Hot spots and burning times: A spatiotemporal analysis of calls for service to establish police demand

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Abstract

Establishing police demand is important to optimally allocate scarce police resources in space and time. To contribute to the existing knowledge on the optimization of policing and crime prevention strategies worldwide, we examine the spatiotemporal pattern of calls for service (CFS), with a focus on the urgency of the calls (as measured by the police priority codes), in Antwerp (2017-2020), Belgium. To disentangle the space-time pattern of the priority codes, we apply the average nearest neighbour statistic, global and local Moran's I, Getis-Ord Gi, and emerging hot spot analysis. Our results demonstrate that the spatial, temporal, and space-time patterns of the priority codes differ and that more urgent CFS are more demanding in terms of allocated police vehicles than less urgent CFS. Based on the findings of this paper, we recommend to include priority codes in future police patrol routing solutions to make patrol strategies more realistic. An important aspect will be to increase/decrease the number of available units depending on the spatiotemporal pattern of the CFS per priority code. Instead of only working with fixed shifts, there is a need to deploy peak shifts during times of peak demand.*

***Keywords**:* Priority; Exploratory (spatial) data analysis; micro level; space-time pattern; LISA; Antwerp (Belgium)

1. Introduction

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Over the last two decades, both geographers and criminologists gained more interest in the geography of crime and crime prevention, instead of just focusing on characteristics of the offender (Helbich & Leitner, 2017; Newton & Felson, 2015; Vandeviver & Bernasco, 2017). In 1989, Sherman et al. observed that 50.4% of all calls for service (CFS) in Minneapolis (United States) for which a police car was dispatched were concentrated in 3.3% of all addresses and intersections. Their research was influential, since it marked the first analysis of CFS on a micro scale, which was, among other things, facilitated by the increasing number of police stations equipped with computer aided dispatch systems (Lee et al., 2017; Sherman et al., 1989; Sherman, 1995). The introduction of national emergency numbers along with developments in data recording, storage, and analysis suddenly provided the police with reliable information on the time and place of an incident, and captured many events which were not shown in, e.g., crime reports (Luan et al., 2016; Mastrofski, 1990; Sherman et al., 1989; Wain & Ariel, 2014). Sherman et al. (1989) state that: "Calls to the police provide the most extensive and faithful account of what the public tells the police about crime, with the specific errors and biases that that entails" (Sherman et al., 1989, p. 36). Consequently, CFS act in this paper as the demand for police service from the public, in time and space, to which the supply of police resource should be matched (Bowers, 1999). Over or under supply of police presence can be inefficient and potentially harmful because incident response times may become too long or the intensity of certain hot spots can become excessive in the absence of police surveillance (Davies & Bowers, 2019; Mukhopadhyay et al., 2016). It can also affect people's fear of crime and feeling of safety (Dau et al., 2021b).

Laufs et al. (2020) discuss five drivers of police demand: (1) *the baseline*, the minimum level of police resource to remain operational (context dependent), (2) *cyclical factors*, drivers with discrete dates, such as large-scale cultural events, (3) *the seasons* of the year, (4) *one off incidents*, for example, natural disasters, a large sporting event, or the marginalisation of certain groups after a specific incident (e.g., terrorist attack), and (5) (*localised) emerging trends*, 'new types or forms of crime, or non-crime problem, that were previously unseen (at least in the local context) but that suddenly take up disproportionate amounts of resources […]' (Laufs et al., 2020, p. 10). As stated by Laufs et al. (2020) based on these five drivers, police demand is surely not a static measure.

To optimally deploy police officers in the field, in other words, to match demand and supply, officers and police chiefs not only have to know where a CFS will occur, but also when it will occur (Townsley, 2008). Initially, the geography of crime was dominated by a focus on the spatial characteristics of crime, but over the past years its temporal component is addressed as well and the lessons that can be learned from these analyses to improve crime control activities (Hu et al., 2018; Luan et al., 2016; Shiode et al., 2015; Spicer et al., 2016; Weisburd et al., 2006; Ye et al., 2015). Therefore, geographical analysis and crime mapping are important aspects of police work in its evidence-based and data driven transition

during the last two decades (Dau et al., 2021a) and have the ability to optimize the targeted management of police officers in time and space (Chen et al., 2017; Dewinter et al., 2020; Watanabe & Takamiya, 2014).

With space-time studies in North America, Brazil, and other countries around the world the generalizability of the law of crime concentration or the routine activity theory increases (de Melo et al., 2015) and 'have led to the accumulation of new findings on the space-time signature of different types of crime' (Shiode et al., 2015, p. 697). We want to contribute to this by analysing the space, time, and space-time pattern of police demand in Antwerp (Belgium), more specifically, with a focus on prioritization of CFS. In the case of the Antwerp police, the CFS are dispatched to the officers accompanied by a code indicating the urgency of the incident. This code, the priority code, is assigned by the dispatch centre and gives an indication of the severity of an incident. Depending on the priority code, response times should be minimized. The most critical incidents, e.g., life-threatening incidents, are given priority over less serious ones and officers are allowed to use their siren and flashing lights to clear the right of way and thus reduce response times. Police officers act firstly based on the priority and only secondly on the type of incident and "*[…] in the process of identifying geographical areas that are to be prioritized for patrolling, it is irrational to value serious assault and verbal harassment equally*" (Kärrholm et al., 2020, p. 16). Nevertheless, this aspect of police patrol is underexposed in spatiotemporal analysis of crime or CFS data.

Most papers focus on specific types of recorded crime or CFS, hence, they can only make a statement about these crimes/incidents (Boivin, 2018; Chun, 2014; Chung & Kim, 2019; Curtis-Ham & Walton, 2017; Hu et al., 2018; Nelson et al., 2001; Shiode et al., 2015). Moreover, among others in our study area there is a difference between the two data sets. *CFS* contain offences or incidents reported to the police by the public to which police officers were dispatched. *Recorded crime* consists of reports generated by officer-initiated activity and CFS that have resulted in an official police report. For example, De Melo et al. (2015) applied the spatial point pattern test to a crime data set with sixteen different classifications (categorised as robbery, theft and rape). On the street segment level, the spatial patterns of these crime types exhibited spatial similarity. Other examples are the analysis of crime and crash data in order to define optimal patrol routes to reduce the total dispatch time (Kuo et al., 2013) or the application of spatial analysis techniques to analyse the crime deterrent effect of police stations (Fondevila et al., 2021). The space-time analysis techniques used in these studies are valuable, but the approach differs from what we want to achieve in this paper by focusing on CFS and priority codes. Shiode et al. (2015) examine by means of a network-based space-time search window technique the space-time characteristics of robbery, burglary, drug-related crime, and vehicle theft, and managed to identify different types of hotspots (i.e., persistent warm spots and a short-term outburst). The same crime types, with the addition of (sexual) assault, are analysed in Boivin (2018) to test routine activity

theory. Geographical weight regression modelling demonstrated that, for these crime types, a large population can be associated with increased as well with decreased levels of crime. In general, burglary, robbery, theft, and violent crime turn out to be popular crimes to investigate in time and space literature (Chun, 2014; Chung & Kim, 2019; Curtis-Ham & Walton, 2017; Hu et al., 2018). Moreover, the scale of research has improved tremendously during the last 30 years (Nelson et al., 2001; Valente, 2019), but some analysis techniques (Chun, 2014; Chung & Kim, 2019) or data availability (Boivin, 2018; Megler et al., 2014) prevent analysis on individual address or street segment level. Thus, many studies perform analysis on aggregated data, e.g., census tract level or on a higher temporal scale, e.g., months or seasons (Andresen & Malleson, 2013). We do not want to detract from the contribution that these studies make to the literature, but we would like to highlight a gap in the literature that we will address in this paper: the space-time analysis of CFS data with a focus on the priority codes. The research question of interest in this paper is whether there is a difference in the space-time patterns of incidents with a different priority code? This information can then be used for the daily operation of police patrol.

This paper is organised as follows. First, an overview is given of the data set and the methods used to analyse the space-time patterns of the CFS. Second, the Results Section consists of three parts, discussing the main (1) space, (2) time, and (3) space-time patterns, followed by the Discussion and Conclusion Sections.

2. Data and Methods

2.1. Antwerp: CFS data and the road network

Antwerp's police force is responsible for the safety of 530,104 inhabitants (2020), spread over an area[6] of ca. 204 km². We focus on CFS obtained from the emergency response unit. These officers are dedicated to emergency call response and engage in proactive police patrol: visible or marked patrol in order to prevent crime and maintain social order (Wain & Ariel, 2014). The Antwerp Police Department (APD) is the largest local police force in Belgium in terms of personnel and is divided in six zones. The West region is spread over the right and left bank of the river Scheldt, also stretching over the old medieval city centre (see Fig. 1). City and Centre are both located in the nineteenth century belt of Antwerp and are characterized by densely built neighbourhoods, and zones North, East, and South are situated in the twentieth century belt. Unfortunately, we have no insight into all incidents that take place in the port area because the port falls under the jurisdiction of the Belgian *Federal* Police. Thus only the CFS in which an officer from the APD was involved, are included for analysis.

[6] 72 km² is occupied by the seaport.

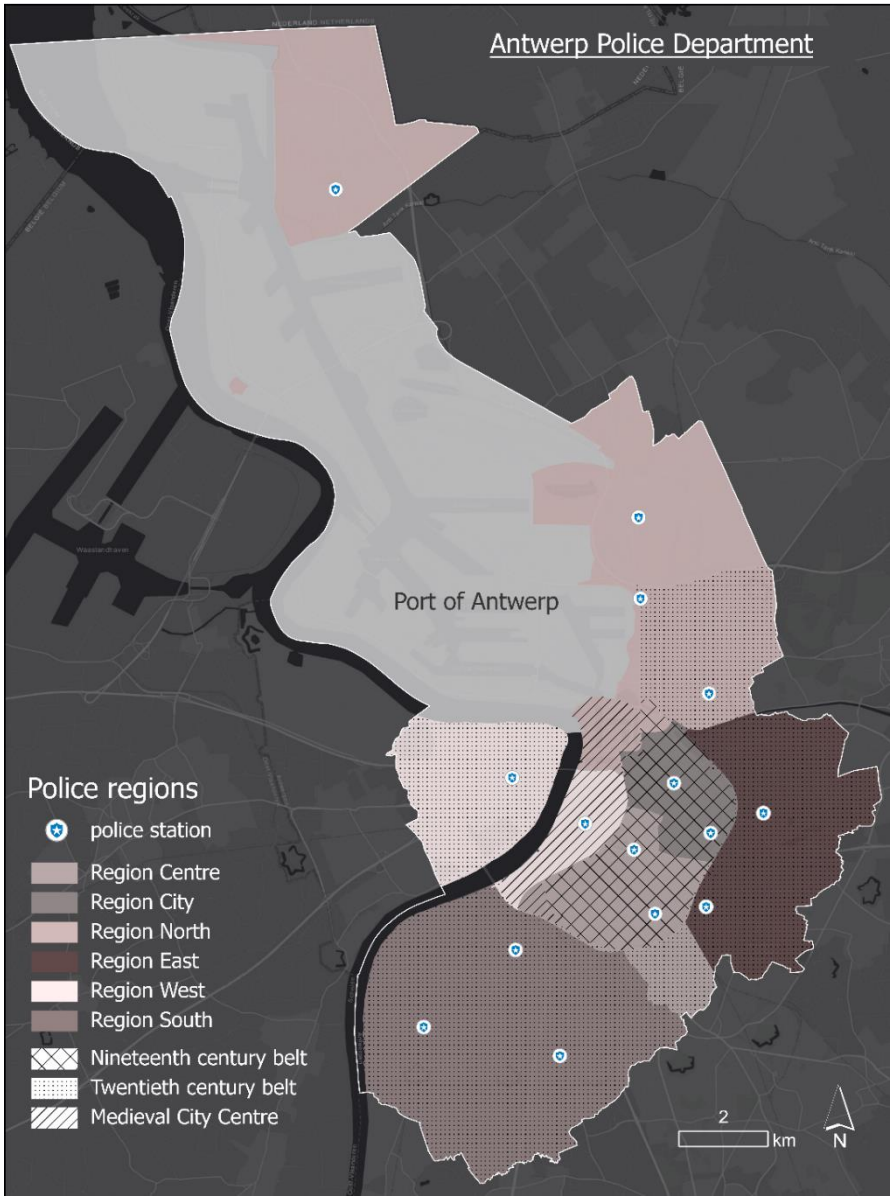

Fig. 1. Antwerp Police Department

Within a four-year period (2017-2020), 560,580 CFS occurred. The CFS data set contains detailed information about the time, place, and priority code of each incident. Each CFS receives a priority code (prio) that is inversely proportional to the urgency and ranges from zero to four. Highly urgent, life-threatening incidents, requiring immediate intervention receive code zero, and officers are allowed to use the vehicle's siren and/or flashing lights in order to minimize response time. This is the period between when a CFS is recorded and the time the first police vehicle arrives on site (Dewinter et al., 2020). Very low urgency incidents, such as parking violations, receive code four. In total, our data consists of 2,160 highly urgent, life-threatening incidents that require immediate intervention (0.39%; prio 0) and 7,953 prio 1 incidents (1.42%; absolute priority without direct risk to someone's life), in comparison to 156,628 prio 2 (27.94%; urgent and risk of escalation), 292,683 prio 3 (52.21%; routine (traffic) intervention), and 101,118 prio 4 incidents (18.04%).

All CFS were geocoded and matched to one of the 31,147 street segments in Antwerp. A street segment is defined as the section of a street between two intersections, and can be, e.g., a part of the highway or an unpaved road in a park as well. We have deliberately chosen to include all the different types of segments in the data set, because they are all part of the public domain; the working area of the police. By focusing on such a small unit of analysis, we are able to minimize aggregation bias (Vandeviver & Steenbeek, 2019).

2.2. Methods

Exploratory (spatial) data analysis (EDA) is applied to detect space-time patterns and possible anomalies. Therefore, a range of descriptive and spatial statistics, and space-time pattern mining tools are performed on the data set by using R (version 4.0.1) and ArcGIS Pro[7] (version 2.7.1) interchangeably. A straightforward method to conduct EDA does not exist, but based on existing research on space-time patterns of CFS data or crime data, we perform several techniques (Andresen, 2017; Anselin et al., 2000; Felson & Poulsen, 2003; Herrmann, 2013, 2015). The analyses are divided in three parts, first we focus on the spatial characteristics of the data set, second on the time aspects, and third, the findings on space and time are integrated in emerging hot spot analysis.

2.2.1 Spatial statistics

The data set consists of point features, where each point represents an event (an incident). On this micro level of analysis, the focus is on the presence or absence of an incident rather than on some measured attribute. To know which spatial pattern the incidents exhibit, the average nearest neighbour (ANN) statistic is used. This statistic calculates the observed mean distance ($\bar{D}_O$), this is the average of the distances from each point to its nearest neighbour (d_i), and compares this to the average expected distance ($\bar{D}_E$) in the case of a random distribution of the points. The nearest neighbour index is equal to the ratio of the observed to the expected mean distance. The pattern exhibits clustering if the index is less than 1, and dispersion if greater than 1. In (1), n corresponds to the total number of CFS, and A is the area of Antwerp (Antrop et al., 2013).

$$ANN = \frac{\bar{D}_O}{\bar{D}_E} = \frac{\frac{\sum_{i=1}^{n} d_i}{n}}{\frac{0.5}{\sqrt{n/A}}} \qquad (1)$$

Because police patrol street segments and some spatial tools require aggregated data instead of point data, each incident is matched to its corresponding street segment and the frequency of CFS at each

[7] ESRI, ArcGIS desktop: Release, 2.7.1. Redlands, CA: Environmental Systems Research Institute, 2021

street segment is counted. We use the Global Moran's I statistic to test for spatial autocorrelation. Global Moran's I ranges from -1, indicating negative spatial autocorrelation or a dispersed pattern, to +1, meaning positive spatial autocorrelation or a tendency towards a clustered spatial pattern, if the z-score and p-value are statistically significant. A value equal to zero represents a random pattern (Goodchild, 1986). To determine the threshold distance which reflects maximum spatial autocorrelation, we first run the incremental spatial autocorrelation tool in ArcGIS Pro. The outcome of this analysis is displayed in a line graph, where a peak in z-score indicates the threshold distance in which the spatial autocorrelation is most pronounced.

Since the Moran's I statistic is a global statistic, which only tells whether the spatial pattern is clustered, dispersed or random, and not where potential clusters of, in our case, street segments with high or low values are located, we also apply the Local Moran's I statistic. This statistic shows where statistically significant clusters of high (high-high cluster) and low (low-low cluster) values, as well as, where outliers are located. A value is considered to be a statistically significant spatial outlier if the street segment has a high frequency of CFS and the surrounding segments all have low frequencies (HL), or the other way around, if a segment with a low frequency is surrounded by segments with high frequencies (LH). Another local indicator of spatial association statistic (LISA) is Getis-Ord Gi* (Gi*) or (optimized) hot spot analysis. This statistic calculates, given a set of weighted features, statistically significant hot and cold spots of incidents (Andresen, 2017; Anselin, 1995; Anselin et al., 2000). Getis-Ord Gi* only identifies clusters of high-high (high z-score and small p-value) and low-low (low negative z-score and small p-value) local incidents (Getis & Ord, 1992; Ord & Getis, 1995). We compare Gi* to the outcome of Local Moran's I. Both can be shown on a map (Andresen, 2017; Anselin, 1995). All these spatial statistics are calculated in ArcGIS Pro, using the Spatial Statistics Toolbox.

$$Global\ I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad (2)$$

$$Local\ I = \frac{x_i - \bar{X}}{S_i^2}\sum_{j=1, j\neq i}^{n} w_{i,j}(x_j - \bar{X}) \qquad (3)$$

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2\right]}{n-1}}} \qquad (4)$$

2.2.2 Time pattern analysis

Not a single hot spot is hot 24/7, 52 weeks a year. To know at what time of the day hot streets or areas are 'hot', we examine the time pattern of the CFS by creating a time heat map (Herrmann, 2013, 2015). This specific type of heat map is a graphic, which displays the number (full data set) or proportion (priority codes) of CFS for each day of the week (y-axis) and for each hour of the day (x-axis).

Consequently, potential time patterns in the data set become visible. Moreover, we also establish the median minute of crime, crime quartiles, crime's daily timespan, and the, e.g., 5-to-5 share of offenses (Felson & Poulsen, 2003). The median minute of incidents is 'that minute of the day by which exactly half of the incidents have occurred' (Felson & Poulsen, 2003, p. 597). The incident quartiles are those minutes of the day by which a quarter and 75% of the CFS took place. The number of minutes between these two periods is the daily timespan or the inter-quartile range. A higher timespan is generated when CFS are more dispersed over the day. Last, the 5-to-5 share of offenses analyses the proportion of CFS occurring between 5:00 AM and 4:59 PM. This is used to determine the time pattern throughout the day; a lower proportion of CFS indicates a later incident pattern (Ashby & Bowers, 2013; Felson & Poulsen, 2003). To analyse potential variability in the time patterns of the days of the week, we extend Felson and Poulsen's (2003) approach by calculating the parameters for each day separately.

2.2.3 Space-time Pattern Mining: Emerging Hot Spot Analysis

To visualize the space-time pattern of the CFS the space-time pattern mining tool 'Emerging Hot Spot analysis' is applied. Before it is possible to run this tool on the data set, a space-time cube, as shown in Fig. 1, is created by aggregating the incident points. To create these space-time cubes, the CFS are aggregated[8] in hexagons with a diameter of 300 m. This diameter ensures that each hexagon contains sufficient CFS while minimizing the effect of aggregation bias (Fotheringham & Wong, 1991). By creating a space-time cube (netCDF data structure) data can be visualized in three dimensions: the x and y dimensions represent space and a third axis represents time (Esri ArcGIS Pro, n.d.).

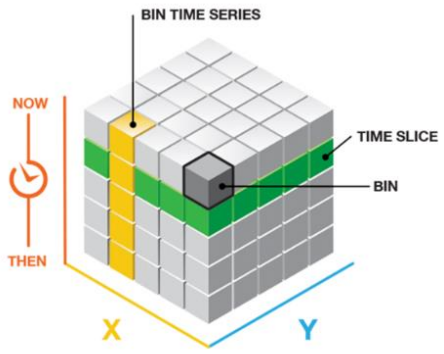

Fig. 2. Example of a space-time cube (Source: Esri ArcGIS Pro (n.d.)).

The cube is made up of small 'bins', which can have the same location ID or the same time-step ID. Bins with the same location ID are associated with the same area in space and will represent a time series. A time slice contains bins with the same time-step ID, i.e., these bins are associated with the same time-step interval. Subsequently, this space-time cube is used by the emerging hot spot analysis tool to

[8] This is automatically done in ArcGIS Pro.

identify hot spots in space and time. The statistic that will be calculated for each bin is a space-time implementation of Getis-Ord Gi* (Esri ArcGIS Pro, n.d.). The bins that will be included in each analysis neighbourhood of the Getis-Ord Gi* statistic are determined by the conceptualization of the spatial relationships and the neighbourhood time-step value (default settings are used). The eventual hot and cold spot trends are evaluated by the Mann-Kendall trend test, a rank correlation analysis. Eventually, each time series will be identified as a new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, or historical hot or cold spot. The output of this tool can be visualized in 2D and in 3D (Esri ArcGIS Pro, n.d.).

3. Results

3.1 The spatial pattern of police demand on point and street segment level

The observed mean distance of the ANN statistic for the full data set (all incidents 2017-2020) is 0.59 meters and the expected mean distance is 9.54 meters, resulting in an ANN index equal to 0.061. Given that this index is less than one and almost equal to zero the CFS exhibit a clustered pattern on this micro scale of analysis. In Table 1 the ANN indices for the different priority codes and the separate zones are included as well, all resulting in a clustered pattern on point level. The more urgent calls are less clustered than priority codes 3 and 4 and of the six zones, zone West experiences the most clustered pattern.

Table 1

Average nearest neighbour indices

Data set	ANN	z-score
Full data set	0.061	-1344.39*
prio 0	0.39	-54.28*
prio 1	0.36	-108.94*
prio 2	0.13	-656.64*
prio 3	0.092	-940.10*
prio 4	0.16	-509.06*
North	0.057	-486.25*
East	0.078	-513.74*
South	0.082	-518.15*
West	0.032	-574.15*
City	0.055	-593.78*
Centre	0.057	-601.6*

*p < 0.001

Given the absence of a peak in the z-scores for the incremental spatial autocorrelation, this tool has not led to an unambiguous result for the threshold distance. The ever-increasing z-scores could be a result of aggregating the point data to street segments, generating a too coarse aggregation level. The only lower level of analysis are the addresses, but as discussed in 2.2.1, police patrol along street segments, and some degree of aggregation is necessary to perform the Global and Local Moran's I statistics. Hence, we will stick to this level of analysis. What we do know from this statistic is that within a threshold distance of 577 meters every feature has at least one neighbouring feature. The Global Moran's I statistic is the highest for this threshold distance and the value slightly decreases (but still positive) as the distance increases. As shown in Table 2, the Global Moran's I Index for this threshold distance is equal to 0.104, indicating positive spatial autocorrelation. The global Moran's I indices for the priority codes and the six zones exhibit, in line with the ANN indices, positive spatial autocorrelation with only small variations between the indices. As with the ANN indices, prio 0 exhibits a slightly less clustered pattern than prio 3, indicating that prio 3 incidents are more clustered on both, street segment and incident level. On the level of the zones, the incidents per street segment are least clustered in North and the most in City. North is scattered over the northern part of Antwerp, which may have affected this outcome.

Table 2

Global Moran's I indices

Data set	Global Moran's I	z-score
Full data set	0.104	105.2*
prio 0	0.027	29.34*
prio 1	0.050	54.4*
prio 2	0.074	74.92*
prio 3	0.13	135.42*
prio 4	0.043	49.86*
North	0.024	15.95*
East	0.12	22.06*
South	0.075	22.73*
West	0.14	42.25*
City	0.15	18.73*
Centre	0.066	11.22*

*$p < 0.001$

The Gi* statistic or hot spot analysis (see, left map Fig. 3) results in four significant hot spots of CFS: the entire city centre and three clusters of street segments northeast, east, and southwest of this area. In accordance with Local Moran's I (see, Fig. 3 right) several cold spots are scattered around the 'hot' city

centre. When we zoom in on these hot and cold spots, we can see, on the one hand, that the CFS tend to cluster (i.e., hot spots) around regional roads which connect the city centre with the surrounding districts and municipalities, around squares, in shopping streets, around the central train station, and in streets with night-time economy. On the other hand, the cold spots mainly correspond to the Zoo of Antwerp, parks, nature reserves, and the port area. The Local Moran's I statistic provides us with even more detail by showing significant outliers. Within the high-high clusters, for example, some street segments experience significantly less incidents, resulting in low-high outliers. An example of such an outlier is the dark blue triangle in the middle of the city centre. This is a park. Inversely, low-low clusters are scattered around the centrally located city centre, and are interrupted in several places by street segments with a noticeably higher frequency of incidents.

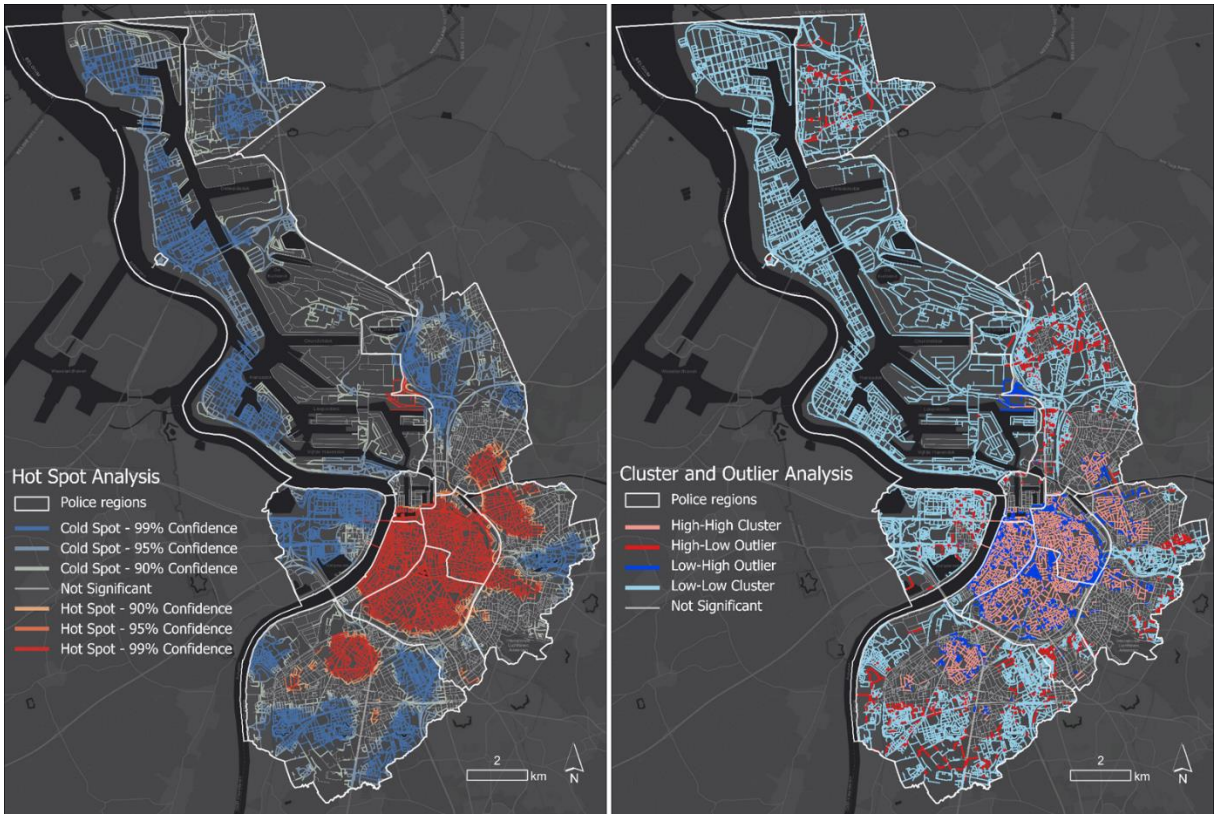

Fig. 3. Getis-Ord Gi* (left) and Local Moran's I statistic (right) of the CFS data of Antwerp, aggregated on street segment level (2017-2020).

Fig. 4 enriches our knowledge on the level of the five priority codes. In comparison with the outcomes of Global Moran's I in Table 2, the priority codes with the highest indices, prio 2 and 3, but also 4, show a similar pattern as for all CFS (Fig. 3). In the case of priority codes 0 and 1 this pattern is less apparent. For prio 0 incidents, low-high outliers are predominant in the city centre compared to high-high clusters and the size of the clusters is notably smaller than for prio 3 or 4 CFS. In general, however, the places

where hot street segments or high-low outliers occur are similar for all priority codes, with a big cluster in the city centre and three smaller surrounding clusters, but the higher the prio codes, the bigger the size of these hot spots. The low-low clusters expand as well as the prio code increases, but they are more regularly interrupted by hot street segments.

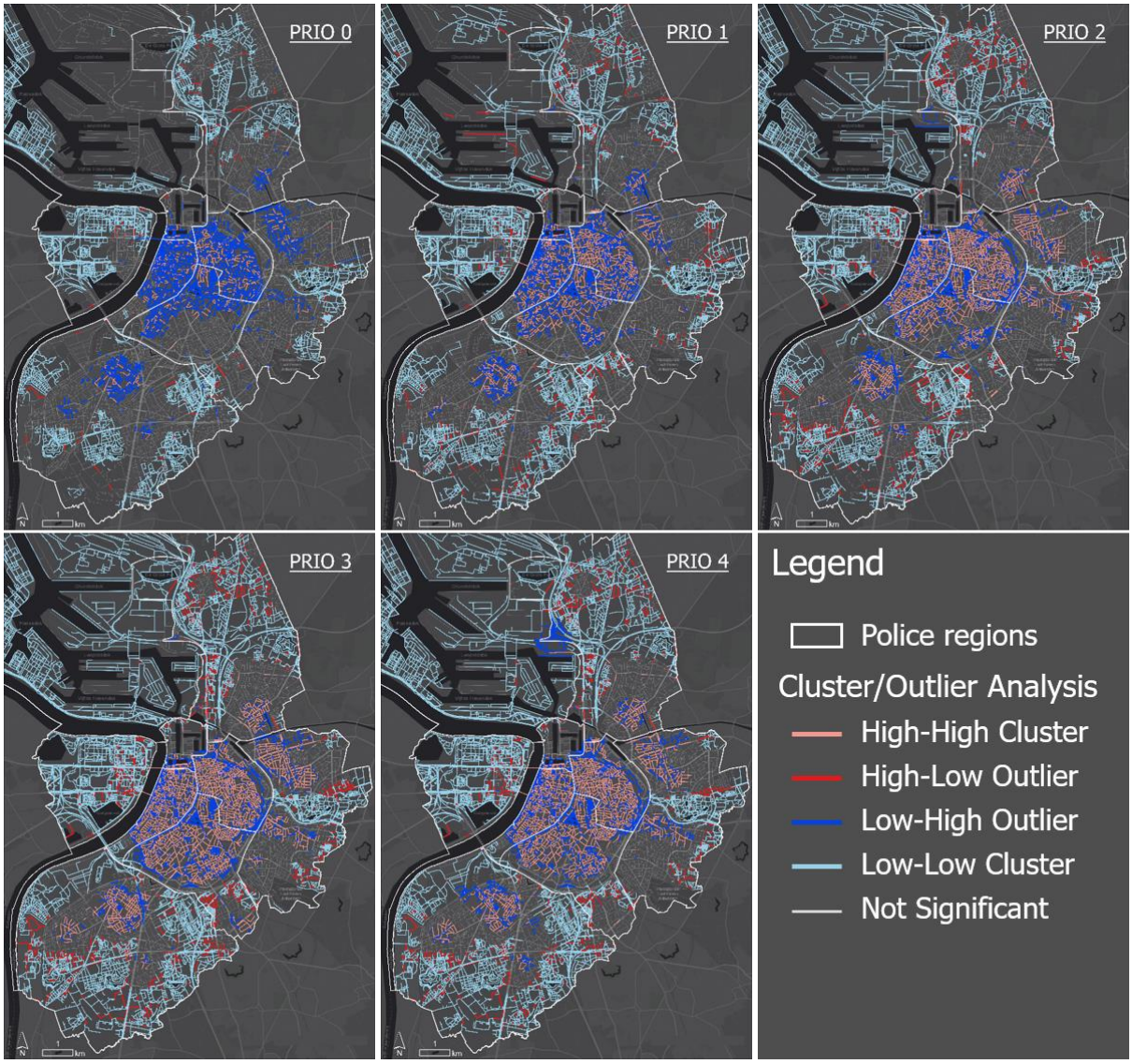

Fig. 4. Outcome of the Local Moran's I statistic for the CFS data per priority code (2017-2020).

3.2 Time pattern of the emergency incident call data

First, we examine the time aspect on a monthly scale of analysis. On this meso level, the pattern in Fig. 5 is not stable but shows an increasing pattern from the beginning of January until the end of June, which is followed by a sharp decline during the summer holiday in July and August, after which the number of CFS per day increases again in September, to end with a rather constant number of CFS in October,

November and December (cf. seasonal driver of demand). The difference in the number of CFS between the different priority codes is very high, with only a small amount of urgent incidents compared to prio 2, 3, or 4 incidents. The curve of the prio 0 incidents shows a fairly constant pattern with no outliers. By contrast, the prio 1 curve has four peaks that are the result of stormy weather with very high wind speeds. Each of the four peaks can be related to storm damage caused by a storm in one of the four years in our data set.

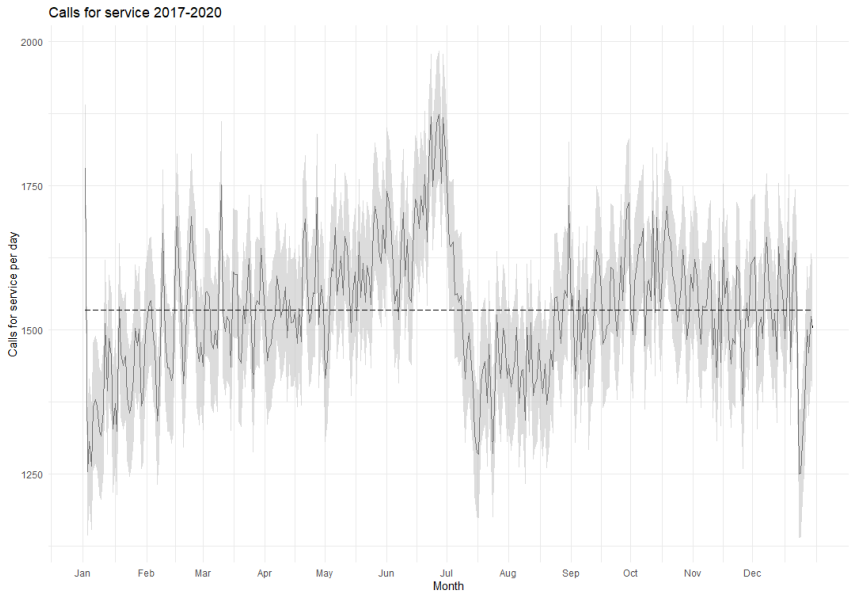

Fig. 5. Emergency call incidents per day (2017-2020).

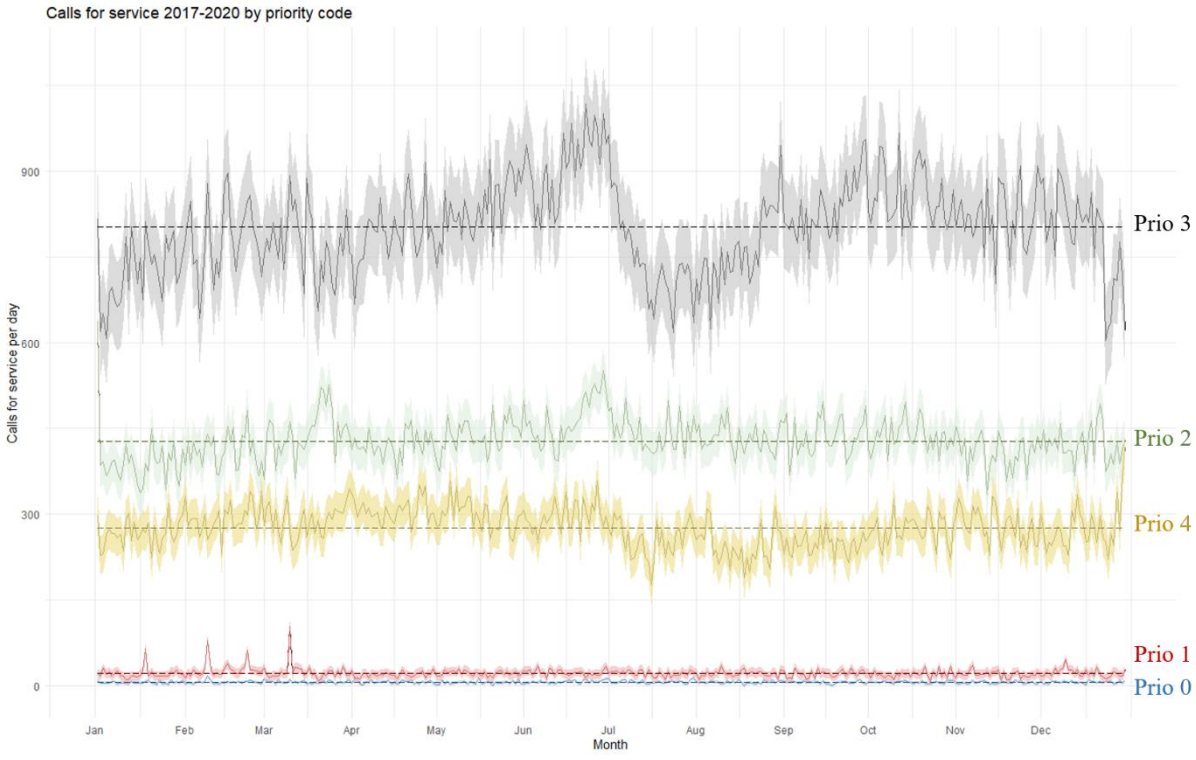

Fig. 6. CFS in Antwerp per day for each priority code (2017-2020).

Second, Figs. 7 and 8 zoom to a smaller scale of analysis and focus on CFS by day of week and hour of day. The time heat map in Fig. 7 is generated from the CFS of the full data set. Fig. 7 gives an indication of the time pattern and allows to identify hour blocks with an increased number of incidents per hour, but does not allow to make statistically significant statements. On weekdays, CFS are elevated during morning rush hour (7 am until 12 am). On weekends and Sundays in particular, this pattern is less pronounced. Instead, Friday and Saturday evenings and nights appear to be 'hotter' than weeknights. Apart from the increased number of CFS during the morning rush hour, Fig. 7 also indicates a rise in incidents in the afternoon and from 7 PM until 8 PM. Across all weekdays, 5 and 6 AM is the quietest period.

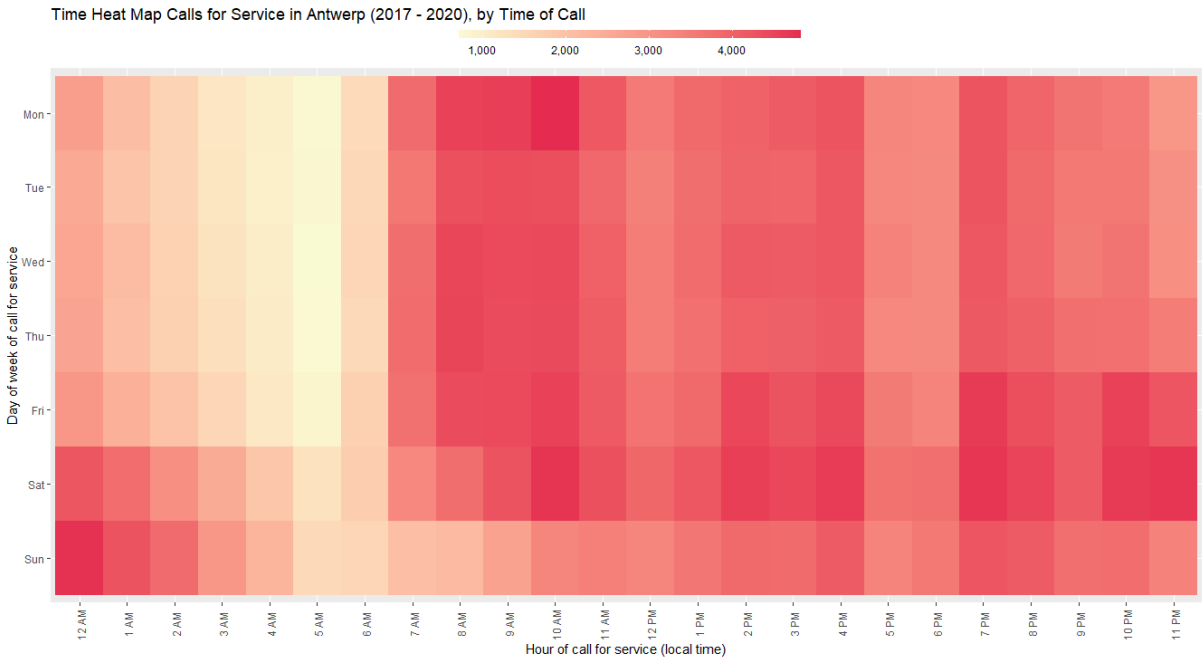

Fig. 7. Time heat map of the CFS in Antwerp by day of week and time of day, 2017-2020.

For priority codes 0 and 1 no clear pattern can be established, however, the proportion of prio 0 calls increases on Friday evening and Saturday evening/night. The proportion of prio 2 calls rises throughout the day, with a higher proportion from 4 PM until 5 PM and from 7 PM until 8 PM, and a slightly increased proportion on Friday and Saturday evening/night. Priority codes 3 and 4 exhibit more or less the same pattern as prio 2, except for their higher proportion of CFS between 7 and 11 AM.

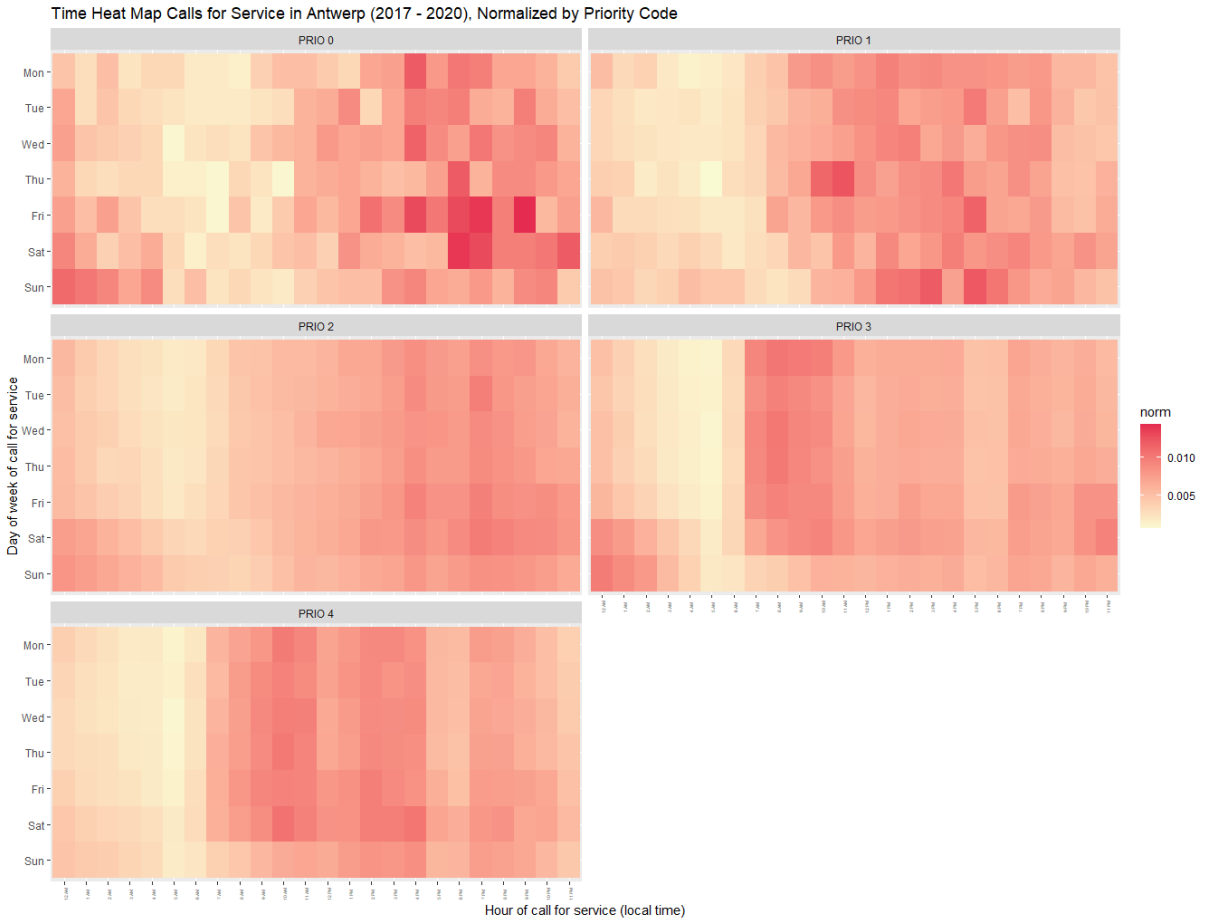

Fig. 8. Time heat map of the CFS in Antwerp by day of week and time of day per priority code, 2017-2020.

Third, the parameters of Felson and Poulsen (2003) are summarized in Table 3. The time of the first quartile minute steadily increases throughout the week; on Monday a quarter of the CFS occurs between 5:00 AM and 10:50 AM, while this shifts on Sunday to 12:20 AM. The time span exhibits a similar pattern, which means that the dispersion of CFS over the day increases over the days of the week, however, on Sunday the time span is clearly shorter than on the other days. On Friday and Saturday, the time span is the longest and the 5-to-5 share of incidents the lowest. A more dispersed pattern over the day means a more clustered pattern at night, and a lower proportion of CFS between 5:00 AM and 4:59 PM corresponds to a later incident pattern on Friday and Saturday, which corresponds to the increasing number of CFS on Friday and Saturday night/evening, as shown in the time heat map (Fig.7). Moreover, these simple indicators, as they are called by Felson and Poulsen (2003), reveal differences between the temporal patterns of the priority codes. The most urgent incidents have a remarkably low 5-to-5 share of incidents and thus a clustering of CFS in the evening and night, characterised by a short time span. By 2:23 PM, only a quarter of the CFS had occurred, while on an average day this is already at 11:21 AM. The time pattern of CFS with prio 1 and 2 is similar but is, especially for incidents with prio 1, slightly earlier. In contrast, prio 3 incidents have an early time pattern with a very long time span, which

means the CFS are spread throughout the day and evening. The highest 5-to-5 share is for prio 4 CFS; about 60% of the prio 4 CFS occur before 5 o'clock in the evening.

Table 3

Time analysis based on the first, median, and third quartile minute, the time span, and the 5-to-5 share of crime.

day of week	First quartile minute	median minute	third quartile minute	time span (minutes)	5-to-5 share of incidents
Monday	10:50 AM	3:42 PM	8:44 PM	594	57.01%
Tuesday	10:59 AM	3:58 PM	8:59 PM	600	55.7%
Wednesday	10:57 AM	3:52 PM	8:56 PM	599	56.13%
Thursday	11:04 AM	4:07 PM	9:20 PM	616	54.59%
Friday	11:35 AM	4:59 PM	10:28 PM	653	50.07%
Saturday	11:59 AM	5:22 PM	10:52 PM	653	48.35%
Sunday	12:17 PM	4:55 PM	9:31 PM	554	50.39%
average day	11:21 AM	4:24 PM	9:37 PM	616	53.00%
prio 0	2:23 PM	6:35 PM	10:35 PM	492	39.63%
prio 1	12:10 PM	4:21 PM	8:38 PM	508,5	53.99%
prio 2	1:10 PM	5:51 PM	10:08 PM	538	45.15%
prio 3	10:40 AM	3:56 PM	9:46 PM	666	54.90%
prio 4	11:07 AM	3:23 PM	8:22 PM	555	59.89%

3.3 Space-time visualisation of police demand

Finally, the emerging hot spot analysis (see, Fig. 9) allows us to combine time and space. The bin time series in Fig. 9 consist of one day and the time-step interval is one hour. In both cases (prio 0 and 1 and prio 3), the city centre turns red, indicating the presence of significant hot spots of CFS. For the two most urgent categories, the hot spots in the city centre intensify throughout the day. This means that the hot spots in these locations are significant for ninety percent of the time-step intervals, including the final time step and the intensity of the clustering of high counts significantly increases every hour. These hot spots are surrounded by sporadic hot spots, i.e., hot spots that are alternately significant, but never a cold spot, and consecutive hot spots, i.e., locations with a single uninterrupted run of statistically significant hot spot bins in the final time-step intervals (less than ninety percent of all bins are statistically significant). Cold spots of prio 0 and 1 incidents are located in the north and south of Antwerp. The spatial pattern of hot and cold spots is similar for prio 3 incidents, although the hot spots in the city centre are mostly persistent hot spots, meaning that a location has been a statistically significant hot spot for ninety percent of the time-step intervals without a discernible trend (i.e., the number of events is high during the entire day). The hot spots surrounding these persistent hot spots are

mainly intensifying hot spots, sporadic hot spots, and oscillating hot spots. The oscillating hot spots were at the start of the day statistically significant cold spots, but they have turned into a statistically significant hot spot for the final hours of the day. The area occupied by this big hot spot is again much larger than for the urgent CFS. In both cases, the cold spots are predominantly persistent, except in the northernmost part of Antwerp, where the intensity of the clustering of low counts in each time step significantly decreases, but these locations are still significant cold spots.

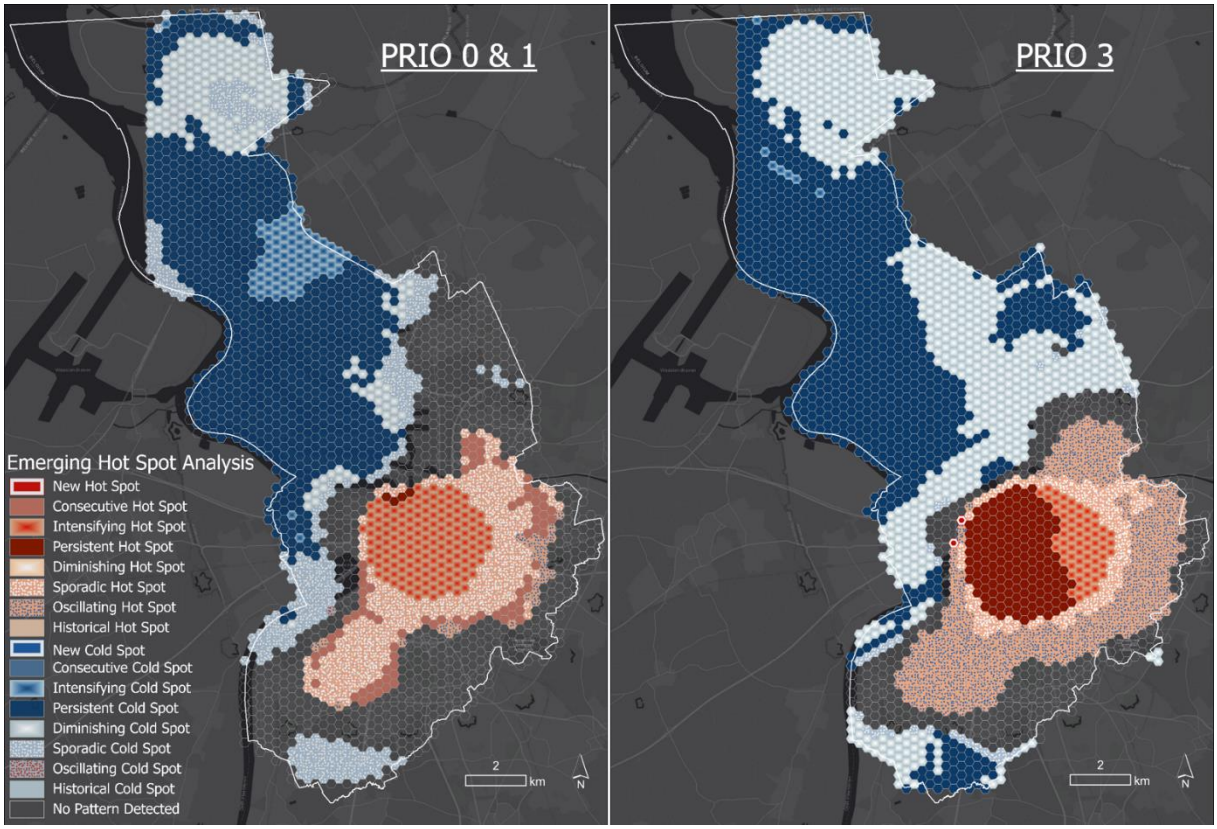

Fig. 9. Emerging Hot Spots analyses of prio 0 and 1 (left) and prio 3 (right) CFS in Antwerp (2017-2020).

The emerging hot spot maps show a more widespread occurrence of hot spots than Local Moran's I or Getis-Ord Gi*, inter alia, because of the aggregation in hexagons. In general, we were able to detect four clusters of street segments with high levels of CFS, one big cluster representing the city centre, one in the northeast, one in the east, and one in the southwest of Antwerp.

4. Discussion

The main objective of this paper is to establish daily police demand by examining the space-time pattern of the CFS data set (2017-2020) of the Antwerp Police Department. Several exploratory (spatial) data analysis techniques are used to analyse the space, time, and space-time patterns of the overall data set and of the five priority codes. On the one hand regularities are established in the space-time pattern of the CFS. On the other hand, we detected a number of anomalies, which have to be addressed.

4.1 A spatial perspective on calls for service

The fact that the emergency incidents in Antwerp are clustered in time and in space is not surprising. In line with other exploratory research papers on the space-time pattern of crime or CFS data, a number of hot spots are detected in Antwerp. The biggest and most notable hot spot is located in the city centre of Antwerp. This area contains the historical city centre, but also the main shopping streets, restaurants and entertainment areas, the railway station, and lots of smaller and bigger businesses. A real central business district (CBD) as there is, for example, in Barrera et al. (2013) and in Luan et al. (2016) is not clearly present in Antwerp. Instead, Antwerp has over the years expanded around the old medieval city centre, which is located near the river Scheldt. Barrera et al. (2013) reported clustering of several types of crimes near the CBD. The concentration of offences in these areas corresponds as well to the findings of other research on space-time patterns in cities. Feng et al. (2016) identified, for example, wholesale markets, shopping centres, aggregation zones of passenger flows, and zones with high population mobility as places with a higher number of incidents. Nakaya and Yano (2010) focused in particular on snatch-and-run offences and reported clustering in the city centre and around railway stations and Luan et al. (2016) also point to areas with highways, a local university, and a regional shopping centre. In the classification of the drivers of police demand (see Introduction) this corresponds to the baseline (Laufs et al., 2020).

4.2 Space-time representation of priority codes

The prioritization of CFS and the analysis thereof is vital to organize police patrol cost-effective and ethical (Kärrholm et al., 2020). Our analysis revealed that the spatial, temporal, and space-time patterns of the five priority codes differ. First, the most urgent CFS, prio 0, are spatially the least clustered. The hot spots are smaller and more often interrupted by street segments with a significantly lower number of CFS (low-high outliers). Although the number of street segments where at least one CFS occurs is much lower for prio 0 than for, e.g., prio 3 CFS (4.62% versus 35.16%, respectively), the average number of incidents per segment increases much more sharply (1.5 CFS/segment versus 26.7 CFS/segment, respectively). Hence, the small number of prio 0 CFS is a possible explanation for the limited clustering. A substantive explanation could be that these severe prio 0 CFS are rare and less place and opportunity-related than the less urgent CFS. Second, the highest proportion of prio 0 incidents occurred on Friday evening and Saturday evening/night and they have a later time pattern than the other priority codes, which is also evidenced by the fact that the hot spots in the city centre of Antwerp become more intense during the course of the day. If we compare this to prio 3 calls, we see that these clusters of incidents are much bigger and a clearer time pattern can be discerned, with a higher proportion of incidents on weekdays during the morning rush hour and in the weekend, on Friday and Saturday evenings and nights. This also corresponds to Newton (2015) and Herrmann (2015). The former focused

on crime in the night-time economy, the latter, among other things, on violent crimes (murder, shootings, and assaults). Both reported a significant increase in disorder starting on Friday and Saturday afternoon until the early morning. Third, the drop in the number of prio 3 CFS in the summer months of July and August seems to contradict research on crime seasonality, which often reports a rise in crime in the summer (McDowall et al., 2011), but this may be due to a reduced morning rush hour caused by the summer holiday (e.g., summer shutdown of the building sector, school holiday…). Thus, this is probably caused by the type of incidents classified under prio 3, i.e., about 50% are traffic-related CFS. Furthermore, prio 1 calls show a similar spatial and temporal pattern as prio 0 CFS, but the incidents occur earlier in the day. The patterns of prio 2 and prio 4 calls are comparable to those of the prio 3 calls.

4.3 Priority codes as an alternative to crime harm

How crime or incident types can be valued based on their severity is studied in the crime harm literature. Sherman (2013) developed the Crime Harm Index (CHI) to analyse how much harm different types of crime cause by days of imprisonment. According to Weinborn et al. (2017) harm is even three times more concentrated than crime counts and, therefore, the CHI is a useful statistic for crime analysis and decision-making (Curtis-Ham & Walton, 2017; Kärrholm et al., 2020). In the meantime, some countries have already developed their own, local version of the CHI (Andersen & Mueller-Johnson, 2018; Curtis-Ham & Walton, 2017; Kärrholm et al., 2020); this is not yet the case for Belgium. The crime harm literature states that allocating scarce police resources to harm spots instead of hot spots of crime counts can prevent the more serious crimes (Kärrholm et al., 2020; Sherman, 2013; Sherman et al., 2016; Weinborn et al., 2017). A downside of the CHI is that it can give a distorted understanding of the situation. Weinborn et al. (2017) illustrate this with an example of two places with exactly the same harm values, where in one place a lot of minor incidents occurred and in another place there is one incident that carries a very high penalty (e.g. homicide). If police would only focus on crime harm but not on crime count, scarce resources might be allocated to tragic, yet isolated incidents. The classification by priority/urgency gives, albeit in a more operational way, a similar idea of the severity of CFS and also makes it possible to analyse incident count. In Antwerp, all types of CFS cluster in the city centre. This is a place where a lot of people congregate and interact, resulting in crime opportunities and, consequently, an increase in CFS (Fenimore, 2019; Newton, 2015). However, Fenimore (2019) reported that in Washington DC more serious crimes occurred further away from the city centre. Although the hot spots in our analysis are substantially smaller for the urgent incidents, the places where the hot spots occur are similar. The question "where to deploy police officers" can therefore be answered in the same way for all priority codes. But in Antwerp, prio 0 (and 1) CFS are given priority over the other incidents and on average more vehicles are dispatched to these CFS than to CFS with a higher

priority code (2-3-4). In our sample, on average four police units[9] responded to a prio 0 CFS, three to prio 1, 1.5 to prio 2, and one unit to prio 3 or prio 4 calls. In 89% of the prio 0 CFS more than one unit responded to the incident. This proportion slightly drops to 76% for prio 1 CFS and declines remarkably for prio 2 (29%), prio 3 (9%), and prio 4 (11%) CFS. Therefore, when a prio 0 or prio 1 call occurs, it will require more resources than prio 2, 3 or 4 CFS and since these CFS occur in general at a later time of day and tend to cluster on Friday and Saturday night/evening, we would recommend the police to respond more flexible to these increases in urgent police demand.

4.4 Implementing prioritization in police patrol routing strategies

A lot of police patrol routing strategies use historical crime or incident data to define patrol routes (Azimi & Bashiri, 2016; Calvo et al., 2017; Chen et al., 2017). However, priority codes have never been included in such a patrol strategy. Yassen et al. (2017) do define a stopping time based on the priority of each hot spot, but the main objective of their routing strategy is to maximise the coverage of hot spots. In other words, they do not take into account the priority of the CFS themselves and the impact on the available resources. Quite often only the most urgent CFS are considered in a patrol strategy (e.g., Saint-Guillain et al., 2021), which does not allow for a correct estimation of the daily demand for police (i.e., underestimation of the actual demand for police). As we demonstrate in this paper, the urgency of a CFS has repercussions on the spatial and temporal distribution as well as on the operation of the police. The more urgent CFS have a greater impact on patrol operation than a prio 3 or a prio 4 call. An example to illustrate this: if a police zone has a call rate of six calls per hour and we know that in our case the average number of responding cars per call differs depending on the priority code, the adjusted call rate can be much higher than six. If six incidents with prio 3 occur, only *six* units are likely to respond, but if there are 1 prio 0, 2 prio 2, 1 prio 3, and 2 prio 4 calls for service, in the worst case, *ten* units are assigned (Green, 1984). Nevertheless, we cannot ignore the large differences in absolute values between the priority codes. There appears to be a disparity between the incidental demand for police and the structural demand for police (see, Table 4). There are 35,064 hours in our data set. Even if we weigh urgent calls by the average number of vehicles responding, the number of critical CFS per hour remains notably lower than for non-urgent calls. Although critical incidents are on average more demanding when they occur (i.e., incidental police demand), low urgency calls take up structurally more police resources (i.e., structural police demand).

[9] In Antwerp, there are always two police officers per vehicle.

Table 4

CFS per hour weighted by the average number of vehicles responding

Priority codes	# CFS	# vehicles	# CFS per hour	# CFS per hour weighted by # vehicles
Prio 0	2,160	4	0.062	0.25
Prio 1	7,953	3	0.23	0.68
Prio 2	156,628	1.5	4.47	6.70
Prio 3	292,683	1	8.35	8.35
Prio 4	101,118	1	2.88	2.88

The analysis of space-time properties of priority codes and its implementation in crime prevention and police patrol routing strategies have the ability, on the one hand, to prevent system overload (e.g., later in the day) and, on the other hand, to avoid oversupply of police presence. We can clarify this with an example of our own study area: Dau et al. (2021a) demonstrated that in Antwerp there is an overall decline in the level of police deployed over the course of the day (e.g., due to staffing plans or administrative work). This contradicts with our findings and indicates a possible mismatch of police demand and police presence in our study area. The discovery of this misalignment highlights the added value of our research for the Antwerp Police Department. Based on this example and, more in general, on the findings of this paper, we would recommend to include priority codes in future police patrol routing solutions to make patrol strategies more realistic. An important aspect will be to increase/decrease the number of available units depending on the number of CFS per priority code. Instead of only working with fixed shifts (e.g. APD), there is a need to deploy peak shifts depending on the historical CFS data. This is an avenue for future research.

4.5 Extending the framework

To this point we have not yet questioned how we analysed ‘police demand’. In a scoping review on police demand management, Laufs et al. (2020) criticize the sole focus on CFS data to study police demand. They split ‘police demand’ into reactive, protective, and organisational demand. The first type, reactive or public demand, is what was analysed in this paper and relates to the deployment of both personnel and equipment, mostly based on CFS. However, as a result of this reactive analysis, hot spots and burning times are established to then implement in preventative or proactive police work. Before proactive policing can be analysed it must first be implemented in the policing strategy. Therefore, spatiotemporal analysis is essential to provide police agencies with the necessary information on where and when incidents occur. In a next step, the effectiveness and efficiency of the proactive patrol strategy can be established. The last type of demand, organisational demand, is inherent to the organisation of the police and is created by processes, protocols, administrative tasks, and bureaucracy (Laufs et al.,

2020). We do not have data on this type of demand, since this is beyond the scope of the current, applied research objective.

4.6 Limitations

The objective was to fathom the space-time pattern of the entire CFS data set with a focus on the priority codes, resulting in a better understanding of the overall demand for police resource. This should in turn result in effective and efficient supply strategies. When comparing the findings for Antwerp – a mid-sized European city – with some other study areas worldwide, similarities are evident. What stands out in the other research papers on the space-time pattern of CFS is the specific focus on one or several types of CFS. Although we were specifically interested in the overall, daily pattern of the calls, this can be seen as a limitation of this research paper because detailed comparisons with other research papers were difficult. A second limitation of our research is related to the geocoding process. We detected some flaws in the geocoding algorithm that have to be solved for future analysis. These problems are caused by missing information, e.g. house numbers, an exclusive focus on distance instead of on the correct street name, and inaccuracies in the street segment layer. Andresen et al. (2020) discuss the fact that geocoding algorithms have the potential to introduce error into analysis, but this does not by definition mean that the data set is not accurate. If the flaws are random and if the geocoding match rate is above 85 percent, which is the case (94,79%), they conclude that the geocoded pattern is still representing the actual spatial pattern (Andresen et al., 2020). Third, based on our data set the exact time when a vehicle was dispatched to a CFS is known, but the underlying action could have happened before. Therefore, analysing the time aspect of CFS is associated with temporal inaccuracy.

5. Conclusions

Information on small spatial and temporal scales of analysis, as studied here, is necessary to efficiently deploy the available resources of any police force in the world. The results of this paper demonstrate that even differences between the days of the week can have an impact on the daily organisation of police strategies and staffing requirements. The first objective of this paper was to determine the space-time pattern of the Antwerp CFS in order to improve the current patrol strategy of the Antwerp Police Department to a more evidence-based and data-driven policing strategy. Antwerp is characterized by its dense historical city centre, which is surrounded by the twentieth century belt where parks, residential areas, and some more industrial zones alternate. This pattern is in some way reflected in the spatial pattern of the demand for police: the hot city centre is surrounded by an alternating pattern of hot and cold spots. The time pattern fluctuates over the months and differs on weekdays and in the weekend, with clear clusters between the morning rush hour and on Friday and Saturday evening/night. Comparing the space-time patterns of cities all over the world and of different sizes will improve our understanding

of where and when CFS cluster in time and space. In this paper similarities are detected in the space-time pattern of police demand in Antwerp and in Beijing (China), Kyoto City (Japan), The Regional Municipality of Waterloo (Canada), thirteen middle-sized American cities, and a study area in England. Last, the analysis of the priority codes is closely related to the crime harm literature and can be used to enrich research into crime harm. Our analysis of the priority codes gives insight in both, the severity of an incident and the number of incidents in space and time. In turn, this information can be used in police patrol routing strategies and for the efficient allocation of scarce police resources.

References

Andersen, H. A., & Mueller-Johnson, K. (2018). The Danish Crime Harm Index: How it works and why it matters. *Cambridge Journal of Evidence-Based Policing*, *2*(1-2), 52–69. https://doi.org/10.1007/s41887-018-0021-7

Andresen, M. A. (2017). Mapping Crime Prevention: What We Do and Where We Need to Go. In S. LeClerc (Ed.), *Crime Prevention in the 21st* (pp. 113–126). https://doi.org/10.1007/978-3-319-27793-6_9

Andresen, M. A., & Malleson, N. (2013). Crime seasonality and its variations across space. *Applied Geography*, *43*, 25–35. https://doi.org/10.1016/j.apgeog.2013.06.007

Andresen, M. A., Malleson, N., Steenbeek, W., Townsley, M., & Vandeviver, C. (2020). Minimum geocoding match rates: an international study of the impact of data and areal unit sizes. *International Journal of Geographical Information Science*, *34*(7), 1306–1322. https://doi.org/10.1080/13658816.2020.1725015

Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*, *27*(2), 93–115.

Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tital, G. (2000). Spatial analyses of crime. In D. Duffee (Ed.), *Measurement and Analysis of Crime and Justice* (pp. 213–262). US Department of Justice.

Antrop, M., Maeyer, P. de, Neutens, T., & van de Weghe, N. (2013). Metrisch-ruimtelijke analyse. In M. Antrop, P. de Maeyer, T. Neutens, & N. van de Weghe (Eds.), *Geografische Informatiesystemen* (pp. 229–284).

Ashby, M. P. J., & Bowers, K. (2013). A comparison of methods for temporal analysis of aoristic crime. *Crime Science*, *2*(1), 1–16.

Azimi, S. A. Z., & Bashiri, M. (2016). Modeling police patrol routing and its problem-solving technique based on the ant colony optimization algorithm (case Study: Iran's Police). *Research Journal of Applied Sciences*, *11*(7), 536–546.

Barrera, D. J., Cagang, S., & Capistrano, D. (2013). Spatial and temporal maps of reported crimes in Dumaguete City, Negros Oriental, Philippines. *PRISM*, *18*(1), 11–24.

Boivin, R. (2018). Routine activity, population(s) and crime_ Spatial heterogeneity and conflicting Propositions about the neighborhood crime-population link. *Applied Geography*, *95*, 79–87.

Bowers, K. (1999). Exploring links between crime and disadvantage in north-west England: an analysis using geographical. *International Journal of Geographical Information Science*, *13*(2), 159–184.

Calvo, H., Godoy-Calderón, S., Moreno-Armendáriz, M. A., & Martínez-Hernández, V. M. (2017). Forecasting, clustering and patrolling criminal activities. *Intelligent Data Analysis*, *21*(3), 697–720. https://doi.org/10.3233/IDA-170883

Chen, H., Cheng, T., & Wise, S. (2017). Developing an online cooperative police patrol routing strategy. *Computers, Environment and Urban Systems*, *62*, 19–29. https://doi.org/10.1016/j.compenvurbsys.2016.10.013

Chun, Y. (2014). Analyzing Space–Time Crime Incidents Using Eigenvector Spatial Filtering: An Application to Vehicle Burglary. *Geographical Analysis*, *46*, 165–184.

Chung, J., & Kim, H. (2019). Crime Risk Maps: A Multivariate Spatial Analysis of Crime Data. *Geographical Analysis*, *51*, 475–499.
Curtis-Ham, S., & Walton, D. (2017). Mapping crime harm and priority locations in New Zealand: A comparison of spatial analysis methods. *Applied Geography*, *86*, 245–254. https://doi.org/10.1016/j.apgeog.2017.06.008
Dau, P. M., Vandeviver, C., Dewinter, M., Witlox, F., & Vander Beken, T. (2021a). How concentrated are police on crime? A spatiotemporal analysis of the concentration of police presence and crime. Advance online publication. https://doi.org/10.31235/osf.io/rxa8h
Dau, P. M., Vandeviver, C., Dewinter, M., Witlox, F., & Vander Beken, T. (2021b). Policing directions: A systematic review on the effectiveness of quantitative police presence. *European Journal on Criminal Policy and Research*, 35. https://doi.org/10.31235/osf.io/ezk5f
Davies, T., & Bowers, K. (2019). Patterns in the supply and demand of urban policing at the street segment level. *Policing and Society*, *30*(7), 795–817. https://doi.org/10.1080/10439463.2019.1598997
de Melo, S. N., Matias, L. F., & Andresen, M. A. (2015). Crime concentrations and similarities in spatial crime patterns in a Brazilian context. *Applied Geography*, *62*, 314–324.
Dewinter, M., Vandeviver, C., Vander Beken, T., & Witlox, F. (2020). Analysing the Police Patrol Routing Problem: A Review. *ISPRS International Journal of Geo-Information*, *9*(3), 157. https://doi.org/10.3390/ijgi9030157
Esri ArcGIS Pro. (n.d.). *Emerging hot spot analysis (space time pattern mining)*. https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/emerginghotspots.htm#
Felson, M., & Poulsen, E. (2003). Simple indicators of crime by time of day. *International Journal of Forecasting*, *19*(4), 595–601. https://doi.org/10.1016/S0169-2070(03)00093-1
Feng, J., Dong, Y., & Song, L. (2016). A spatio-temporal analysis of urban crime in Beijing: Based on data for property crime. *Urban Studies*, *53*(15), 3223–3245. https://doi.org/10.1177/0042098015612982
Fenimore, D. M. (2019). Mapping harmspots: An exploration of the spatial distribution of crime harm. *Applied Geography*, *109*, 1–10. https://doi.org/10.1016/j.apgeog.2019.06.002
Fondevila, G., Vilalta-Perdomo, C., Pérez, M. C. G., & Cafferata, F. G. (2021). Crime deterrent effect of police stations. *Applied Geography*, *134*, 11.
Fotheringham, A. S., & Wong, D. (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning a*, *23*(7), 1025–1044.
Getis, A., & Ord, J. K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis*, *24*(3), 189–206.
Goodchild, M. F. (1986). *Spatial autocorrelation*. *CATMOG: Vol. 47*. Geo Books.
Green, L. (1984). A multiple dispatch queueing model of police patrol operations. *Management Science*, *30*(6), 653–664. https://doi.org/10.1287/mnsc.30.6.653
Helbich, M., & Leitner, M. (2017). Frontiers in Spatial and Spatiotemporal Crime Analytics—An Editorial. *ISPRS International Journal of Geo-Information*, *6*(3), 73. https://doi.org/10.3390/ijgi6030073
Herrmann, C. R. (2013). Street-Level Spatiotemporal Crime Analysis: Examples from Bronx County, NY (2006–2010). In M. Leitner (Ed.), *Crime Modeling and Mapping Using Geospatial Technologies* (pp. 73–104). Springer Netherlands. https://doi.org/10.1007/978-94-007-4997-9_4
Herrmann, C. R. (2015). The dynamics of robbery and violence hot spots. *Crime Science*, *4*(33), 1–14. https://doi.org/10.1186/s40163-015-0042-5
Hu, Y., Wang, F., Guin, C., & Zhu, H. (2018). A spatio-temporal kernel density estimation framework for predictive crime hotspot mapping and evaluation. *Applied Geography*, *99*, 89–97. https://doi.org/10.1016/j.apgeog.2018.08.001
Kärrholm, F., Neyroud, P., & Smaaland, J. (2020). Designing the Swedish Crime Harm Index: an Evidence-Based Strategy. *Cambridge Journal of Evidence-Based Policing*, *4*(1-2), 15–33. https://doi.org/10.1007/s41887-020-00041-4
Kuo, P.-F., Lord, D., & Walden, T. D. (2013). Using geographical information systems to organize police patrol routes effectively by grouping hotspots of crash and crime data. *Journal of Transport Geography*, *30*, 138–148.

Laufs, J., Bowers, K., Birks, D., & Johnson, S. D. (2020). Understanding the concept of 'demand' in policing: a scoping review and resulting implications for demand management. *Policing and Society*, 1–24. https://doi.org/10.1080/10439463.2020.1791862

Lee, Y., Eck, J. E., O, S., & Martinez, N. N. (2017). How concentrated is crime at places? A systematic review from 1970 to 2015. *Crime Science*, *6*(1), 1–16. https://doi.org/10.1186/s40163-017-0069-x

Luan, H., Quick, M., & Law, J. (2016). Analyzing Local Spatio-Temporal Patterns of Police Calls-for-Service Using Bayesian Integrated Nested Laplace Approximation. *ISPRS International Journal of Geo-Information*, *5*(9), 162. https://doi.org/10.3390/ijgi5090162

Mastrofski, S. D. (1990). Prospects of change in police patrol: A decade in review. *American Journal of Police*, *9*(3), 1–79.

McDowall, D., Loftin, C., & Pate, M. (2011). Seasonal cycles in crime, and their variability. *Journal of Quantitative Criminology*, *28*(3), 389–410. https://doi.org/10.1007/s10940-011-9145-7

Megler, V., Banis, D., & Chang, H. (2014). Spatial analysis of graffiti in San Francisco. *Applied Geography*, *54*, 63–73. https://doi.org/10.1016/j.apgeog.2014.06.031

Mukhopadhyay, A., Zhang, C., Vorobeychik, Y., Tambe, M., Pence, K., & Speer, P. (2016). Optimal Allocation of Police Patrol Resources Using a Continuous-Time Crime Model. In Zhu, Q., Alpcan, T., Panaousis, E., Tambe, M., Casey, W. (Ed.), *Decision and Game Theory for Security* (Vol. 9996, pp. 139–158). https://doi.org/10.1007/978-3-319-47413-7

Nakaya, T., & Yano, K. (2010). Visualising Crime Clusters in a Space-time Cube: An Exploratory Data-analysis Approach Using Space-time Kernel Density Estimation and Scan Statistics. *Transactions in GIS*, *14*(3), 223–239. https://doi.org/10.1111/j.1467-9671.2010.01194.x

Nelson, A., Bromley, R., & Thomas, C. (2001). Identifying micro-spatial and temporal patterns of violent crime and disorder in the British city centre. *Applied Geography*, *21*(3), 249–274. https://doi.org/10.1016/S0143-6228(01)00008-X

Newton, A. (2015). Crime and the NTE: multi-classification crime (MCC) hot spots in time and space. *Crime Science*, *4*(1). https://doi.org/10.1186/s40163-015-0040-7

Newton, A., & Felson, M. (2015). Editorial: crime patterns in time and space: the dynamics of crime opportunities in urban areas. *Crime Science*, *4*(1). https://doi.org/10.1186/s40163-015-0025-6

Ord, J. K., & Getis, A. (1995). Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis*, *27*(4), 286–306.

Saint-Guillain, M., Paquay, C., & Limbourg, S. (2021). Time-dependent stochastic vehicle routing problem with random requests: Application to online police patrol management in Brussels. *European Journal of Operational Research*, *292*(3), 869–885. https://doi.org/10.1016/j.ejor.2020.11.007

Sherman, L. W. (1995). Hot spots of crime and criminal careers of places. *Crime and Place*, *4*, 35–52.

Sherman, L. W. (2013). The rise of evidence-based policing: Targeting, testing, and tracking. *Crime and Justice*, *42*, 377–343.

Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, *27*(1), 27–55.

Sherman, L. W., Neyroud, P. W., & Neyroud, E. (2016). The Cambridge Crime Harm Index: Measuring total harm from crime based on sentencing Guidelines. *Policing*, *10*(3), 171–183. https://doi.org/10.1093/police/paw003

Shiode, S., Shiode, N., Block, R., & Block, C. R. (2015). Space-time characteristics of micro-scale crime occurrences: an application of a network-based space-time search window technique for crime incidents in Chicago. *International Journal of Geographical Information Science*, *29*(5), 697–719.

Spicer, V., Song, J., Brantingham, P., Park, A., & Andresen, M. A. (2016). Street profile analysis: A new method for mapping crime on major roadways. *Applied Geography*, *69*, 65–74. https://doi.org/10.1016/j.apgeog.2016.02.008

Townsley, M. (2008). Visualising space time patterns in crime: the hotspot plot. *Crime Patterns and Analysis*, *1*(1), 61–74.

Valente, R. (2019). Spatial and temporal patterns of violent crime in a Brazilian state capital: A quantitative analysis focusing on micro places and small units of time. *Applied Geography*, *103*, 90–97. https://doi.org/10.1016/j.apgeog.2019.01.006

Vandeviver, C., & Bernasco, W. (2017). The geography of crime and crime control. *Applied Geography*, *86*, 220–225. https://doi.org/10.1016/j.apgeog.2017.08.012
Vandeviver, C., & Steenbeek, W. (2019). The (In)Stability of Residential Burglary Patterns on Street Segments: The Case of Antwerp, Belgium 2005–2016. *Journal of Quantitative Criminology*, *35*(1), 111–133. https://doi.org/10.1007/s10940-017-9371-8
Wain, N., & Ariel, B [B.] (2014). Tracking of Police Patrol. *Policing*, *8*(3), 274–283. https://doi.org/10.1093/police/pau017
Watanabe, T., & Takamiya, M. (2014). Police patrol routing on network voronoi diagram. *Proceedings of the 8th International Conference on Ubiquitous Information Management and Communication*, *101*, 1–8.
Weinborn, C., Ariel, B [Barak], Sherman, L. W., & O' Dwyer, E. (2017). Hotspots vs. harmspots: Shifting the focus from counts to harm in the criminology of place. *Applied Geography*, *86*, 226–244. https://doi.org/10.1016/j.apgeog.2017.06.009
Weisburd, D., Wyckoff, L. A., Ready, J., Eck, J. E., Hinkle, J. C., & Gajewski, F. (2006). Does crime just move around the corner? A controlled study of spatial displacement and diffusion of crime control benefits. *Criminology*, *44*(3), 549–592.
Yassen, E. T., Arram, A., Ayob, M., & Nazri, M. Z. A. (2017). A constructive heuristic for police patrol routing problems. *Science & Technology*, *25*(S), 87–96.
Ye, X., Xu, X., Lee, J., Zhu, X., & Wu, L. (2015). Space–time interaction of residential burglaries in Wuhan, China. *Applied Geography*, *60*, 210–216. https://doi.org/10.1016/j.apgeog.2014.11.022

Declarations

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