University of HUDDERSFIELD

University of Huddersfield Repository

Newton, Andrew D.

Crime and the NTE: multi-classification crime (MCC) hot spots in time and space

Original Citation

Newton, Andrew D. (2015) Crime and the NTE: multi-classification crime (MCC) hot spots in time and space. Crime Science, 4. p. 30. ISSN 2193-7680

This version is available at http://eprints.hud.ac.uk/id/eprint/26186/

The University Repository is a digital collection of the research output of the University, available on Open Access. Copyright and Moral Rights for the items on this site are retained by the individual author and/or other copyright owners. Users may access full items free of charge; copies of full text items generally can be reproduced, displayed or performed and given to third parties in any format or medium for personal research or study, educational or not-for-profit purposes without prior permission or charge, provided:

- The authors, title and full bibliographic details is credited in any copy;
- A hyperlink and/or URL is included for the original metadata page; and
- The content is not changed in any way.

For more information, including our policy and submission procedure, please contact the Repository Team at: E.mailbox@hud.ac.uk.

http://eprints.hud.ac.uk/

Newton *Crime Sci (2015) 4:30*
DOI 10.1186/s40163-015-0040-7

Crime Science
a SpringerOpen Journal

RESEARCH Open Access

Crime and the NTE: multi-classification crime (MCC) hot spots in time and space

Andrew Newton*

Abstract

This paper examines crime hot spots near licensed premises in the night-time economy (NTE) to investigate whether hot spots of four different classification of crime and disorder co-occur in time and place, namely violence, disorder, drugs and criminal damage. It introduces the concept of multi-classification crime (MCC) hot spots; the presence of hot spots of more than one crime classification at the same place. Furthermore, it explores the temporal patterns of identified MCC hot spots, to determine if they exhibit distinct spatio-temporal patterns. Getis Ord (GI*) hot spot analysis was used to identify locations of statistically significant hot spots of each of the four crime and disorder classifications. Strong spatial correlations were found between licensed premises and each of the four crime and disorder classifications analysed. MCC hot spots were also identified near licensed premises. Temporal profiling of the MCC hot spots revealed all four crime types were simultaneously present in time and place, near licensed premises, on Friday through Sunday in the early hours of the morning around premise closing times. At other times, criminal damage and drugs hot spots were found to occur earlier in the evening, and disorder and violence at later time periods. Criminal damage and drug hot spots flared for shorter time periods, 2–3 h, whereas disorder and violence hot spots were present for several hours. There was a small spatial lag between Friday and Saturday, with offences occurring approximately 1 h later on Saturdays. The implications of these findings for hot spot policing are discussed.

Keywords: Policing, Licensed premises, Alcohol, Multi-classification crime (MCC) hot spots, Spatio-temporal analysis

Background

There is a longstanding recognition that the locations of alcohol consumption and crime co-occur (Gorman, Speer, Gruenewald, & Labouvie, 2001; Home Office, 2003; Scott and Dedel, 2006; Newton and Hirschfield, 2009a). This often fuels the wider debate over the 'causal' versus 'non-causal' relationship between alcohol and crime (Dingwall, 2013; Horvath and Le Boutillier, 2014). A growing concern is the prevalence of clusters of crime, termed hot spots, in urban areas with concentrations of licensed premises, synonymous with the Night-Time Economy (NTE). For the purposes of this paper licensed premises are considered those selling alcohol for on and or off premise consumption; examples include pubs, bars, nightclubs, hotels, off licenses, supermarkets, convenience stores, restaurants, cafes, takeaways, cinemas and social clubs. Sherman (1995, p 36) defines crime hot spots as 'small places in which the occurrence of crime is so frequent that it is highly predictable, at least over a 1-year period and this paper examines hot spots over 12–36 months. In addition to the known geographical clustering of crime near licensed premises, NTE hot spot areas also exhibit clear temporal patterns, especially on Friday and Saturday evenings and early mornings, which correspond with premise closing times (Block and Block, 1995; Newton and Hirschfield 2009b; Popova, Giesbrecht, Bekmuradov, & Patra, 2009; Uittenbogaard and Ceccato, 2012; Conrow, Aldstadt, & Mendoza, 2015). Thus there are clear spatial and temporal patterns to NTE crime hot spots.

There is a sound theoretical basis for the presence of hot spots in the vicinity of licensed premises. Routine activity theory (Cohen and Felson, 1979) and crime pattern theory (Brantingham and Brantingham, 1993) contend that persons, both potential offenders and victims, exhibit systematic movement patterns governed by their day to day undertakings, termed routine activities. Certain places

*Correspondence: a.d.newton@hud.ac.uk
The Applied Criminology Centre, The University of Huddersfield, Queensgate, Huddersfield HD1 3DH, UK

Springer

© 2015 Newton. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

are frequented regularly, for example home, place of work or leisure, termed activity nodes. The routes travelled between nodes are known as paths. This movement develops a person's awareness space, and crime is shown to be more likely on the edges of these activity nodes (Bowers, 2014). Places at which several offenders and victims converge form multiple awareness spaces, which increase the likelihood of crime. Eck, Clarke, and Guerette (2007) identify a number of 'risky facilities' where concentrations of crime are evident. Indeed, a small minority of facilities contribute the majority of offences at all risky facilities, termed the 'iron law of troublesome places' (Wilcox and Eck, 2011: 476). Examples include shopping centres, busy road junctions, hospitals, schools, train and bus stations, and entertainment districts. Places with clusters of licensed premises represent recreational activity nodes, where there is a convergence of people in time and space. This coming together may create unplanned but favourable crime opportunities, termed crime generators; or draw in offenders to bars and localities with known opportunities for offending, termed crime attractors (Brantingham & Brantingham, 1995). Within NTE areas both of these eventualities are plausible.

A number of explanations exist for the occurrence of crime in NTE areas (for good overviews see Finney, 2004; Graham & Homel, 2008). These include: cultural factors, relating to societies use and acceptance of alcohol; person factors based on an individual's responses and beliefs about alcohol consumption; the psychopharmacological properties of alcohol and their influence on an individual's behaviour; and contextual factors, the physical and social circumstances of where and when alcohol is consumed. Recently a focus for NTE research has been on premise density and premise opening hours. Explanations for crime have focussed on: NTE places deemed to have 'too many' licensed premises, those saturated with a high density of premises (Livingston, 2008; Pridemore & Grubesic, 2013); and, premises open 'too long', with concerns over the length of time premises can remain open for, based around extensions granted in trading hours (Chikritzhs & Stockwell, 2002; Holmes et al., 2014). What is clear is the relationship between crime and alcohol is multi-faceted. A useful explanation is offered by Elvins and Hadfield (2003) who suggest a combination of factors are likely account for crime in NTE areas, including: places with high densities of licensed premises in urban areas; the convergence of large number of persons at these places; crowding of persons within drinking venues in close proximity in confined spaces, often leading to 'vertical drinking'; the consumption of alcohol, often in large quantities; poor management of NTE places; and, the cumulative build up of 'environmental stresses' over the course of an evening.

Efforts to tackle problems of crime in the NTE have predominantly but not exclusively focussed on: better place management (Madensen & Eck, 2008); alcohol education and awareness schemes; regulation of licensing, legislation and enforcement (Hadfield and Newton 2010); increasing the costs of unit prices of alcohol (Booth et al., 2008); regulating the number of, and opening times of premises (Chikritzhs & Stockwell, 2002); and high visibility police patrols. Whilst the merits of each approach have and will continue to be debated in the literature (see Graham & Homel, 2008; Humphreys & Eisner, 2014; Holmes et al., 2014), the focus of this paper is on the use of police patrols in NTE areas.

A recent movement in policing has been a resurgence of hot spot policing, 'targeted on foot patrols', fuelled by the willingness of a number of police forces to implement randomised control trials (RCTs) of hot spot policing effectiveness (Ratcliffe, Taniguchi, Groff, & Wood, 2011; Braga, Papachristos, & Hureau, 2012; Groff et al., 2015). Successes are evident for hot spot policing targeting burglary, repeat calls for service, nuisance bars, drugs, and violent crime, in particular when focussed on hot spots defined tightly in both place and time. A caveat identified in the literature is that the effectiveness of the policing tactic used often is dependent on the type of hot spot policed.

The process of hot spot policing involves identifying hot spot areas, and then subsequently targeting patrols at these places in a systematic fashion. It is contended here that this reflects more general current trends in policing,[1] of using evidence gleaned from crime analysis or crime intelligence to inform police response. Many including the author advocate a problem solving/evidence based approach to policing and crime reduction. Two of the most well know examples of this are Problem Orientated Policing (Goldstein, 1990) and Intelligence Led Policing (Ratcliffe, 2008). At the simplest level of explanation, the analyst or police officer is encouraged to: firstly identify a crime problem through some form of suitable analysis of crime or other data; then, to further examine the identified problem to understand the mechanisms driving it and the context of its setting; the next step is to identify and implement possible solutions; and the final stage is to monitor and or evaluate the effectiveness of the measure implemented.

This paper focusses on the first stage of the process, known as 'scanning' in the SARA model (Ashby & Chainey, 2012) or 'Intelligence' in the 5Is approach

[1] In the UK the College of Policing has recently launched the What Works Crime Reduction Centre, http://whatworks.college.police.uk/Pages/default.aspx; the US has a long standing Centre for Problem Orientated Policing (POP) http://www.popcenter.org/about/?p=whatiscpop; and the Society of Evidence Based Policing launched in 2012 http://www.sebp.police.uk/.

(Ekblom, 2011). The process of identifying crime hot spots for subsequent deployment of hot spot policing tends to be atemporal. This is a reflection of both software availability and analytical skills (Newton and Felson, 2015). Furthermore, sample sizes are larger when crime is not dissected by time of day, which increases the robustness of hot spot analysis. Moreover, once a crime hot spot has been identified, subsequent analysis by time of day enables identification of when to implement hot spot policing at detected hot spots. Perhaps an important component of high crime places overlooked here is that analysts are encouraged to be crime specific, and thus tend to examine single crime classifications, for example violent crime. This is not unexpected, the spatial patterns of burglary will not closely resemble those of street robbery, nor should they be expected to.

However, areas with concentrations of licensed premises are known to be highly criminogenic and not just for violence. Associations have been demonstrated between licensed premises and a number of crime types, most notably violence and aggression, but also criminal damage, disorder, and drug use (Scott & Dedel, 2006; Graham & Homel, 2008; Newton and Hirschfield, 2009b). Indeed Yang (2010) demonstrated longitudinally that correlations in time and place exist between violence and disorder. Furthermore, offenders have been shown to be versatile in the types of crime they commit (Roach & Pease, 2014), and indeed police may overestimate the specialised nature of offending. Thus, if offenders are known to commit several types of crime, and several types of crimes have been shown to be related to NTE places, should analysis of crime at these places be focussed on single crime classifications?

This discussion has demonstrated that: particular NTE places experience more than one crime type; offenders are known to be versatile in the types of crime they commit, and that one of the limitations of spatio-temporal analysis is that segmenting data in both time and place can substantially reduce sample size. Combing several 'related' crime types into a single analysis is a possible solution here. Therefore, this research aims to investigate whether multi-classification crime (MCC) hot spots exist near licensed premises, and if so, do they exhibit distinctive spatio-temporal patterns. More specifically, it examines four crime types known to be associated with licensed premises, namely violence against the person, criminal damage, drugs, and disorder incidents (anti-social behaviour), to ascertain how these crimes manifest in NTE hot spots both in time and place. The following research questions were formulated for this study.

Research questions:

- Is there spatial correspondence between the locations of hot spots for different crime and disorder classifications near licensed premises (violence, criminal damage, disorder and drugs)?
- Do MCC hot spots correspond temporally, that is to say, when a place is a hot spot for violence, is it also a hot spot for criminal damage?
- Do MCC hot spots fluctuate over time, for example does a place experience criminal damage, and then later in the day or a different day of the week experience violence against the person?

Methods

Data

This study used crime and disorder data for an anonymised case study area in England. Its residential population is approximately 1.5 million persons and includes a mixture of large towns and several rural villages, covering a geographical area of approximately 600 km^2. Offence data were obtained for the 3 years period 1st January 2007 to 31st December 2009 for crimes categorised as violence against the person (VAP), criminal damage (CD), and drugs; based on the UK Home Office 2010 counting rules for recorded crime. Incident data for calls for service for disorder (non-crimed) were also obtained for the 12 month period 1st January to 31st December 2007. An additional dataset used was a licensed premise database for the case study area, and 6047 premises were identified as 'open' during the considered time period (2007–2009).

Data processing

The crime and disorder data were cleaned to include only those containing a known time of offence, and those with geo-spatial references outside of the case study area were also excluded. This resulted in a sample of: 64,440 VAP offences; 83,159 CD offences; 18,270 drugs offences, and 346,022 disorder incidents. A Geographical Information Science (GIS) software program was used to calculate the distance from each offence or incident to the nearest licensed premise, and the results of this are shown in Table 1. This demonstrates that for all crime and disorder types the mean distance to a licensed premise was approximately 130–170 m. Median distances ranged from 80 to 125 m. Considering these distances and other studies using buffer analysis to examine crime near licensed premises (Newton and Hirschfield, 2009b; Ratcliffe, 2012), a 250 m threshold was selected as an appropriate distance to represent crime and disorder 'near' licensed premises in this study. As shown in Table 2, for all crime and disorder types analysed, 50–65 % of all crime and disorder offences (varying by crime or disorder classification) occurred within 250 m of a licensed premise.

Table 1 Average distances of offences to licensed premises (metres)

Offence/incident	N	Distance to nearest licensed premise (m)		
		Mean	Median	SD
Disorder	346,022	167.5	119.5	197.7
Violence against person	64,640	132.4	84.2	173.4
Criminal damage	83,159	163.4	124.6	178.6
Drugs	18,270	149.1	85.4	225.6

Table 2 Percentage of offences and incidents near licensed premises (within 250 m)

Offence/incident	N < 250 m	Percentage	Total N
Disorder	188,756	54.6	346,022
Violence against person	41,538	64.3	64,640
Criminal damage	44,570	53.6	83,159
Drugs	11,870	65.0	18,270

The temporal nature of offences

It was previously identified that NTE hot spots exhibit distinct spatial and temporal patterns, with crime peaks evident on Friday and Saturday evening, or the early hours of Saturday and Sunday morning, around premise closing times. In order to examine this further the time of all crime and disorder in NTE hot spots (within 250 m) were re-coded with a value representing both the time of day and day of week (termed week-hour, 'WH' for this study). There are a total of 168 h in a week, and thus each crime and disorder incident was assigned a WH[2] value from 6 to 173.

Figure 1 shows the weekly temporal distribution of each crime and disorder type and reveals distinctive patterns in the WH of VAP, CD, drugs and disorder. For all crime and disorder types there are clear peaks during the evening and early hours of the morning on all days. However, there are some differences in the patterns observed; the highest peaks for disorder are on Friday evening followed by Saturday evening, with lower peaks from Sunday though to Thursday; VAP peaks on Saturday evening, followed by Sunday, Saturday, and Monday, with lower peaks Tuesday to Thursday; drug offences peak on Saturday evenings, followed by Friday and Sunday, with more irregular peaks during the rest of the week; for CD the highest peaks are Sunday evening, followed by Saturday and Friday; peaks during the rest of the week are again lower, but the reduction is less than that of other crime types. Disorder, CD and drugs also exhibit two separate peaks during Saturday evenings which are not evident for VAP. CD tends to have two distinct peaks in the evening most days of the week, unlike disorder and VAP which have single evening peaks all days except Saturday. Overall, there are clear and distinct temporal patterns evident for each crime type.

It is possible that using 3 years of data may skew the results as the temporal patterns of each crime may have changed over time. In order to test this the WH values for each time period were compared by year, thus WH values for 2007 were compared with those of 2008 (2007–2008), and WH values for 2008 compared with those of 2009 (2008–2009). Mann–Whitney tests were used to compare the means (non-parametric independent samples). The results were as follows: for VAP 2007–2008, $z = -0.253$, $p = 0.8$; for VAP 2008–2009 $z = -0.7$, $p = 0.48$; for CD 2007–2008 $z = -0.35$, $p = 0.25$; for CD 2008–2009 $z = -0.18$, $p = 0.6$, for drugs 2007–2008 $z = -1.5$, $p = 0.12$, and for drugs 2008–2009 $z = -0.46$, $p = 0.09$. This suggests that there were no significant differences in WH crime times for VAP, CD or drugs over any of the comparative time periods, and therefore that the WH temporal patterns of each of the three crime types remained stable over the 3 years period. As only 12 months of data were available for disorder, tests for this were not conducted. However, it is assumed that these are also likely to have remained stable, based on the stability of the recorded crime results.

Identifying hot-spots

A range of methods can be used to identify crime hot spots including thematic mapping, kernel density estimations, nearest neighbourhood hierarchical clustering, and the Getis Ord GI* statistic (Eck, Chainey, Cameron, & Wilson, 2005; Chainey & Ratcliffe, 2005; Levine, 2015). For this analysis the Getis-Ord GI* method (Getis & Ord, 1992; Ratcliffe, 2010; Chainey, 2014) was used to identify significant hot spot areas of crime around licensed premises. The advantage of this method over other hot spot mapping techniques is that it identifies small grid areas that are statistically significant, and returns a z[3] score that measures the strength or intensity of the clustering and its significance. This method also produces tightly defined hot spot areas appropriate for hot spot policing.

[2] A value of 6 represents the time period 6.00 a.m. to 6.59 a.m. on a Sunday morning; 23 represents 11.00 p.m. to 11.59 p.m. on a Sunday evening; 24 represents midnight to 0.59 a.m. on a Monday morning; 47 represents 11.00 p.m. to 11.59 p.m. on a Monday evening; 48 is midnight to 0.59 a.m. on a Tuesday; and so forth. A look up reference for this is provided in Additional file 1: Appendix S1.

[3] The higher the z score the greater the clustering, and a z score equal to or above 1.960 is significant at the 95 % confidence level, and equal to or above 2.576 significant at the 99 % level.

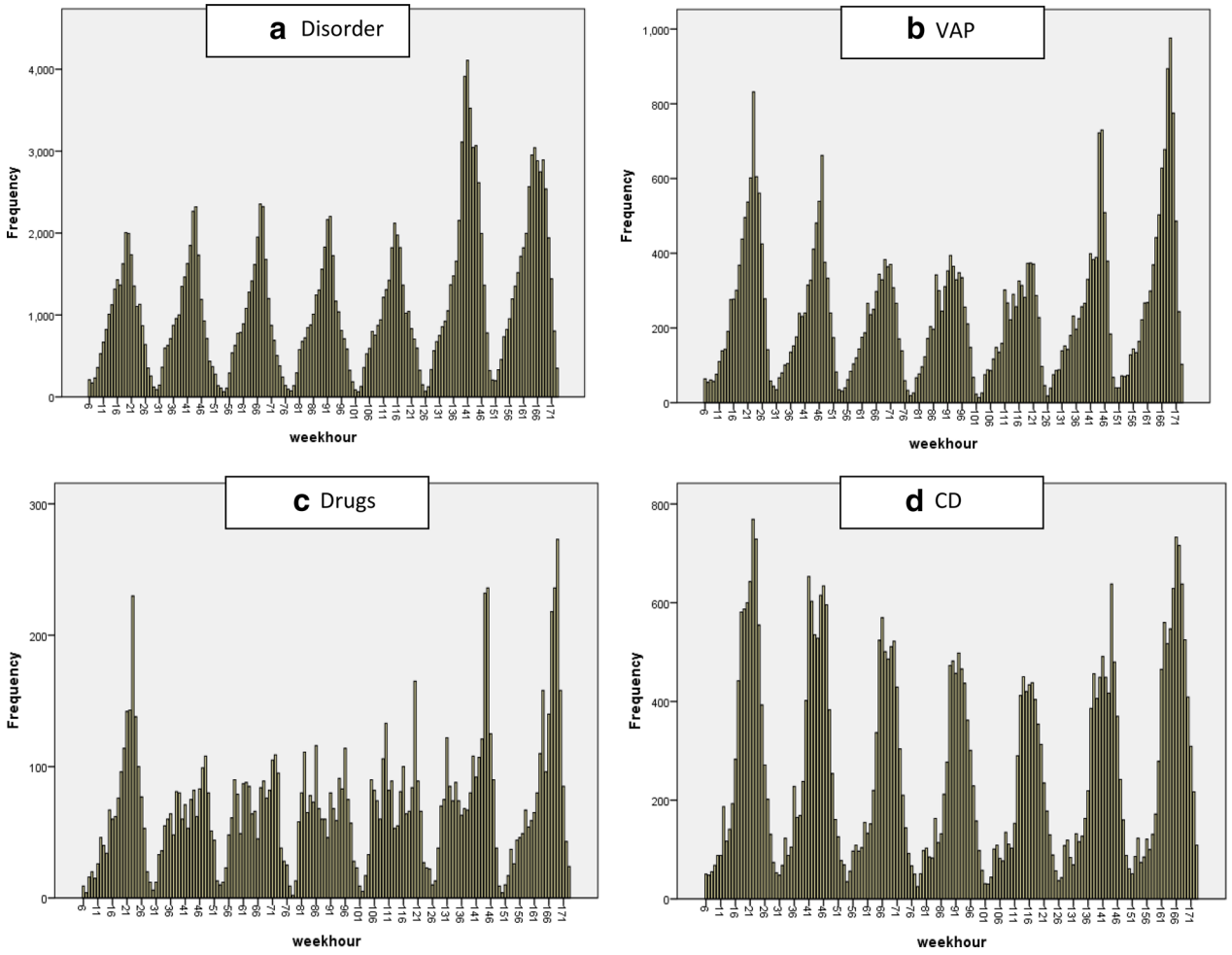

Fig. 1 Weekly-hourly[2] crime frequencies (Sunday to Saturday) four each of four crime types (**a**–**d**). *CD* criminal damage, *VAP* violence against person

Using the GIS software a 250 m grid matrix was generated across the study area resulting in 104,958 grids. A GIS was used to count the number of crimes in each grid repeated for VAP, CD drug offences, and disorder incidents. This analysis used all crimes within the case study area. An alternative approach would be to only select crimes within 250 m of premises, but this may skew the hot spot generation. For each of the four classifications of crime and disorder, GI* hot spots were calculated[4] using ArcGIS spatial statistics toolbox. Figure 2 shows the case study area, the 250 m grids, and the location of licensed premises. The results of the hot spot analysis are shown in Fig. 3a–d, which maps the location of hot spots. Note in these maps only grids which are clustered with 99 % confidence or greater ($z \geq 2.576$) are displayed, with hot spots superimposed by the locations of licensed premises in the case study area. The images are rotated for anonymity.

There are distinct spatial hot spots evident in Fig. 3, which correlate with urban areas containing high densities of licensed premises. Upon first glance similar hot spot patterns are apparent for VAP, CD, disorder and drugs. However a more detailed visual inspection reveals subtle differences. The extent of the hot spots around urban centres is greater for VAP and disorder, and more tightly concentrated for drugs and CD. Towards the bottom of the case study area there are hot spots of VAP, CD and disorder, but not for drug offences. Towards the right of the map there is an area with large concentrations of VAP, drugs, disorder, and CD, but close inspection reveals the extent of this is much more spread for VAP than the other three crime types. On these maps only grid cells that are significant hot spots at 99 % confidence interval are displayed. There were 2970 such cells, and these cells are now examined further.

[4] The parameters for this were to use a fixed distance band, with a threshold (spatial lag) of 355 m (based on 250 m grids).

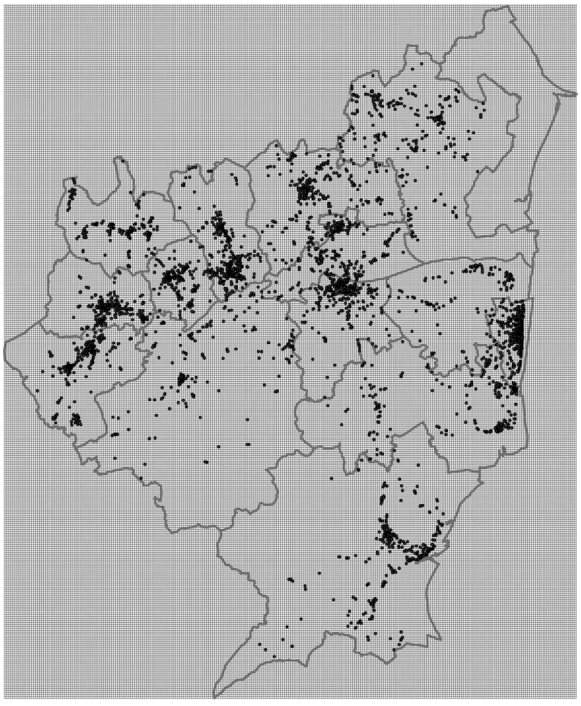

Fig. 2 Case study area with 250 m grids and licensed premises

Results

The first research question was to examine the degree to which hot spots of different crime classifications co-exist spatially, in other words occur at the same place. Analysis of all grids in the study area using Spearman's Rank revealed strong statistically significant correlations for each crime and disorder type (Table 3) with the location of licensed premises; the strongest relationship was between premises and disorder, followed by CD, VAP, and drugs. All crime and disorder types were correlated with premises at $R > 0.7$, $p < 0.01$ which indicates a high degree of correlation between the location of licensed premises, and crime and disorder events in the case study area.

Further analysis was undertaken using only grids significant at the 99 % level (2970) which contained a significant hot spot for at least one of the four crime and disorder classifications examined. 2435 grids contained a licensed premise, and unsurprisingly all of these grids were identified as a statistically significant hot spot for at least one crime type. Further analysis revealed 2485 grids of the 2970 were hot spots for VAP (83 %), 2385 for CD (80 %), 2160 for disorder (72.7 %), and 1307 for drugs (44 %). Each grid could contain a hot spot for one, two, three, or all four crime types, and a Conjunctive Case Analysis (CCA, Miethe, Hart, & Regoeczi, 2008) was used to examine the 256 (4^4) possible combinations here.[5] The results of this are presented in Table 4. This found 1214 grids, 40 % of the significant crime hot spot grids, were statistically significant hot spots for all four crime classifications. A further 663 grids (22 %) were significant hot spots for at least three types of crime. This shows strong evidence of an overlap in the location of hot spots for VAP, disorder, CD and drugs near licensed premises and suggests strong evidence in the case study area that MCC hot spots are present near licensed premises.

Profiling the 'hottest' hot spots

The research has thus far demonstrated that MCC hot spots are present spatially, thus hot spots of VAP are also hot spots of CD for example. The purpose of research questions two and three are to further examine the MCC hot spots temporally, to ascertain whether the different crime types found in the MCC hot spots occur at the same time, at different times of day, or different days of the week. Therefore the top twenty hot spot grids were identified for further profiling. To determine these top twenty cells, the 'hottest hot spots', cells that were statistically significant hot spots for all four types of crime and disorder (VAP, CD, drugs and disorder) were identified. There were 1214 of these cells. Cells with the highest combined z scores[6] were selected to represent the twenty 'hottest' hot spots. A profile of each of these cells is provided in Table 5. At these twenty 250 m grid cells over the 3 years period (12 months for disorder) there were a high number of crime and disorder incidents ranging from: 78 to 802 for VAP; 252 to 1736 for disorder; 37 to 182 for CD; and 8 to 265 for drugs. The number of license premises in each grid ranged from a minimum of 3 to a maximum of 96. In order to examine the temporal profiles of these cells, the WH values of each crime type for each cell was calculated, and the results of this are presented in Fig. 4. The frequencies of offences by time of day were divided into five equal quintiles, and these are colour coded as per the table key. Those in red represent the 20 % of times with the highest levels of crime for each classification, VAP, CD, disorder and drugs.

Figure 4 shows the temporal profiles of the 20 hottest MCC hot spots. There were seven WH time periods (each WH is 1 h of the week) that had high levels (coloured red in Figure) of crime and disorder for all four crime and disorder categories at the same time and same place: Thursday 2.00 a.m. to 2.59 a.m.; Friday 1.00

[5] An alternative here may be the use of Multiple Classification Analysis (MCA), also known as factorial ANOVA. However, as this is used for linear data, and spatial crime data often follows a negative binomial distribution, this was not considered appropriate here.

[6] Calculated as combined z score of each of four crime classifications from GI* analysis.

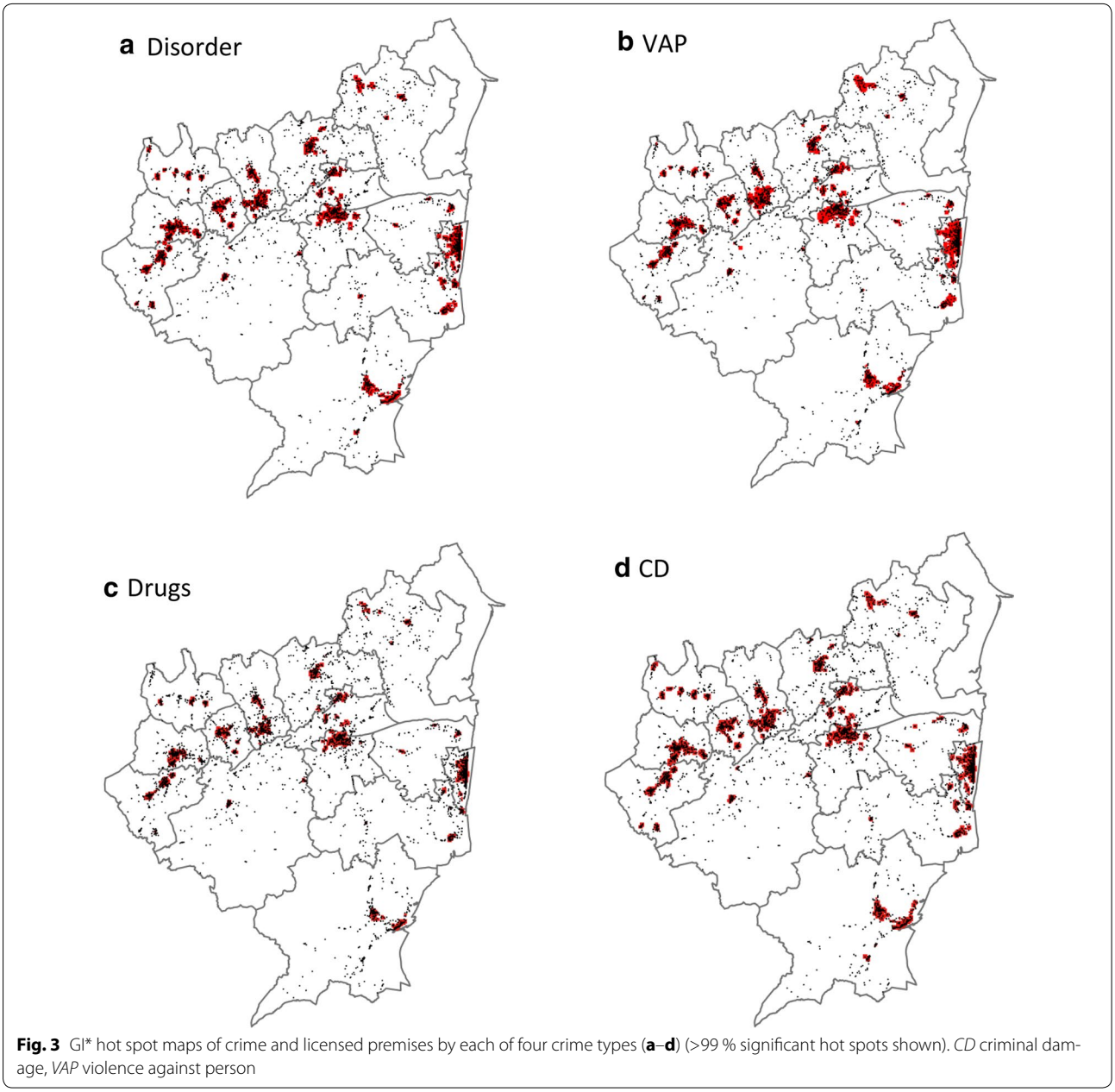

Fig. 3 GI* hot spot maps of crime and licensed premises by each of four crime types (**a**–**d**) (>99 % significant hot spots shown). *CD* criminal damage, *VAP* violence against person

Table 3 Correlations between licensed premises and crime hot spots (250 m grid based analyses)

Spearman's Rho correlation with licensed premises	VAP	CD	Drugs	Disorder
N	10,948	10,948	10,948	10,948
P	0.805	0.913	0.712	0.937
Sig	0.001	0.001	0.001	0.001

a.m. to 2.59 a.m.; and Saturday midnight to 02.59 a.m. There were some further distinctive temporal patterns identified in the MCC hot spots. Disorder is prevalent Wednesday through Sunday evenings; on Sunday peaks were at 7.00 p.m., 9.00 p.m., and from midnight to 2.59 a.m.; on Wednesday from 1.00 a.m. to 2.59 a.m.; on Thursday from midnight to 3.59 a.m.; on Friday from 6.00 p.m. until 2.59 a.m.; and then on Saturday from 7.00 p.m. until 3.59 a.m. Thus there is an extended period of disorder on Friday and Saturday, which last for several hours. There are also some disorder peaks on Tuesday afternoon not found for other crime types. VAP followed similar patterns to that of disorder. However, the length of the peaks was shorter, occurring slightly later on Sunday until 3.59 a.m., and generally VAP starts later in the evening

Table 4 Hot spot grids (99 % significance) and crime and disorder types

Crime type	VAP	CD	Disorder	Drugs	Total
Number of grids	2485	2385	2160	1307	2970
Percentage of grids (%)	83.7	80.3	72.7	44.0	100.0
CCA analysis of grids by hot spot types					
	VAP	**CD**	**Disorder**	**Drugs**	**Number of cells**
Presence (1) or absence of a hot spot (0) of a hot spot	1	1	1	1	1214
	1	1	1	0	609
	1	0	1	1	25
	0	1	1	1	16
	1	1	0	1	5
	1	0	1	1	5
	0	1	1	1	3

Table 5 Top 20 grid profiles (the hottest hot spots)

Grid_ID	Premises (N)	VAP (N)	VAP (z score)	Disorder (N)	Disorder (z score)	CD (N)	CD (z score)	Drugs (N)	Drugs (z score)	Total z	All Crime (N)
54124	63	530	106.86	784	79.88	143	53.27	115	88.87	4920.74	1602
54125	17	146	110.88	800	85.18	58	71.53	42	98.01	7206.67	1056
54126	5	92	53.64	338	54.96	85	60.76	28	51.21	3220.20	553
54417	19	187	92.54	532	64.97	37	36.61	39	78.63	3035.92	809
54418	44	756	126.20	1736	94.52	172	58.94	187	109.04	6647.91	2871
54419	35	468	120.32	876	90.04	182	71.75	129	103.21	7615.46	1685
54420	3	126	55.78	384	53.56	126	57.49	54	52.79	3143.88	704
54712	9	224	103.58	498	83.26	101	55.67	53	92.81	5353.51	887
54713	49	78	95.60	266	74.95	67	66.00	22	85.40	5807.23	439
54714	8	87	50.04	252	41.41	56	52.54	26	49.79	2707.54	427
55006	75	124	56.56	472	50.91	90	43.30	27	62.40	2809.36	718
55007	96	83	54.28	348	50.54	72	51.74	30	53.89	2893.05	538
55301	48	205	58.52	266	56.72	103	60.62	49	49.79	3133.43	635
55595	7	96	54.69	338	50.27	79	57.71	8	46.01	2760.01	527
62448	16	202	78.72	542	57.60	93	36.24	56	73.11	2786.24	910
62449	8	181	88.94	642	68.99	63	43.52	83	87.14	3950.09	981
62450	4	100	73.80	436	62.44	49	41.63	28	81.31	3520.88	622
62742	11	185	80.64	458	61.20	66	38.65	35	81.78	3302.21	756
62743	22	802	90.40	1234	76.17	182	49.05	265	94.39	4796.07	2539
62744	23	166	77.13	1018	64.33	78	41.48	42	82.57	3566.55	1319
Totals	562	4838		12,220		1902		1318			20,578

Z score based on Getis Ord (GI*) hot spot significance (>2.576 = 99 % significant)

than disorder. The corresponding periods of disorder and violence also seem to occur 1 h later on a Saturday than they do on a Friday. Drugs followed a more unusual pattern; offences occurred on Thursday to Sunday evenings correlating with VAP and disorder, and there were some unique peaks early Friday morning at 9.00 a.m. and 11.00 a.m. Drug offence peaks tended to be for 1 h only with the exception of Thursday through Sunday. CD tended to occur at much earlier time periods during the day, for example: on Sunday between 6.00 p.m. and 8.00 p.m., and then 10.00 p.m. to midnight; at 5.00 p.m. on a Monday and Thursday; and 5.00 p.m. and 7.00 p.m. on a Saturday.

Discussion of findings

The top 20 'hottest' hot spots identified (based on 250 m grid cells) accounted for less than half a percent of all the

Time of Day		6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	1	2	3	4	5
Sunday	Disorder	22	30	18	22	26	26	46	48	64	48	50	50	80	92	74	96	74	72	112	110	128	54	60	20
	VAP	4	1	8	2	4	6	9	6	15	34	24	22	31	29	43	37	62	97	71	113	90	74	35	10
	CD	4	5	2	1	4	1	6	5	6	8	6	19	22	25	15	17	22	15	27	14	14	18	21	5
	Drugs	0	2	0	0	2	0	2	5	2	4	4	7	9	9	11	15	8	41	16	17	10	9	1	0
Monday	Disorder	4	10	12	30	34	44	76	58	50	72	50	78	76	68	64	66	62	74	60	88	80	48	16	4
	VAP	6	3	6	6	5	9	12	11	21	19	27	21	23	19	19	27	36	69	56	58	57	61	21	3
	CD	1	4	3	7	1	1	9	6	6	10	12	30	18	18	16	16	17	27	14	23	12	16	8	6
	Drugs	0	0	0	0	2	5	2	4	7	10	11	8	7	6	4	9	6	13	19	20	6	8	2	0
Tuesday	Disorder	6	6	26	24	32	64	60	94	102	64	104	80	72	84	74	64	52	64	56	68	76	58	20	6
	VAP	1	3	2	3	10	12	10	17	21	29	20	18	15	28	22	25	41	37	37	48	50	40	20	1
	CD	0	0	3	5	3	5	6	7	9	6	12	27	20	11	9	18	15	13	16	14	12	10	6	5
	Drugs	2	0	1	0	4	0	6	1	9	9	6	2	7	3	11	7	16	9	28	12	0	1	6	0
Wednesday	Disorder	4	12	20	30	58	52	74	84	90	86	66	54	72	62	82	88	68	74	74	94	100	60	22	8
	VAP	2	2	1	7	6	5	9	17	24	33	21	15	21	29	27	29	24	50	35	44	51	39	16	5
	CD	1	3	0	4	4	7	6	5	6	12	9	18	23	9	11	17	15	20	14	18	16	7	8	0
	Drugs	0	0	0	8	4	5	9	5	5	8	4	2	3	8	13	7	8	3	4	8	5	3	4	0
Thursday	Disorder	6	2	14	32	44	50	52	80	72	68	82	66	82	66	62	66	58	80	132	154	138	166	80	22
	VAP	4	0	4	7	13	10	14	7	13	22	25	16	18	10	21	23	26	37	73	82	90	83	37	7
	CD	1	2	4	2	3	0	3	4	3	3	13	27	8	19	10	10	8	13	18	19	22	24	12	3
	Drugs	0	0	1	7	3	6	5	9	7	2	3	7	0	4	8	4	2	11	52	22	18	5	4	3
Friday	Disorder	6	6	22	28	40	60	42	54	74	88	90	68	92	122	128	140	140	172	226	228	190	150	84	30
	VAP	1	5	1	4	5	15	17	10	18	20	17	19	15	10	20	29	37	48	92	112	101	90	45	6
	CD	1	4	4	5	5	1	10	5	11	5	14	22	19	11	17	15	17	23	21	31	23	18	10	6
	Drugs	0	0	2	14	6	12	5	8	3	2	2	4	4	7	2	4	10	22	24	42	16	20	10	2
Saturday	Disorder	22	14	26	22	48	50	70	66	92	82	96	118	82	106	108	104	146	202	286	338	312	244	142	54
	VAP	2	1	4	5	5	8	11	7	20	21	16	28	17	25	32	44	37	65	123	178	173	121	58	17
	CD	2	1	2	1	0	4	6	8	6	5	8	30	16	26	10	19	22	15	33	35	28	28	26	14
	Drugs	0	0	0	3	0	5	0	4	4	4	5	5	6	12	11	11	13	36	45	76	51	27	11	6

Colour Key

ASB: 31-56; 57-71; 72-91; 92+

VAP: 18-27; 28-49; 51-73; 74+

CD: 6 to 10; 11 to 16; 17 to 21; 22+

Drugs: 5 to 7; 8 to 10; 11 to 14; 15+

Fig. 4 The 'Hottest' hot spot profiles by time of day and crime type (MCC hot spots): values indicate crime counts

grids that contained a crime or disorder incident (6165 cells), yet contained over 5 % of all crime and disorder incidents analysed across the entire case study area. Moreover, a 7 h time window (Thursday 2.00 a.m. to 2.59 a.m., Friday 1.00 a.m. to 2.59 a.m., and Saturday midnight to 02.59 a.m.), which represented 4 % of the 168 WH intervals over a week), accounted for nearly 15 % of all crimes at these top 20 hot spots alone. Therefore crime is highly concentrated at these times in these places. This 7 h time frame is important as at these times MCC hot spots co-existed both in time and space, for all four crime classifications examined. The most plausible explanations for this are the high volumes of persons likely to be present at these times and places create multiple opportunities for crime, supported by crime pattern theory, routine activity theory, and the non-specialised nature of many offenders. Indeed conterminously at the same places and locations there may be suitable targets and lack of capable guardians in these micro places for drugs, criminal damage, disorder and violence. At these time periods hot spot policing may require a range of tactics, due to the diverse nature of multiple crime types prevalent.

At other times of the day MCC hot spots were also evident but not for all crime types. On Friday and Saturday afternoons disorder was evident from 6.00 p.m. until the early hours of the morning, whereas violent offences tended to occur after midnight. This may be reflective of a number of factors, perhaps disorder is a signal crime of later violence (similar to the Innes, 2004). Alternatively later in the evening, the number of persons in the NTE settings may increase, but to fewer locations; cumulatively more alcohol is consumed, and the result that disorder may escalate into more serious violence. Criminal damage offences occur earlier in the evening than violence. An interesting finding is the apparent spatial lag between Friday and Saturday; both have similar patterns but offences are approximately 1 h earlier on Fridays. This may reflect cultural difference and routines; those who partake in the NTE on Friday's may do so straight from work, whereas those who go out on Saturdays may have constrained activities on Saturday afternoons, or go out with different friend groups or their partners, thus drinking in the NTE may start slightly later on Saturdays.

There are a number of limitations to this study. Police recorded crime and disorder data is known to be subject to both underreporting and errors in the accuracy of geo-coding (Chainey and Ratcliffe, 2005; Newton and Hirschfield, 2009a). It would be useful to supplement this data with hospital accident and emergency data (A & E) or ambulance data. According to Shepherd, Ali, Hughes, and Levers (1993) six in seven of those attending A & E for violent injuries are not in recorded crime statistics. However, health data does not always contain location specific information on when and where crime occurs, and this data is not always available to the police. It is suggested a more robust future analysis incorporating A & E data is likely to confirm the presence of MCC hot spots near licensed premised.

There are limitations in the arbitrary 250 m buffer distance, and the use of the GI* statistic. Analysis using

alternative buffers (100 m, 400 m) found no discernible differences in patterns of crime observed. A possible limitation of the GI* is it identifies too many hot spot areas significant at 99 %. Future analysis could compare the use of a corrected Bonferonni approach rather than Gausian for determining Z-score (Chainey, 2014). This technique also identifies cells that have low crime counts, as it is based on neighbourhoods surrounding cells rather than just inside a cell in its calculation; alternative hot spot techniques should be used explored and compare MCC hot spots.

Conclusions

This paper has presented strong evidence for the presence of MCC hot spots near clusters of premises, known to be particularly criminogenic places. This is not surprising, given the literature on crime opportunity, crime pattern theory, routine activities, risky facilities, and crime attractors and generators. However, what this research does begin to question is the conventional wisdom of hot spot analysis and hot spot policing being wholly crime specific, using single crime classifications at highly criminogenic places. Hot spots of VAP, CD, drugs and disorder were identified at the same locations in the study area, near to licensed premises. Moreover, the results show that at particular time periods (seven hourly periods of a 168 h week) all four crime and disorder types occurred conterminously in both time and space. At other times only one or two hot spots were present, and at some times of the day hot spots were not found. This has clear implications for hot spot policing in terms of tactics used and when best to target resources. Further exploration and explanation of these patterns is warranted to assist in effective hot spot policing deployment and tactics at MCC hot spot locations.

A range of methods could be incorporated to refine future analysis. In particular more statistical time based analysis should test: whether MCCs are clustered in time and space; if the space–time clustering occurs continuously or within defined time periods; or if there is a space time interaction (Levine, 2015). Suggested tests here are to use the Knox and Mantel tests to examine the interactions between licensed premises and the MCC hot spots identified. Furthermore circular statistics could be incorporated, for example the use of Rayleigh's test to examine significant clustering by time of day, or the Watsons U test to examine for differences in two temporal datasets (Wuschke, Clare, & Garis, 2013) by month, season or year.

As observed by Townsley (2008) characteristics of crime hot spots can alter over time, with periods of emergence, persistence, and decline. Therefore any future analysis that is developed should also consider how MCC hot spots may emerge and dissipate over time near licensed premises, and whether they are stable hot spots or occur more sporadically. Moreover, there are seasonal variations in crime patterns and discretionary routines influenced by daylight hours and temperature (Tompson & Bowers, 2015) and this may influence MCC hot spots near licensed premises.

At present there are a number of studies using predictive crime mapping or crime forecasting (Chainey, 2014). Perhaps predicting MCC hot spots should form part of this research. Indeed, Shekhar, Mohan, Oliver, and Zhou (2012) attempt to do similar, by testing for the emergence of crime trends with multiple crime types. MCC hot spots have been identified near licensed premises, but perhaps alternatives exist, for example: burglary hot spot analysis could also consider patterns of theft of, and theft from vehicle; the locations of street robbery could be compared with pickpocketing and theft from person; at drug locations a number of crimes associated with illicit trade could be examined. In other places known to be criminogenic, it may be important to identify alternative configurations of MCC hot spots.

VAP, CD, drugs and disorder have all been shown to relate to licensed premises, but more detailed information on types of premises, density and opening hours should also be taken into account before prioritising hot spot policing. Indeed a final question that remains is the implications of this research for hot spot policing and resource targeting. It is possible to continue to police hot spots based on single crime types effectively. It is not known if focussing on the places and times of MCC hot spots is likely to be more effective in reducing crime, as theoretically more offenders are likely to be present at MCC than single crime hot spots, thus police may be more likely to deter or apprehend offenders at MCC hot spots. However, tactically it may be more difficult to police MCC areas, targeting multiple types of crime may require several concurrent tactics that may conflict. MCC hot spots have been shown to contain different crime types over time, criminal damage and disorder earlier in the day and violence at later times. It is not known if early intervention here would reduce crime at later times of the day, or if police would need to remain at these MCC hot spots for longer time periods. It is suggested an RCT of MCC hots spot patrols near licensed premises may shed some light on this question.

Additional file

Additional file 1. Appendix 1: Look up table for 'WH' weekly-hour values in Fig. 1.

Abbreviations
CD: criminal damage; GIS: geographical information science; MCC: multi-classification crime; NTE: night-time economy; VAP: violence against the person; WH: week hour.

Competing interests
The author declares no competing interests.

Received: 3 July 2015 Accepted: 30 September 2015
Published online: 19 October 2015

References

Ashby, M., & Chainey, S. (2012). *Problem solving for neighbourhood policing*. London: UCL Press.
Block, R. L., & Block, C. R. (1995). Space, place and crime: Hot spot areas and hot places of liquor-related crime. In D. Weisburd & J. E. Eck (Eds.), *Crime and place: crime prevention studies* (4th ed., pp. 145–184). Monsey: Criminal Justice Press.
Booth, A., Meier, P., Stockwell, T., Sutton, A., Wilkinson, A., Wong, R., & Taylor, K. (2008). *Independent review of the effects of alcohol pricing and promotion. Part A: systematic reviews*. Sheffield: University of Sheffield.
Bowers, K. (2014). Risky facilities: crime radiators or crime absorbers? A comparison of internal and external levels of theft. *Journal of Quantitative Criminology, 30*(3), 389–414.
Braga, A., Papachristos, A., & Hureau, D. (2012). *Hot spots policing effects on crime: Campbell Systematic Reviews, 8*, 1–97.
Brantingham, P. J., & Brantingham, P. L. (1993). Environment, routine and situation: toward a pattern theory of crime. *Advances in criminological theory, 5*, 259–294.
Brantingham, P. J., & Brantingham, P. L. (1995). Criminality of place: crime generators and crime attractors. *European Journal on Criminal Policy and Research, 3*, 5–26.
Chainey, S. (2014). Examining the extent to which hotspot analysis can support spatial predictions of crime. Doctoral thesis, UCL (University College London).
Chainey, S., & Ratcliffe, J. H. (2005). *GIS and crime mapping*. Chichester: Wiley.
Chikritzhs, T., & Stockwell, T. (2002). The impact of later trading hours for Australian public houses (hotels) on levels of violence. *Journal of Studies on Alcohol, 63*, 591–599.
Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: a routine activity approach. *American Sociological Review*, 588–608.
Conrow, L., Aldstadt, J., & Mendoza, N. S. (2015). A spatio-temporal analysis of on-premises alcohol outlets and violent crime events in Buffalo, NY. *Applied Geography, 58*, 198–205.
Dingwall, G. (2013). *Alcohol and Crime*: Cullompton: Willan Publishing.
Eck, J., Chainey, S., Cameron, J., & Wilson, R. (2005). *Mapping crime: understanding hotspots*. Washington DC: National Institute of Justice.
Eck, J. E., Clarke, R. V., & Guerette, R. T. (2007). Risky facilities: crime concentration in homogeneous sets of establishments and facilities. In G. Farrell, K. Bowers, S. D. Johnson, & M. Townsley (Eds.), *Crime prevention studies* (pp. 225–264). Cullompton: Willan Publishing.
Ekblom, P. (2011). *Crime Prevention, Security and Community Safety using the 5Is Framework*. Basingstoke: Palgrave Macmillan.
Elvins, M., & Hadfield, P. (2003). *West end stress area: night-time economy profiling: a demonstration project: Durham*. UK: Department of Sociology and Social Policy, University of Durham.
Finney, A. (2004). *Violence in the night-time economy: Key findings from the research. Research Findings*, 214 (pp. 1–6). London: Home Office.
Getis, A., & Ord, J. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis, 24*(3), 189–206.
Goldstein, H. (1990). *Problem oriented policing*. New York: McGraw-Hill.
Gorman, D. M., Speer, P. W., Gruenewald, P. J., & Labouvie, E. W. (2001). Spatial dynamics of alcohol availability, neighborhood structure and violent crime. *Journal of Studies on Alcohol, 62*, 628–636.
Graham, K., & Homel, R. (2008). *Raising the Bar: Preventing aggression in and around bars, pubs and clubs*. Cullompton: Willan Publishing.
Groff, E. R., Ratcliffe, J. H., Haberman, C. P., Sorg, E. T., Joyce, N. M., & Taylor, R. B. (2015). Does what police do at hot spots matter? *The Philadelphia Policing Tactics Experiment: Criminology, 53*(1), 23–53.
Hadfield, P., & Newton, A. (2010). *Factsheet: alcohol, crime and disorder in the night-time economy*. London: Alcohol Concern.
Holmes, J., Guo, Y., Maheswaran, R., Nicholl, J., Meier, P., & Brennan, A. (2014). The impact of spatial and temporal availability of alcohol on its consumption and related harms: a critical review in the context of UK licensing policies: drug Alcohol. *Review, 33*(5), 515–525.
Horvath, M., & Le Boutillier, N. (2014). Alcohol use and crime. *The encyclopedia of criminology and criminal justice* (pp. 1–7). USA: Blackwell Publishing Ltd.
Humphreys, D., & Eisner, M. (2014). Do flexible alcohol trading hours reduce violence: a theory-based natural experiment in alcohol policy? *Social Science and Medicine, 102*, 1–9.
Innes, M. (2004). Signal crimes and signal disorders: notes on deviance as communicative action. *The British Journal of Sociology, 55*(3), 335–355.
Levine, N. (2015). *CrimeStat: A Spatial Statistics Program for the Analysis of Crime Incident Locations* (*v 4.02*). Washington, D.C: Ned Levine & Associates, Houston, Texas, and the National Institute of Justice.
Livingston, M. (2008). Alcohol outlet density and assault: a spatial analysis. *Addiction, 103*, 619–628.
Madensen, T. D., & Eck, J. E. (2008). Violence in bars: exploring the impact of place manager decision-making. *Crime Prevention & Community Safety, 10*(2), 111–125.
Miethe, T. D., Hart, T. C., & Regoeczi, W. C. (2008). The conjunctive analysis of case configurations: an exploratory method for discrete multivariate analyses of crime data. *Journal of Quantitative Criminology, 24*(2), 227–241.
Newton, A., & Hirschfield, A. (2009a). Violence and the night-time economy: a multi-professional perspective. An introduction to the Special Issue. *Crime Prevention and Community Safety, 11*(3), 147–152.
Newton, A., & Hirschfield, A. (2009b). Measuring violence in and around licensed premises: the need for a better evidence base. *Crime Prevention and Community Safety, 11*(3), 171–188.
Newton, A., & Felson, M. (2015). Editorial: crime patterns in time and space: the dynamics of crime opportunities in urban areas. *Crime Science, 4*(11). doi:10.1186/s40163-015-0025-6.
Office, Home. (2003). *Drinking, crime and disorder: home office research findings* (Vol. 185). London: Home Office.
Popova, S., Giesbrecht, N., Bekmuradov, D., & Patra, J. (2009). Hours and days of sale and density of alcohol outlets: impacts on alcohol consumption and damage: a systematic review. *Alcohol and Alcoholism, 44*(5), 500–516.
Pridemore, W. A., & Grubesic, T. H. (2013). Alcohol outlets and community levels of interpersonal violence spatial density, outlet type, and seriousness of assault. *Journal of Research in Crime and Delinquency, 50*(1), 132–159.
Ratcliffe, J. (2008). *Intelligence-led policing*. Cullompton: Willan.
Ratcliffe, J. (2010). Crime mapping: spatial and temporal challenges. In A. Piquero & D. Weisburd (Eds.), *Handbook of quantitative criminology* (pp. 5–24). New York: Springer.
Ratcliffe, J. (2012). The spatial extent of criminogenic places: a changepoint regression of violence around bars. *Geographical Analysis, 44*(4), 302–320.
Ratcliffe, J., Taniguchi, T., Groff, E., & Wood, J. (2011). The Philadelphia foot patrol experiment: a randomized controlled trial of police patrol effectiveness in violent crime hot spots. *Criminology, 49*, 795–831.
Roach, J., & Pease, K. (2014). Police overestimation of criminal career homogeneity. *Journal of Investigative Psychology and Offender Profiling, 11*(2), 164–178.
Scott, M., & Dedel, K. (2006). *Assaults in and Around Bars, problem-oriented guides for police problem-specific guides series no. 1*, 2nd edn. Washington, DC: Office of Community Oriented Policing Services, US Department of Justice.
Shekhar, S., Mohan, P., Oliver, D., & Zhou, X. (2012). Crime pattern analysis: a spatial frequent pattern mining approach (No. TR-12-015): Minnesota: Dept Of Computer Science And Engineering, Minnesota University Minneapolis.
Shepherd, J. P., Ali, M. A., Hughes, A. O., & Levers, B. G. H. (1993). Trends in urban violence: a comparison of accident department and police records. *Journal of the Royal Society of Medicine, 86*(2), 87–88.
Sherman, L. W. (1995). Hot spots of crime and criminal careers of places. *Crime and place, 4*, 35–52.
Tompson, L. A., & Bowers, K. J. (2015). Testing time-sensitive influences of weather on street robbery. *Crime Science, 8*(4), 1–11.

Townsley, M. (2008). Visualising space time patterns in crime: the hotspot plot. *Crime patterns and analysis, 1*(1), 61–74.
Uittenbogaard, A., & Ceccato, V. (2012). Space-time clusters of crime in Stockholm, Sweden. *Review of European Studies, 4*(5), p148–p156.
Wilcox, P., & Eck, J. (2011). Criminology of the unpopular: implications for policy aimed at payday lending facilities. *Criminology & Public Policy, 10*, 473–482.
Wuschke,K., Clare, J., Garis, L. (2013). Temporal and geographic clustering of residential structure fires: a theoretical platform for targeted fire prevention. *Fire Safety Journal*, *62*(A), 3–12.
Yang, S. M. (2010). Assessing the spatial–temporal relationship between disorder and violence. *Journal of Quantitative Criminology, 26*(1), 139–163.

Submit your manuscript to a SpringerOpen journal and benefit from:

► Convenient online submission
► Rigorous peer review
► Immediate publication on acceptance
► Open access: articles freely available online
► High visibility within the field
► Retaining the copyright to your article

Submit your next manuscript at ► springeropen.com