixels*. The NKDE works by extending the bandwidth distance along the street network; hence, the NKDE generates linear hotspots.

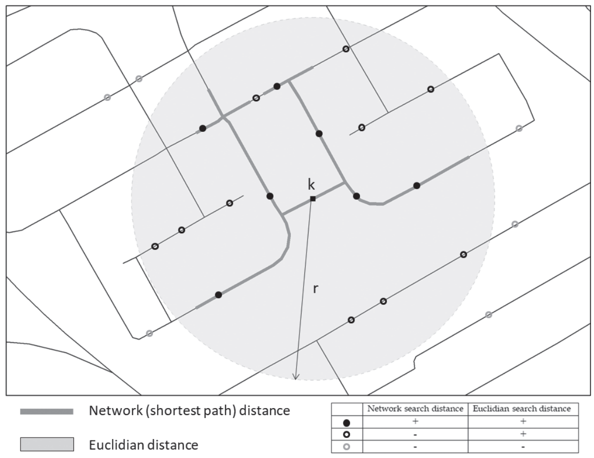

Figure 1: The difference between the 200 metres search regions of a network (shortest path) and Euclidean distances

Although the limitations of the planar KDE applied to network events seem obvious, some authors still disregard them. For example, Erdogan, Yilmaz, Baybura and Gullu (2008) used the planar kernel density to calculate the density of accidents in a 0.5 km search radius along highways. In a study aimed at identifying crash hotspots in a road network, Thakali, Kwon and Fu (2015), as well as Rouzbeh and Shahriar (2017) used the planar KDE in the identification of crash black-sites. The planar KDE was also used by Anderson (2009) in the study of spatial patterns of injury-related road accidents, as well as by Blazquez and Celis (2013) in the spatial analysis of child pedestrian crashes.

The extension of a kernel function to a network environment is not a straightforward process. A network has its own topology, where line segments are represented by links and the endpoints of segments by nodes. The fact that many links can share the same node complicates the kernel function computation. When a kernel function traverses a node, its search bandwidth includes all line segments that share that node with the same "value", resulting in an overestimation of density around the nodes (Okabe et al., 2009). To avoid the overestimation of density around the nodes, Okabe et al. (2009) proposed the equal-split discontinuous and the equal-split continuous kernel functions, and proved their unbiasedness around the nodes in a network space. In the case of the equal-split discontinuous kernel (Okabe et al., 2009), the kernel "value" at nodes is split equally into outgoing segments, thus making the kernel function discontinuous at the nodes. For example, if there are two outgoing segments from a node, the kernel density is divided equally and assigned to each link while keeping the total value unchanged (Figure 2).

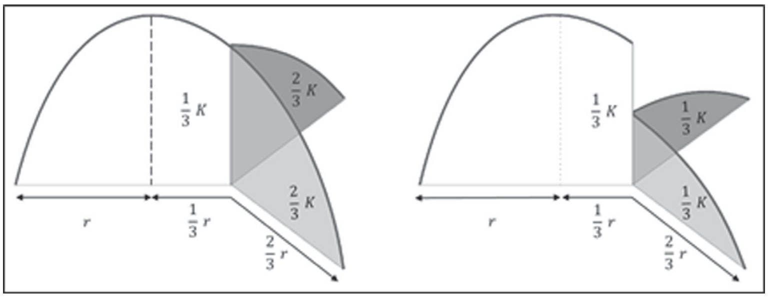

Figure 2: Illustration of the network kernel density function (left) and the network discontinuous kernel function (right) at a node

In case of the equal-split continuous kernel function (Okabe et al., 2009), values are adjusted by increasing the value of outgoing segments and decreasing the value of incoming segments in a discontinuous algorithm in order to preserve the kernel continuity across the node (Moradi, Rodríguez-Cortés, & Mateu, 2018). Unlike the discontinuous kernel function, which only traverses "forward", the continuous function traverses both "forward" (the value increases) and "backward" (the value decreases), which increases its computation time, but preserves the continuity of the function and keeps the total value unchanged.

5 Network Analysis of Traffic Accidents in the Municipality of New Belgrade (Belgrade, Serbia) – A Comparison Between Planar KDE and NKDE Outputs

5.1 Study Area

This study focuses on the municipality of New Belgrade, which is one of the 17 municipalities of Belgrade, Serbia's capital and its largest city. New Belgrade is a highly urbanised municipality and the central business district of Serbia. According to official data, it stretches over 4,096 hectares of land and is populated by 214,506 people (permanent residents), while the Ministry of the Interior of the Republic of Serbia estimates that this municipality has 300,000 inhabitants. The New Belgrade road network consists of around 460 km of primary, secondary and tertiary roads, including a section of the highway (E70 route).

5.2 Data

In police practice, street crimes and traffic incidents are the most prevalent types of "linear" incidents. Unfortunately, the Serbian police did not engage in a practice of storing street crime data with enough location details that would enable successful and precise geocoding, particularly in the case of crimes committed away from any building with a (street) number. At the same time, traffic accidents were recorded with high spatial accuracy because traffic police officers were equipped with GPS receivers. As a result, the longitude and latitude are available for all traffic accidents. Therefore, the distribution of this type of linear incidents was selected to be spatially analysed in this paper. It should be noted that the distribution of traffic accidents was traditionally analysed only by traffic safety professionals, however, it has recently come into the focus of crime analysts, too. There is growing evidence that in the scope of a strategy known as Data-Driven Approaches to Crime and Traffic Safety (DDACTS), the combining of crime and traffic crash locations may serve as a valuable input for an effective allocation of police resources. Although criminal offences and vehicle crashes are not similar problems that can be solved by applying the same policing strategy, the evidence of research studies conducted across the USA shows that highly visible traffic enforcement may indeed have an impact on both problems (Carter & Piza, 2018).

The dataset used in this study covers a period of three years (from 2016 to 2018). The data provided in the Excel format were converted into a GIS shapefile, and projected and mapped by using the ESRI ArcGIS. All traffic accidents involving parked vehicles were excluded from the provided dataset and a total of 7,126 traffic accidents were mapped. The street network was downloaded from the *OpenStreetMap*, clipped to the study area boundary, and reduced only to the highway, primary, secondary and tertiary roads. Traffic accidents were snapped to the closest street segment with the search tolerance of 15 metres. These procedures reduced the initial number of traffic accidents to a total of 5,997 (Figure 3).

In view of the fact that small variations in KDE parameters can result in different outputs, the research on the parameter selection included both the planar KDE (Chainey, 2013; Chainey et al., 2008; Hart & Zandbergen 2012; Levine, 2008) and the NKDE (Xie & Yan, 2008). There are still some questions that need to be answered, such as: what are the optimal KDE parameters? How to determine them? Is there a consensus regarding what should be considered as optimal standards? Can they be established at all?

Figure 3: Distribution of traffic accidents across the study area

5.3 Methods

In this study, we applied the planar KDE by using the ESRI ArcGIS software and the network-based KDE (Okabe et al., 2009) by using the SANET Standalone 1.0 software.[5] The results of the network-based KDE were used as input values for computing the Getis-Ord GI* statistics in order to detect statistically significant network-constrained hotspots.

5.3.1 Parameter Selection

The selection of parameters, which is usually subjective, is one of the most sensitive steps in the implementation of the KDE. In practice, most analysts select their parameters through an empirical trial-and-error procedure (van Patten, McKeldin-Conor, & Cox, 2009) or simply use the default GIS options for the KDE, unaware of the potential effect of these settings on the final output (Chainey, 2013: 18; Tompson et al., 2009: 81).

Both the planar KDE and the NKDE require three parameters to be determined: 1) the grid cell/lixel size, 2) the bandwidth (search radius/area), and 3) the calculation method (kernel function). They affect the calculation of the density surface, and, together with 4) the classification scheme, they influence the appearance of the final output (density map).

5.3.2 Kernel Function

There are different kernel functions and the selection of the one to be used depends on how much the user wants to weigh the near points relative to far points. In the event of using the planar KDE, they result in small differences in density values (Levine, 2004) and this may explain why the choice of the optimal kernel functions was rarely the subject of discussion in the crime mapping literature. A similar conclusion

5 SANET. A Spatial Analysis along Networks (Ver. 4.1). Atsu Okabe, Kei-ichi Okunuki and SANET Team, Tokyo, Japan.

could be applied to the NKDE. After comparing the Gaussian and Quartic kernel functions, Xie and Yan (2008) concluded that the choice of kernel functions made little difference in the overall (network) density pattern.

When it comes to the choice of kernel functions, this study uses the defaults provided by the software. The quadratic kernel function is used for both the planar KDE and the NKDE as a predefined function in the ESRI ArcGIS software and the SANET software, respectively.

5.3.3 Bandwidth

The choice of bandwidth has drawn a great deal of attention in disciplines that are widely applying the KDE due to the fact that, when varied, this parameter will result in differences in the KDE output. Too large a bandwidth will conceal the local spatial variation of events (e.g. by drawing attention to an entire street and making it difficult to identify the street segments of true safety concerns), while a narrow search bandwidth may only highlight isolated individual clusters, thus obscuring the larger hotspots. Although crime mapping literature offers different recommendations on the choice of the appropriate bandwidth size for the planar KDE, when it comes to the NKDE, little, if any, work has been published (Boss, Nelson, & Winters, 2018: 105).

Given that distances are calculated differently in the planar KDE and the NKDE, any chosen bandwidth is unlikely to be optimal for both methods. Since the optimal bandwidth in an urban area should be between 100 and 300 metres at the scale of a neighbourhood, block and street (Porta et al., 2009), and since it has been empirically observed that the difference between the Euclidean distances and their corresponding shortest-path distances exceeds 20% when the Euclidean distances are less than 400 metres (Okabe & Sugihara, 2012), the bandwidths used in this study were 250 metres for the planar KDE and 300 metres for the NKDE.

5.3.4 Cell Size

The NKDE lixel length, like the planar KDE cell size, determines the resolution of the density output. As the lixel length increases, the density values along streets lose local variation details. In view of the incident type that represents the subject of this research (traffic incidents), the accuracy of GPS receivers in the urban environment and recommendations from literature, where the optimal lixel length is between 10 and 40 metres (Khalid et al., 2018; Luliang, Zihan, Xia, Fei, Xue, & Qingquan, 2016; Nie et al., 2015; Xie & Yan, 2008), the researchers believed that the appropriate value for both the cell size (planar KDE) and the lixel length (NKDE) in this study should set at 30 metres.

5.3.5 Classification Scheme and Hotspot Threshold Settings

Last but not least, the range settings used for classifying the calculated density values represent an important parameter that may affect the KDE output, since different choices may result in vastly different map outputs. This paper uses incremental multiples of the planar KDE grid cells and the NKDE lixels mean. Calculations for the mean are applied only to the cells/lixels with a value greater than 0, while the cells/lixels with a value greater than 3 times the mean are considered "hot". The mean is a value which may be more easily grasped by a novice map reader (Chainey, Reid, & Stuart, 2002: 32) and has some empirical support in practice (Milić, Popović, Mijalković, & Marinković, 2019).

6 Results and Discussion

In this study, the planar KDE and the NKDE are compared. Although common hot (high density) regions may be identified on both maps, the two maps are generally different. The planar KDE generated circular or ellipsoidal hotspots, while the NKDE generated linear hotspots (Figure 4).

Figure 4: NKDE (bandwidth = 300 m, lixel size= 30 m) and planar KDE (bandwidth = 250 m, cell size = 30 m) hotspots

For the selected bandwidths, the planar hotspots are much greater in extent than those created by using the NKDE and they cover areas outside the street network. Figure 5 shows that almost all linear (NKDE) hotspots are located inside the planar KDE hotspots. Only four "hot" street segments are located outside the planar hotspots, while eleven planar hotspots do not contain any linear hotspots. A similar conclusion – that both approaches show high density clusters of activities approximately at the same locations – was drawn in a research study conducted by Porta et al. (2012) on the basis of a visual comparison between the KDE and the NKDE. point events, such as traffic accidents. Figure 6 shows that the NKDE identified fewer high intensity street segments and provided more accurate results. Its values are distributed only along the street network and, for example, it was able to distinguish between different densities in two traffic lanes of different directions along the same street. The fact that the NKDE output is more precise than the KDE output is consistent with findings presented by other research studies (Tang et al., 2013; Xie & Yan, 2008).

Figure 5: Differences between the planar KDE and NKDE hotspots

Planar hotspots occupy a total area of 3.9 km^2 (9.52% of the total study area), while the total length of linear hotspots is 13.18 km (3% of the total length of the street network). There were 2,911 traffic accidents (48.5%) in the planar hotspots and 1,232 (20.5%) in the linear hotspots. The fact that almost all linear hotspots are encompassed by the KDE hotspots may indicate that the KDE may be useful for detecting a general pattern of incidents. A similar observation can be found elsewhere (Tang, Knodler, & Park, 2013). Planar hotspots cover a much greater area than linear hotspots. When it comes to the problem identification (e.g. the prerequisite for hotspot policing or problem-oriented policing), precision is of utmost importance and in this respect the NKDE shows to be more advantageous. For example, Xie and Yan (2008) state that in order to detect a problem on a street segment, the planar KDE may not be suited for characterising certain

Planar KDE hotspots are mostly concentrated around nodes (street intersections or roundabouts). Due to the planar KDE circular search radius and the Euclidean distance measurement, the search bandwidth may pick up events from incoming and outgoing street segments, and sometimes even from the nearby street segments (Figure 6). This is especially notable if a larger search bandwidth is used. The fact that the KDE is likely to overestimate density was also noted by other researchers (Okabe et al., 2009; Xie & Yan 2008).

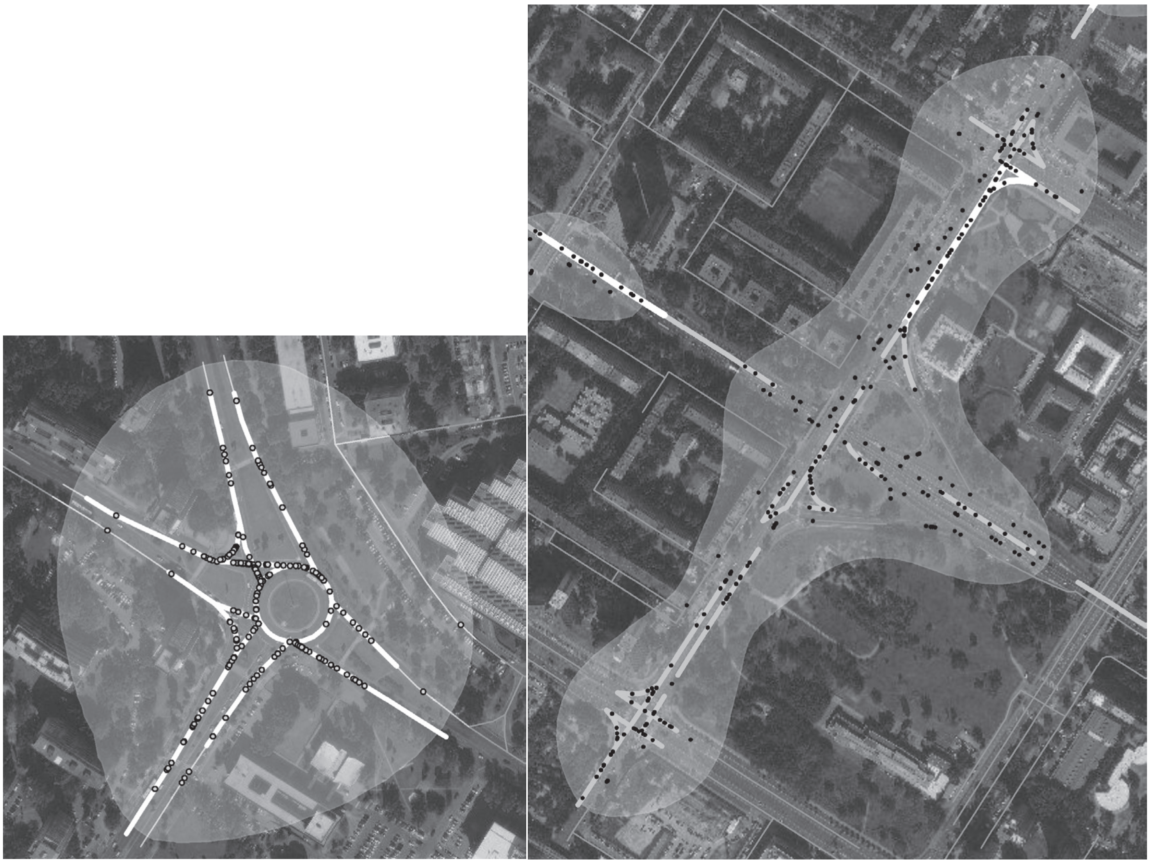

Figure 6: A closer look at the planar hotspots

Both the equal-split continuous and the equal-split discontinuous kernel functions were applied in this study. As explained by Okabe et al. (2009), the advantage of the equal-split discontinuous kernel function stems from a shorter computation time, particularly when applied on a complex network, where network links are less than one quarter of the bandwidth. Figure 7 shows that density values are almost similar. In this study, computation time drastically increased when bandwidths exceeded 250 metres and the maximum bandwidth that our (modest) hardware could compute for the continuous kernel function was 400 metres. The algorithm structure for both functions is similar and the only difference lies in the manner of splitting. Continuous splitting demands more computational time, which means that the discontinuous function should be used when computational time is an important element (Okabe & Sugihara, 2012: 193).

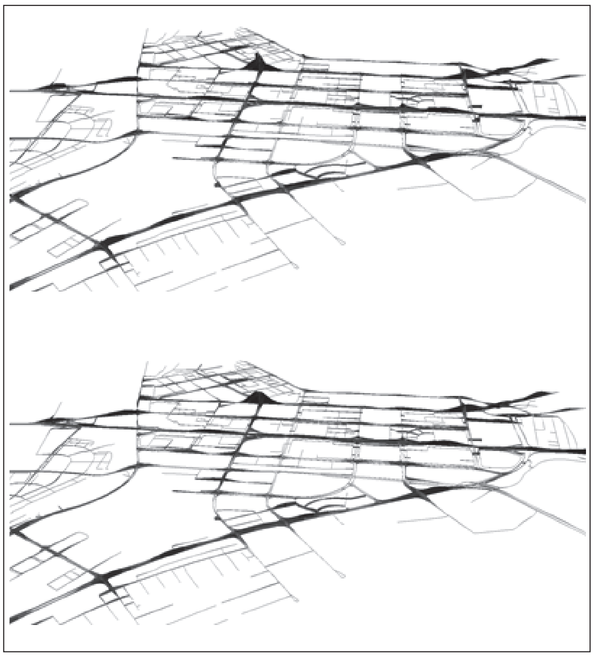

Figure 7: 3D view of the equal-split discontinuous (up) and the equal-split continuous kernel functions (down))

Like the planar KDE, the NKDE is also very sensitive to parameter selection. As the kernel density bandwidth increases, the density results change considerably. When the density bandwidth increases from 150 to 500 metres, local variations are lost and density results become smoother (Figure 8).

When the kernel density bandwidth is at 150 metres, the maximum kernel density of the basic linear unit amounts to 65,241. As the search bandwidth increases, the maximum lixel density rises to 102,306 (Figure 9).

In contrast to the selection of the appropriate cell/lixel size, bandwidth and kernel function, as the parameters that precede the calculation of kernel density, grid cell values are classified and visualized subsequently, which also calls for some subjective decision-making. Unlike with other KDE parameters, available literature has disregarded the influence of different classification methods applied on the calculated density values – including the choice of a threshold that separates "hot" and other values – on the KDE hotspot predictive accuracy (Milić et al., 2019). The impact of different classification schemes on the study data may be observed in Figure 10.

The main limitations of the NKDE are that no statistical inference can be made and that there is no indication of a density threshold above which a hotspot can be confidently

Figure 8: The impact of various bandwidths on the NKDE output – 150 metres (up), 300 metres (middle) and 500 metres (down)

Figure 9: The impact of various bandwidths on the lixel density

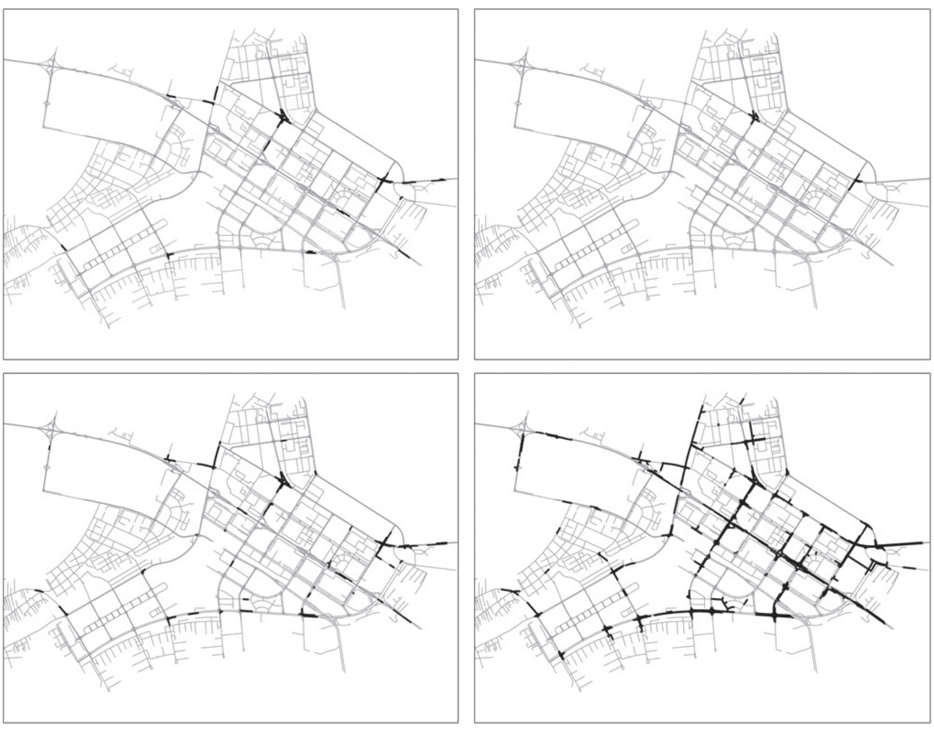

Figure 10: The impact of different classification schemes on the NKDE output – standard deviation classification (upper left), natural breaks classification (upper right), 3 lixels' means classification (lower left) and quantile classification (lower right)

declared (Xie & Yan, 2013). In order to add statistical significance, the NKDE output was used as the input value for computing the Getis-Ord Gi* statistics. The Getis-Ord Gi* works by looking at each feature within a defined distance (neighbourhood) and evaluating the degree to which each feature is surrounded by features with similarly high/low values. Before the application of the Getis-Ord Gi* method, there was a need for "network constraining" because, originally, this method had been intended for "planar" calculations on the polygon and point features. After constructing a spatial weight matrix, spatial relationships among the streets are defined for the purpose of preventing this method from using unconnected street segments in calculations. The resultant z-scores and p-values show where features with either high or low values cluster spatially. For significant positive Z-scores, the larger Z-score indicates a more intense clustering of high values, while for significant negative Z-scores, the smaller z-scores and p-values indicate a stronger clustering of low values (cold spots). As it may be observed in Figure 11, statistically significant "hot" values nearly coincide with the NKDE hotspots. The effectiveness and robustness of the NKDE and the network-constrained Getis-Ord Gi* was confirmed by other researchers (Khalid et al., 2018; Nie et al. 2015).

7 Conclusion

The practice of hotspot policing, which calls for the identification of crime hotspots and the focusing of police resources in these areas, proves to be an effective crime prevention strategy in a range of different environments and for many different crime types (Braga et al., 2019). Traffic accidents, as an incident type which, in addition to crimes, requires police attention, are rarely random in space and time. In most cases, traffic accidents form clusters (also known as black spots) in a space (Mitar & Žnidaršič, 2012). For the purpose of improving road safety, it is vital to identify the street segments where the density of traffic incidents is relatively high, in comparison with other street network segments. If hotspot/black spot analysis does not accurately reflect the spatial patterning of incidents, the subsequent focusing of resources and the implementation of remedial measures will not be effective. This is not an easy task, because it is often unclear where a hot spot begins and where it ends (Buerger, Cohn, & Petrosino, 1995; Paulsen & Robinson, 2004: 314–315).

In order to identify concentrations of incidents (hotspots), police analysts use various spatial statistical methods.

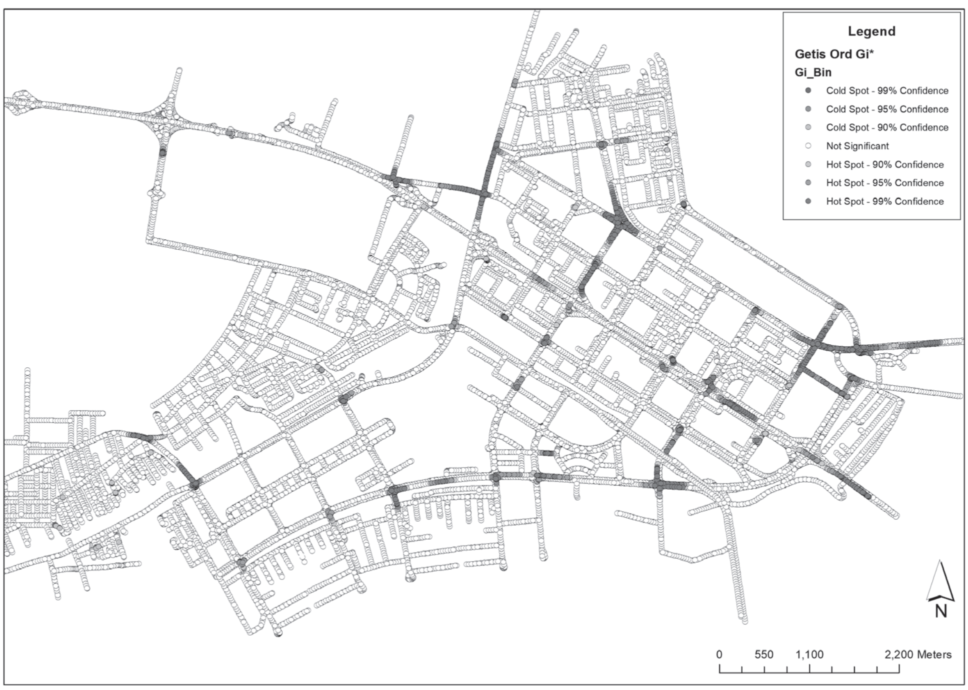

Figure 11: The Getis-Ord Gi* statistics applied to the NKDE output

The KDE is often their first and only choice. Due to its planar circular search radius and the Euclidean distance measurement, the KDE may yield a bias in density estimation when applied to a network distribution. This does not hold true only for traffic incidents (i.e. typical linear incidents), but may also apply to crime incidents, as a result of the influence which the urban setting (street network) may have on their distribution. Analysts, often unaware of this issue, still use the KDE uncritically when analysing linear or "linear-like" distributions.

In view of the benefits of hotspot policing, crime analysts are strongly interested in identifying linear (street) segments where "linear" incidents are concentrated for the purpose of ensuring an effective deployment of resources and initiating remedial measures. If the attention is paid only to proximity, while neglecting connectivity, a distorted picture may be produced as a result.

According to the research presented in this paper, almost all linear (NKDE) hotspots are located inside the planar KDE hotspots. Hence, the planar KDE hotspots may provide a satisfying (general) overview of incident distribution. At the same time, the linear NKDE output ensures a more accurate hotspot identification. The planar KDE covers a space, in which linear incidents cannot occur (e.g. outside streets), while the NKDE can even differentiate between different lanes of the same road segment. Due to its planar search bandwidth, the KDE output (hotspot) may include close, albeit unrelated incidents. Treating unrelated incidents as a single problem may undermine problem-solving efforts when it comes to the problem identification and analysis. Another KDE-related difficulty lies in the overestimation of density at nodes (e.g. street intersections or roundabouts). In this research study, almost all (planar) hotspots in the study area were located around nodes, which became more pronounced when the search bandwidth increased.

The NKDE applicability is often limited to a moderate search bandwidth. As the search bandwidth increases, the NKDE becomes computationally demanding, especially when the equal-split continuous kernel function is used. The tendency of the planar KDE to overestimate density around street nodes, combined with the ability of the NKDE to show linear hotspots more accurately, suggests that the NKDE is more suitable for analysing incidents on street networks. The advantages of the KDE may lie in the fact that it is readily available to crime analysts who are already familiar with this method, and that it may be sufficient for a quick examination of general hotspot patterns reflecting linear incidents in urban environments. At the same time, one should exercise caution – any long-term solutions for problematic locations (hotspots or hot dots) might require the problem to be precisely identified, which, consequently, may tip the scales in favour of the NKDE.

A greater availability of detailed point location data, which is mostly a result of advances in geospatial technologies (GIS, GNSS, etc.), must be accompanied by advances in the analysis methodology and the development of software applications capable of processing them. Due to the recent advancement in the network spatial analysis methods, the identification of network hotspots has become easier and more accurate. These methods must become a part of the crime analyst toolkit and complement the well-known planar methods in the everyday work of analysts. Why is this so important? In an urban environment, the spatial distribution of the majority of police calls for service is influenced by the street network. The network spatial analysis techniques may not only facilitate the identification of problems (network hotspots), but also make the deployment of resources more effective (e.g. police patrol optimisation). On the basis of the existing popularity of the planar KDE in police practice, it can reasonably be expected that the NKDE will be easily accepted both by analysts and by those who are using their products in decision-making (e.g. police managers). Finally, there is a need for additional research which would show how the NKDE works in different network settings (e.g. gridded networks, such as most US cities, vs. less gridded networks, such as European cities), when different types of crime occur on or near the streets, and, in particular, provide guidance as to the optimal choice of its parameters.

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Prepoznavanje uličnih kriminalnih žarišč z uporabo Network Density Estimation

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Skozi zgodovino je bila policija pozorna na lokacije, ki generirajo veliko število kaznivih dejanj in prekrškov. Ta prizadevanja so postala bolj sistematična z uvedbo policijskega dela, usmerjenega na žarišča, v 90. letih 20. stoletja. Veliko raziskav, ki so bile izvedene v zadnjih treh desetletjih, je pokazalo, da lahko usmerjanje policije na lokacije, kjer se kriminaliteta koncentrira (kriminalna žarišča), ustvari preventivne učinke. Če kriminalna žarišča ne odražajo prostorskega zbiranja kriminalitete, potem (intenzivna) kriminalna dejavnost morda ne bo pritegnila pozornosti policije. Z razvojem kartiranja kriminalitete, podprte z razvojem informacijske tehnologije (npr. GIS) in metodo prostorske statistike, lahko policijski analitiki natančneje odkrivajo žarišča, kot je bilo to mogoče v preteklosti. Policijski analitiki uporabljajo za identifikacijo kriminalnih žarišč metodo prostorske statistike, ki temelji na predpostavki dvodimenzionalnega Evklidskega prostora. V urbanih okoljih lahko mreža ulic znatno vpliva na vzorce prostorske porazdelitve kaznivih dejanj. Kazniva dejanja se lahko koncentrirajo vzdolž ulic in oblikujejo linearna žarišča. Pri analizi takšnih linearnih porazdelitev lahko predpostavka homogenega dvodimenzionalnega prostora, ki je osnova »tradicionalnih« metod prostorske statistike, vodi do napačnih zaključkov. Da bi dobili objektivno identifikacijo linearnih žarišč, se morajo te metode prenesti v mrežni prostor. V članku so razložene posebnosti prostorske analize v mrežnem prostoru in njen pomen za analizo kriminalitete. V članku je bila uporabljena mrežna razširitev ene od najbolj priljubljenih metod identifikacije kriminalnih žarišč, tj. metoda ocene gostote jedra (ang. *kernel density estimation*, KDE). Na osnovi primerjave rezultatov mrežne in ravninske KDE so avtorji ugotovili, da mrežne KDE omogočajo bolj natančno identifikacijo žarišč in s tem bolj učinkovito uporabo virov.

Ključne besede: kartiranje kriminalitete, žarišča kriminalitete, prostorske analize, GIS, prometne nesreče

UDK: 343.9