Crime Mapping and Policing

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Summary

The empirical truism that crime clusters geographically has increasingly informed police practice in the first two decades of the twenty-first century. This has been greatly aided by crime mapping, which can be thought of as a summary term for the geographic analysis of data related to crime and disorder. Crime analysts use a range of mapping techniques to describe and explain patterns in data, being mindful of the unique qualities of geographically referenced data. These include point pattern maps, thematic maps, kernel density estimation and GI* statistic maps. Rate maps are also used when the aim is to understand risk of victimisation. Crime maps can be used to identify hot spots for targeted action, identify recently committed crimes that might form part of a linked series, monitor the impact of police initiatives and aid understanding of crime problems. Environmental criminology theory is often used to for the latter of these purposes, as this can explain spatio-temporal patterns revealed through crime mapping and assists in understanding the mechanisms driving the patterns.

The logic for organising police efforts around geographical crime concentration is instinctive: by focusing on a small number of locations with high crime volumes, police can be more focused and hence effective. Thus, 'hot spots policing' has become business as usual in many jurisdictions, focusing attention at small units of geography. Hot spot policing has, in many countries in the early twenty-first century, evolved into 'predictive policing', which is a data driven crime forecasting approach. However, this approach has attracted strong criticism for further entrenching bias in the criminal justice system. Critics argue that the data sets on which the predictive policing algorithms are founded are racially biased and perpetuate police attention on communities of colour. This serves to highlight the

systematic biases that can be present in crime-related data, and professional crime analysts use a range of approaches to mitigate such biases, such as triangulating data sources.

Keywords

Geographical analysis; temporal analysis; hot spot policing; environmental criminology; crime data; mapping techniques.

Historical context

Police officers have long intuited the central role geography plays in crime patterns. Indeed, historical cop shows feature detectives sticking pins in maps to denote locations of interest and this is still undertaken in many jurisdictions in the early twenty-first century (Baraka et al., 2019). This real-world sensibility is bolstered by a substantial body of evidence from particular corners of criminology, that show that crime clusters in space and time, and behavioural geography is directly relevant to investigations of crime (Johnson, 2010; Rossmo & Velade, 2008).

Several influences coalesced in the 1970s and 1980s to propel the development of Geographical Information Systems (GISs), which provide a computerised means of creating maps and conducting spatial analysis. As Chainey and Ratcliffe (2005) report, investment in this form of technology by governments was primarily for military purposes, but also assisted the development of core data collection functions, such as the census. Around the same time, dramatic increases in computer power and improving operating system capability led to GIS applications became commercially viable and hence, GIS companies being founded that still dominate the industry many decades later.

The digitisation of police records of recorded crime, and other data sets, furthered the pace of crime mapping in the 1990s. In the US and UK this was accompanied by a shift to 'intelligence-led policing', which is a policing paradigm that promotes a proactive, rather than reactive, operating model that exploits the information-rich era that was developing. The crux of this approach is the optimal deployment of resources – initially focusing on the most prolific or serious criminals but expanding into a broader range of police functions over time. This nods to the empirical truism that crime concentrates, sometimes acutely, along various dimensions such as people, products and places (Tompson & Townsley, 2010).

By the mid-2000s, intelligence-led policing was one of the dominant policing philosophies in Western democracies (Ratcliffe, 2016). Whilst other policing paradigms have since gained ground (e.g., see Scott, 2017 for a comparison between evidence-based and problem-oriented policing), a focus on policing crime concentration endures.

Being ‘intelligence-led’ not only meant exploiting the use of intelligence collected through human covert sources, but also demanded that crime analysis be used to determine where the most significant crime problems or criminals were located. Crime mapping thus became a central pillar of the intelligence-led policing approach, focusing attention to ‘hot spots’, prolific offenders and repeat victims, enabling the targeting of resources to be far more refined than previously. Due to this, the profession of in-house police crime analysis was founded and grew notably throughout the 2000s.

Crime mapping is used for an impressive variety of purposes in policing. It is routinely used to assist administrative (sometimes known as performance) analysis (Santos, 2016), most notably exemplified by the CompStat process originating in the New York City Police Department and adopted in a range of guises across the world. Crime mapping also assists routine tactical and strategic analysis, particularly those embedded within intelligence-led policing frameworks (Ratcliffe, 2016). For example, as Casady (2008) documents in Lincoln, Nebraska, mapping can greatly assist with the daily briefings frontline police officers receive at the beginning of their shift. Within these intelligence ‘products’ that are used to support tactical and strategic decision-making, maps can aid understanding of crime problems (Eck et al, 2005), identify crime hot spots for targeted action, identify recently committed crimes that might form part of a linked series, and monitor the impact of police initiatives (Chainey and Ratcliffe, 2005). This latter purpose of evaluating the effects of police practices can feed directly into evidence-generation to further evidence-based policing (see Keay & Kirby, 2018).

In conjunction with these more ordinary uses of mapping, spatial analysis and crime mapping are also undertaken for many other police activities, such as communicating crime statistics to the public (Chainey and Tompson, 2012; Groff et al., 2005), tracking police mobility and activity (e.g., patrol routes), supporting multi-agency working (see O’Neill, 2008) and supporting investigations (Rossmo & Velarde, 2008). For the latter, mapping tasks can vary from the simple (e.g., displaying the extent of CCTV coverage at a crime scene), to the complex (e.g., trying to predict the location of the next crime in a 'series' – see Overall & Day, 2008). Crime mapping can similarly assist problem-oriented policing, where understanding the context of a crime problem is pivotal to understanding what kinds of police activity might interrupt the causal mechanisms responsible for crime concentrating in a particular way (Knutsson & Tompson, 2017).

Theoretical foundations of crime mapping

Crime mapping in policing implicitly borrows from two centuries of academic curiosity about the relationship between geography and crime. The origins of this focus on crime can be traced to a handful of key European scholars in the nineteenth century, such as Guerry, Balbi and Quetelet (Andresen, Brantingham & Kinney, 2010). This founding generation of spatial criminologists used the official data of their time; large geographical units such as countries, regions and provinces. These provided the means to systematically compare crime figures against socio-demographic (and other) data collected by the government at that time.

The Chicago School of Sociology continued this tradition in the early twentieth century. These scholars are invariably credited with the first systematic research on how human behaviour is determined by social structure and the physical environment. The bedrock of this branch of urban sociology was human ecology. This was seen by key exponents of the Chicago School, such as Robert E. Park and Ernest W. Burgess, as the study of the spatial and temporal relations of human beings, positioned within communities and neighbourhoods. Thus, these scholars were concentrating their attention on socio-demographic variables within city areas, rather than larger administrative units. The work of the Chicago School is often reduced to the influential social disorganisation theory (Shaw & McKay, 1942); however, many more theoretical and empirical insights came from this collection of researchers who viewed crime and social structure as components of an ecosystem.

The Chicago School is often considered the wellspring of modern environmental criminological theory (Finestone, 1976 as cited by Brantingham & Jeffery, 1991). Environmental criminology comprises a trio of theories which are similarly ecologically focused and are unified by their attention to the immediate situational environments in which crime events occur. They cover:

a) The routine activity approach (Cohen and Felson, 1979), which outlines the social chemistry needed to explain why crimes happen at some times and not others, at some places and not others.
b) The rational choice perspective, which aims to make sense of the crime event through a series of decisions made by the offender (Cornish & Clarke, 1986), and
c) Crime pattern theory, which was intended as a meta-theory to explain the spatial-temporal patterning of crime (Brantingham & Brantingham, 1993).

One of the cornerstones motivating these theories is that crime concentrates in space, sometimes acutely so. The regularity of this empirical observation led Weisburd (2015) to propose that, just like the natural laws that exist in the hard sciences, the 'law of crime concentration' is the first law of the 'criminology of place'. As well as being a sound basis for mapping crime, the consistency of spatial crime concentration can be used to predict where crime may occur next (Chainey et al., 2008).

Geographical crime clusters – often referred to as 'hot spots' in the literature - can be thought of as a special case of crime concentration more broadly. Farrell (2015) proposes 'crime concentration theory', which articulates why repeat offending, repeat and near repeat victimization, geographical hot spots, and hot products are universally found within crime data. His comparison of the mechanisms proposed for repeat victimisation and hot spots suggests that there is future scope to bring different dimensions of crime concentration into a theoretical framework that might benefit conceptualisation.

Contemporary issues in crime mapping

Like most analytic outputs, crime maps are only as good as the data they are representing. Crime is an enduring political subject and, as Barrenche (2019) notes, crime data are often used for purposes beyond policing, such as local government, urban design and planning, the allocation of police budgets and investment in communities. Official police data have, historically, attracted much criticism (Maguire & McVie, 2017). To elaborate, much crime-related data is human-made, therefore the recording of crime is subject to the cognitive biases, personal preferences and perverse incentives that all humans are susceptible to but may be exacerbated by particular political climates. This is particularly acute in countries or regimes where corruption is woven into the apparatus of the state (Faull, 2007), and the collection of reliable crime data is made even more challenging. In some countries researchers have taken to crowdsourcing data to present real time maps of civil unrest and violence to alert and safeguard the public (for example, South Africa's Institute of Security Studies – see Links to Digital Materials).

In addition to this, there can be systemic biases in crime recording when the police either do not recognise a crime has taken place, for example in cases of stalking (Belur et al., 2019). Or, the victims are not believed, such as victims of sexual assault (Stanko, 1996) or not deemed to be deserving of help (Brown & King, 1998; O'Neal, 2019). Victims from deprived communities can similarly be underrepresented in crime data, providing a distorted picture of crime (Barrenche, 2019). Such distortions naturally follow through to map outputs when crime is geographically visualised, and hinder insight into what is driving crime problems. A savvy crime analyst will recognise that they are always working with imperfect data and will try to anticipate ways in which data are systematically biased. For instance, analysts of violent crimes may triangulate data with health authorities or combine survey data with that which is recorded by other agencies (Faull, 2019).

Policing spatial crime concentrations

As mentioned above, the truism that crime clusters geographically has increasingly informed police practice in the first two decades of the twenty-first century. Furthermore, many hot spots are relatively stable over time (see Weisburd & Wire, 2018), meaning that crime is often geographically predictable. The logic for organising police efforts around this dimension of crime concentration is intuitive: by focusing on a small number of locations with high crime volumes, police can be more focused. This is assumed to maximise effectiveness of the police's activities, whether that be to deter crime, to arrest offenders or to help the public. Hence, 'hot spots policing' has become business as usual in many jurisdictions, focusing attention at small units of geography such as well-defined hot spot areas, 'hot streets' or 'hot locations' such as bars or high-rise buildings.

The cumulative evidence base for the effectiveness of hot spots policing demonstrates that it works, insofar that meta-analysis of 65 primary studies has estimated a small, but statistically significant effect size indicating a preventative effect (Braga et al., 2019).

However, *how* hot spot policing works and *on what types of problems*, is still being debated in the literature. The systematic review evidence to date suggests it works on varied crime types, such as violent crime, property crime, and disorder and drug crime outcomes (Braga et al., 2019). Here, policing activities fell into two broad camps. The first was traditional policing tactics, which includes police presence (on foot and in vehicles), enforcement activities, and offender-focused activities. The second was problem-oriented policing, which covers efforts to reduce opportunities for crime at places, sometimes using situational crime prevention techniques (Clarke, 2018). The meta-analytic effects were larger for problem-oriented approaches. However, this masks the fact that these tactics can be used in combination (Telep & Weisburd, 2015) and that problem-oriented policing is often used when an assortment of crime problems is plaguing an area.

The only direct experimental test of different police tactics at hot spots is provided by Groff et al. (2015). These scholars found that offender-focused tactics – ranging from conversational to enforcement interactions – saw the best crime reduction effects at violent crime hot spots in Philadelphia. For other types of crime problems innovative tactics such as building collective efficacy among the business community (Weisburd et al., 2015) or asking the communities that are affected by the crime problem in question what policing tactics they perceive would be most appropriate (Haberman et al., 2016) are promising with regards to extending the breadth of what police *actually do* at hot spots once they are identified, to prevent crime.

One of the fundamental issues with hot spots, though, is that they can fluctuate over time (Ratcliffe, 2010). That could be over the course of a year (more crime in some months), the course of the week (weekend hot spots different than weekday ones), or the hour in a day. For example, Tompson and Townsley (2010) found that robbery hotspots in London varied over time windows corresponding to the main police shift patterns in a day. These spatio-temporal patterns are regularly explained through the lens of routine activity approach (Cohen & Felson, 1979) and crime pattern theory (Brantingham & Brantingham, 1993). Such patterns are important to account for when deploying place-based police resources but are difficult to visualise.

A trend in hot spot policing known as ‘predictive policing’ gained popularity in many countries in the twenty-first century (Hardyns & Rummens, 2018). In essence, this is a data driven crime forecasting approach, on which the deployment of police officers can be based. Much of the academic antecedents of this approach come from environmental criminology (e.g., see Bowers et al., 2004) but have been augmented with insights from other criminological theories (Uchida, 2014) and big data by technology developers. Similar issues outlined above about the choice of police tactics to use in areas identified by the software are applicable here too, although these are not always in conflict with police officer's professional instincts (Ratcliffe et al., 2019).

Predictive policing has come under fire for several reasons. Aside from the concerns about civil rights and privacy that big data bring, this spatial analysis approach has attracted vehement criticism for further entrenching bias in the criminal justice system. Critics argue that the data sets on which the predictive policing algorithms are founded can be a measure of officer- rather than citizen-generated crime reports,- and are an unrepresentative picture of all crimes, due to explicit and implicit racial bias (Jefferson, 2018). And the algorithms are then asserted to direct police to deprived neighbourhoods that are already over-policed (Shapiro, 2017) and where people of colour are more likely to live. Jeff Brantingham, one of the creators of PredPol, a leading predictive policing software company, refutes this in a randomised control trial testing for racial disparities in arrest rates in Los Angeles (Brantingham et al., 2017). This work found that there were no statistically meaningful differences in the proportion of arrests across different racial-ethnic groups between the control and treatment conditions. However, it is unlikely that this is the last word on this contentious issue.

Scholars are currently engaged in ascertaining how predictive policing can be made more equitable. For example, Wheeler (2019) proposes a method that attenuates crime hotspots by varying thresholds of acceptability of racial inequality (the proportion of minoritized persons likely to be subjected to formal police attention). He shows that police activity, such as police stops can be made more equitable but cautions that there are trade-offs in terms of efficiency in targeting high crime areas. Other scholars suggest switching to a broader consideration of 'harm', as seen in crime harm indexes (Sherman & Neyroud, 2016), and making that the focus of predictive algorithms used in policing (Mohler et al., 2018). As crime and harm cluster together (Edelstein et al, 2020) this seems like a promising line of research enquiry if it can simultaneously mitigate known biases within the predictive analytic algorithms. At the very least, predictive policing algorithms need to be transparent so they can be publicly scrutinised, and there have been calls in the UK to establish processes for independent ethical review to provide safeguards that algorithms do not perpetuate bias (Babuta and Oswald, 2019).

Data and techniques

Turning now to the practicalities of crime mapping: whilst it is possible to generate 'analogue' crime maps (see Baraka et al., 2019), crime analysts in high income countries typically use GISs to perform spatial analysis and generate map outputs. GISs can be thought of as "a computer system for capturing, managing, integrating, manipulating, analyzing and displaying data which is spatially referenced to the Earth" (McDonnell and Kemp, 1995: 42). Using geography as the unifier, GISs enable 'layers' of different data to be overlaid and interrogated. Hence, the spatial analysis of crime often involves more than just crime data, such as data on population, schools, deprivation, the location of open-air drug markets, and many more besides. Since crime is complex, with many causes, this means of combining and integrating multiple forms of data is extremely powerful.

Vast geographically-referenced data are generated by policing agencies in the twenty-first century (Tompson and Ashby, in press). In addition to crime data, most police agencies capture calls for service data (e.g., 911/999/111 calls, predominantly from the public), information about missing persons and where they are found, arrest and/or custody data, and pedestrian and vehicle stops. Some agencies also record GPS data that enable police activity to be monitored and analysed. Intelligence data (e.g., a sighting of a wanted offender) may also have a geographical component.

Some police agencies make their crime data open source (see Ashby, 2019) which can be useful for researchers, however there are often data privacy concerns that mean that the data need to be obfuscated in some way to protect the identity of victims (Chainey and Tompson, 2012). Geoprivacy violations occur more with some types of crime than others (Leitner et al, 2018). For example, domestic violence incidents often occur in the victim's residence, and the crime event would thus identify them and their home at the time of the incident. Crimes that are especially harmful, such as sexual violence, may be reported on in the news, and hence the victim or details of the crime might be readily identifiable by even an approximate location of the crime. Thus, open crime data may not be complete – in the UK, national open-source crime data goes through a number of processing steps to alleviate geoprivacy concerns. As well as using geomasking to conceal precise crime event locations, the time of the crime is only provided at a month level of resolution, and sensitive crime types are aggregated to protect victim's privacy (Chainey and Tompson, 2012). Such limitations are acceptable though, as sharing crime data with the public can engender community crime prevention (Eman et al., 2013) and increase transparency (Faull, 2019).

Geographical data have some unique features that map makers need to be acquainted with. First, such data can be recorded, or represented, at three levels of geographical entities: points, lines and polygons (Eck et al., 2005). An example of a point might be a stationary crime event, such as a burglary or stolen vehicle. A line could represent a crime occurring at an unknown point along a journey (e.g., pick-pocking on a bus route, see Tompson et al., 2009; Newton, 2008). A polygon might be used to capture area level information – such as prevention activities undertaken in a particular police district. Different spatial analysis techniques are required for each entity.

Second, a brief note is warranted about how to produce these entities from data with a geographical component. In the modern era this is often automated, but it is not unusual to receive crime data in an aspatial format – in a database file for example. When this occurs, it is necessary to *geocode* the data, so that the geographical coordinates (e.g., latitude and longitude) are found and associated with the data point. This can be done manually – by assigning coordinates to a data point in a GIS – or using various spatial tools that use gazetteer systems to look up addresses and other locations in a spatial database of coordinates. However, crimes that take place in public space, away from registered buildings can be challenging to geocode. For instance, on a beach, in a large industrial parking lot, on a hiking trail in the middle of a forest. Such 'non-addressables' (Tompson et al., 2014) pose difficulties to a map-maker as to how to best represent crimes that occur. A blend of automated and manual geocoding may be necessary in such instances. Other issues, such as partial addresses being recorded in crime data (e.g., on 'Fifth Avenue' with no other information) also thwart geocoding efforts. To minimise systematic bias care should be taken to geocode as much crime data as possible. Using a monte-carlo simulation, Ratcliffe (2004) recommended a geocoding rate of 85% of all crimes as being acceptable for analysis.

When the data are subsequently plotted in a GIS, this needs to be done in reference to the projection systems. In brief, a projection system is a method for representing the spherical surface of the earth on the two-dimensional surface of a map. For large land masses distortions are likely, so projection needs to be customised to the extent and nature of the locations depicted in a map. Often data are stored in different projection systems, which need to be harmonised before analysis can take place. So, analysis is often preceded by a lengthy data processing and manipulation stage.

Santos (2016) splits crime mapping outputs into two types: 'descriptive' and 'analytical'. The former refers to the presentation of police data and statistics according to geographical units of analysis that are familiar to the (often police) audience. So, for instance, police beats, districts, command units, or using other jurisdictional boundaries. In contrast, Santos describes analytical mapping as techniques to identify spatial concentrations of crime using the exact geographical locations of crime events as the input. This latter suite of techniques use spatial analysis to derive summaries of patterns and are not beholden to the boundaries of the descriptive maps.

Descriptive mapping

Descriptive mapping techniques comprise several methods. At the simplest is the point pattern map, which is enduringly popular since it is represents a digitised version of sticking pins in paper maps. Point maps can be extremely useful for depicting the geographical relationships among a small number of events. For example, police agencies may use them to present the pattern of a linked series of crime events, such as aggravated robberies. Or the points can be shaded different colours or created using different symbols to represent different crime types (or differences along another dimension, such as time of day, modus operandi, etc). However, the utility of point pattern maps diminishes as the number of points increase. The human eye is not, typically, good at interpreting lots of points on a map, and a point pattern map with lots of dots can be interpreted in vastly different ways, even by people with expertise in crime analysis (see Eck et al., 2005). For this reason, point pattern maps should be retained for the purpose of understanding the geographical qualities and relationships of a selective sample of points.

Thematic maps – also known as choropleth maps – are also a common way of visualising crime data. These shade in polygonal geographic units familiar to police, such as counties, districts, wards, beats, according to a summary value. For example, this may be the total count of crime in a geographic unit. Such maps are easy to generate and are accessible to a lay audience since the geographical units are relatable and often police deployment or resourcing is organised according to the boundaries of the units. Such maps can also be a useful visual aid to synchronize attention across several agencies that are responsible for servicing a common geography.

Depending on the purpose of the map, sometimes other geographical units are used in thematic mapping. For example, a crime analyst may use census geography to integrate census data into the analysis. If precise crime locational data are available then it is easy to analyse crime at this level of geography but is less straightforward if the crime data are already aggregated to another level of geography (for instance, survey data collated at the police district level to preserve respondent's confidentiality). Geographical boundaries may also be different across agencies that police commonly work with on crime prevention initiatives, such as corrections, the fire service, health, social care, and many more besides. The problem of boundaries not being coterminous – that is, aligned – presents challenges to the crime analyst. However, combining data from multiple agencies can often result in more powerful analysis and therefore should be encouraged when the data processing steps can be overcome.

There are several other limitations of maps that use geographic units of analysis that are worth understanding. For example, the modifiable areal unit problem, or MAUP, occurs when point-based data (for example, crime or other phenomena) are aggregated into polygonal geographic units and the resulting summary values are influenced by the choice of unit and its (modifiable) boundaries (Openshaw, 1984). Thus, it refers to aggregation bias, where statistical results can change depending on the choice of the unit of analysis. Succinctly put, the aggregation of point data to areal units may result in patterns that are an artefact of underlying boundaries, rather than being faithful to the spatial distribution of the data (see Tompson, 2021 for a visual demonstration of this). Hence the MAUP can undermine the reliability of thematic maps.

More subtly the MAUP also refers to the problem of scale; or rather, how large the units of analysis should be. Patterns displayed at large geographic units can hide or distort patterns at more local levels. This is known as the ecological fallacy (Robinson, 1950) and is another form of aggregation bias. The ecological fallacy can be likened to Simpson's paradox, whereby an inference is made about an individual (or collection of individual data points) based on aggregated data for an area. For instance, crime volumes represented on a thematic map may mask lower-level variation, so that an area with a mid-range of crime volume may have both high and low crime areas within its boundaries. Higher levels of geography (e.g., larger areas) are more prone to this issue than smaller units of geography, (Brantingham et al., 1976) and whilst this is a problem for all mapping techniques that use bounded areas, using smaller units of analysis generally mitigates the problems associated with the MAUP.

Analytical mapping

Kernel density estimation (KDE) is another standard technique in a crime analyst's toolbox (Eck et al., 2005). This method offers several advantages over thematic mapping of polygons. It involves aggregating point-level crime data to (usually small) grid cells. Using a user-specified search radius (or bandwidth), an algorithm is used to calculate a continuous surface that represents the density of events per spatial unit. The resulting map is visually attractive and able to represent the geographical distribution of the underlying crime data.

The KDE method is still fallible though. The arbitrary manner of defining the cell size and bandwidth used in the calculations of the density surface can result in wildly different maps. Whilst guidance exists (see Chainey & Ratcliffe, 2005) canonical rules for parameter-setting have yet to emerge. Further, Eck et al. (2005) draw attention to the subjectivity in selecting an appropriate thematic classification system with which to display the density surface. (This is also true of thematically shaded maps, but its impact is greater on density values which are less intuitively interpreted). Nevertheless, KDE remains a popular technique amongst practitioners and researchers alike, for it is easy to perform in GISs.

Another limitation of KDE, and indeed all the methods outlined, is that they identify areas that are hot, but do not quantify if those areas are statistically meaningful or have occurred by chance. One technique that is relatively user-friendly and does compute the statistical significance of hot spots is the GI* statistic (Getis and Ord, 1992). The GI* statistic falls under the suite of statistics known as local indicators of spatial association (Eck et al., 2005). Like KDE, it uses a grid cell input to compare local associations of the density of (say) crime events and compares them against global averages – which are usually generated from the broader study area. The resulting output quantifies the level of significance at which areas are 'hot'. Due to this test now being included in spatial analysis toolboxes in software such as ArcGIS, which is often used by crime analysts, this has become a more commonly applied method in recent years.

The mapping techniques outlined thus far have focused on visualising volumes of data – that is, the frequency of crime events at a given location, or a given point in time. This is important for informing police deployment decisions – for they will strive to go where crime is the highest volume, and therefore have a palpable chance of preventing crime. But there is also a need, in some scenarios, to understand how risk is distributed. For example, are you at a greater risk of being robbed in a central business district (CBD) than a suburban street? Probably not, given the volumes of people passing through CBDs in relation to suburban areas, although this is an unintuitive answer. This example serves to highlight the importance of accounting for the population at risk – if you are but one of many people walking on a street then your *risk* of victimisation is on the low side. If you are one of few people walking on a street your risk is higher. These two scenarios are not though demarcated on a volume map which would show the same data (e.g., crime event) without the context.

To account for the population at risk, analysts ought to create a rate of crime, per some denominator. Which denominator that is very much depends on the crime. Residential population is usually woeful at estimating the risk of crimes like street robbery, business fraud or bicycle theft. Hence, denominators need to be chosen carefully, attentive to both data availability (and limitations) and the opportunity structure underpinning a crime type (Newton & Felson, 2015).

Incorporating underlying populations into mapping techniques is relatively straightforward. Thematic maps require data collected at administrative area level, which is plentiful in many countries due to the census. For KDE, it is a little more challenging since the input data (both crime and population) needs to be at the point data level. Dual KDE is then possible, which is a technique that performs a calculation based on multiple layers of density estimation. As well as incurring all the same limitations of single KDE (Leitner et al., 2018), dual KDE can also result in unintuitive map outputs (Eck et al 2005) so should be used with care and appropriate data.

Contemporary innovations in mapping techniques and purposes

Although the mapping techniques outlined above form the bread and butter of a crime analyst’s day job, the field is continually propelled forwards by innovations in new or underutilised data, or in techniques used. Many police agencies have moved to the use of crime ‘dashboards’, insofar that multiple forms of crime data are summarised and made available on a regular (often daily) basis across the organisation, so that personnel are kept up-to-date with the latest trends. Such dashboards can range in sophistication and often depend on information technology professionals and web developers. Simple ones can though be created with automating the types of tasks that crime analysts routinely perform.

Relatedly, upskilling crime analysts with coding skills can result in a substantial return on investment for police agencies. For example, in New Zealand Police, analysts have generated a script that runs on weekdays to identify crimes that are close in space and time. The crime reports of these events are then gone through in more detail by a crime analyst to assess if they are related, for instance by a common modus operandi or an offender’s known behaviour. Checking all the crimes overnight would be a time-consuming task, but the algorithm reduces this to a manageable volume of crime events that are more likely to be related.

Another example from New Zealand police highlights the ever-expanding methods available to analysts to create maps that are operationally useful. Before this is described, recall the notion of spatio-temporal patterns in crime. The time-stability of hot spots has important practical implications. There is no point the police (or other agencies) targeting action at places that are becoming less hot or are only hot at very specific times, as the resources will not be optimally targeted. Cognisant of this, police analysts at New Zealand Police were tasked with creating maps that represented the patterns of hot spot locations over time, by crime type, so that sporadic and emerging hot spot areas could be considered for targeted police action.

The police analysts chose to employ the ‘emerging hot spots analysis’ tool in ArcGIS© which they refer to as ‘space-time cube analysis’. This follows a process of calculating a GI* statistic (see above) for each user-defined temporal window in each grid cell. A Mann-Kendall trend test is then applied to the GI* statistics to generate a 3D map representing whether a grid cell has had statistically significant volumes of crime over time, and the layers of the 3D bar represent the temporal windows[i].

Figures 1 and 2 depict this method. These use robbery occurrences from 1 January 2019 to 6 October 2021 (n=14,671) and a temporal window of seven days that runs from Tuesday to Monday, to ensure that weekends do not skew the data. By way of context, the study area was the Central Auckland Area which, as a CBD area, has a typically low residential population but high ambient population. Temporal analysis found that robbery was more likely in the early hours of Saturday and Sunday mornings.

Figure 1 displays, first, the 2-dimensional surface of the ten hexagonal grid cells that were found to be statistically significant hot spot areas. However, as the legend indicates, these are ‘sporadic hot spots’, suggesting that the crime patterns are not stable over time, which is often found in empirical investigations of this nature (see, for an academic treatment, Johnson and Bowers, 2008).

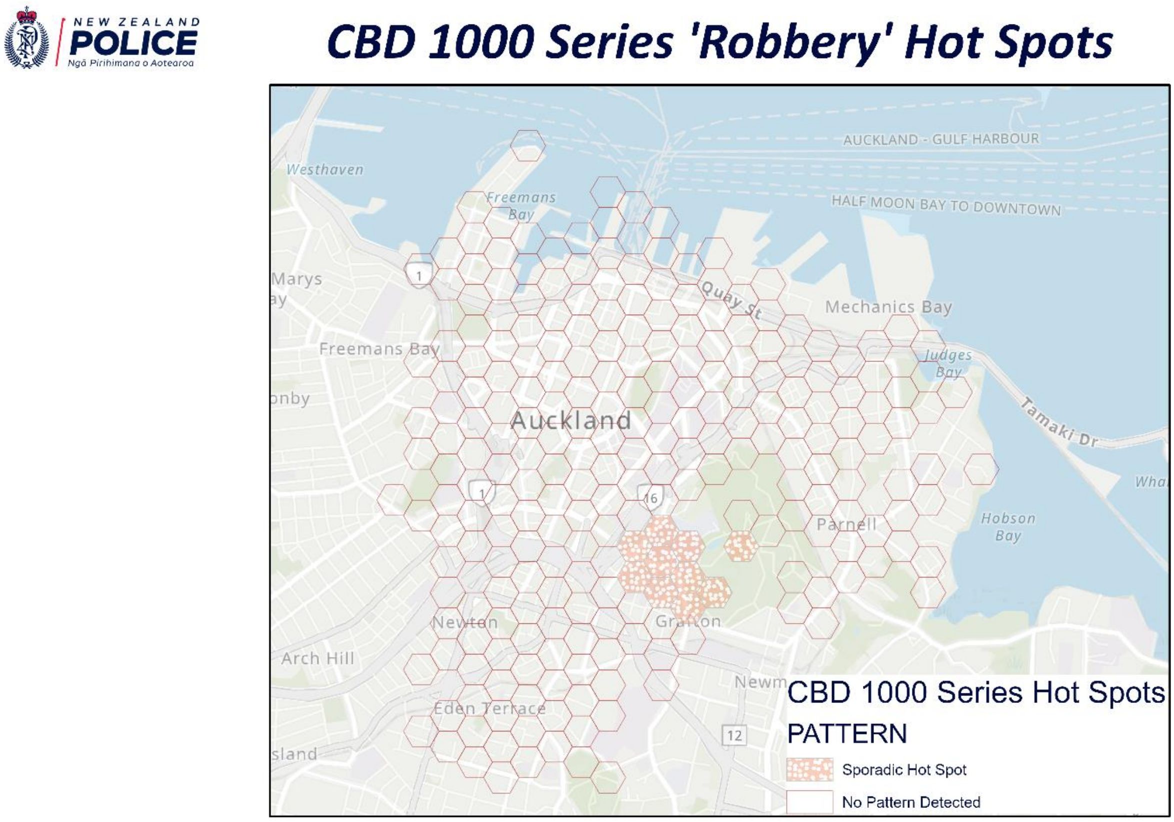

Figure 1 – a two-dimensional map illustrating the grid cells that correspond to sporadic hot spots for robbery in the Central Auckland Area, generated by New Zealand Police analysts. Published with permission from New Zealand Police.

Figure 2 presents the 3D output of the emerging hot spots analysis. Visual inspection of this shows the same ten shaded hexagonal grid cells, but this time overlaid on the map are hexagonal prisms which show the 'hotness' of the cell over time, with the most recent temporal windows closest to the top. Interpretation of this suggests that the shaded cells have recently become statistically significantly hot and warrant police consideration. In contrast, there are other areas of the CBD which have seen statistically significant volumes of robbery in the past but have diminished in 'hotness' in the most recent time period. Such analysis supported the impressions from front line officer experiences and can provide evidence-based reporting to support deployment planning and targeted resourcing to reduce harm in identified 'hot spot' locations.

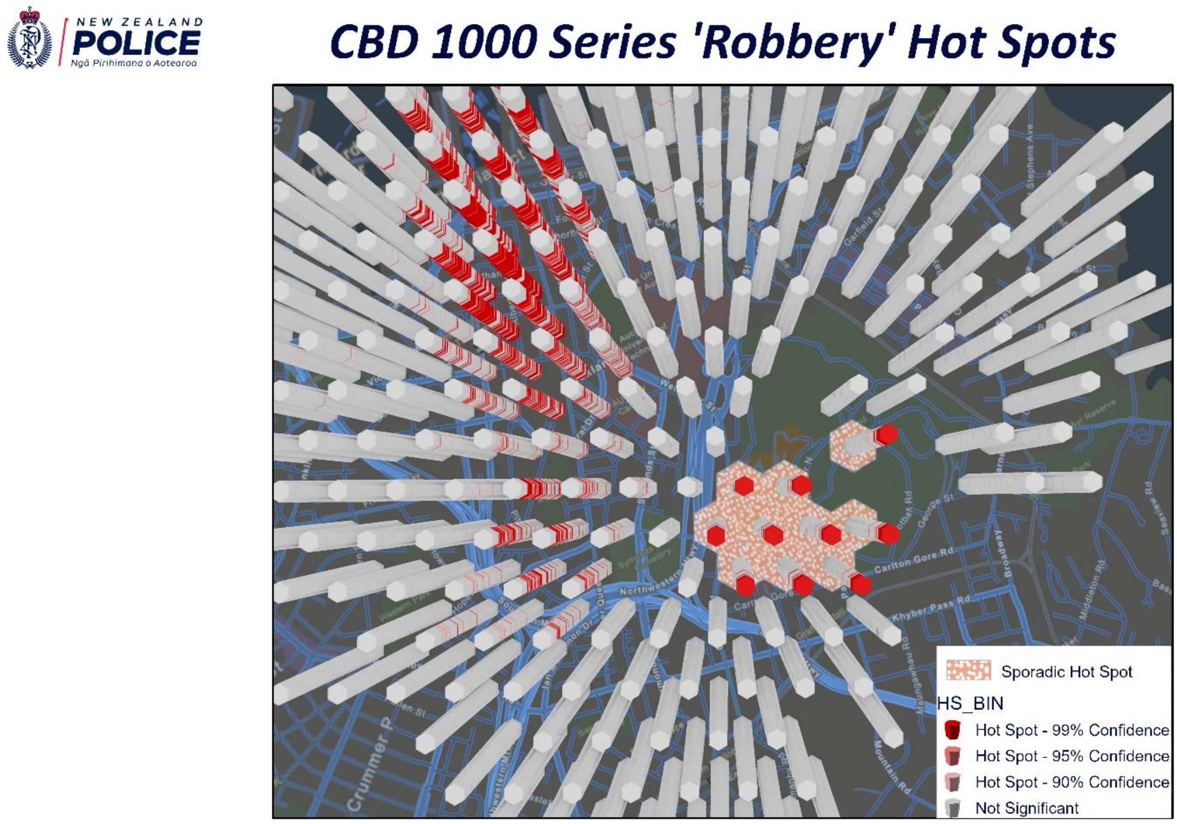

Figure 2 – a three-dimensional map illustrating the grid cells that correspond to sporadic hot spots for robbery in the Central Auckland Area generated by New Zealand Police analysts. 3D prisms present the trends over time, with the top level indicating the most recent time period. Published with permission from New Zealand Police.

Returning to the theme of mapping partial data, another example from New Zealand Police was generated for an experiment of hot spots policing. In this case they were aware of the limitations of relying on crime data alone and wanted to explore how multiple sources of data could lead them to focus our activities more effectively. The analysts mapped demand for service (emergency calls to police), along with crime volume (for street level crime), and crime harm using the New Zealand Crime Harm Index (Curtis-Ham and Walton, 2017). By overlaying the three sets of data using a 200m fishnet grid square they revealed a limited number of areas of the study site with the concurrent highest levels of demand, volume and crime harm (see Figure 3, with each data source in a different coloured hatching). This then informed the trial of deploying police to hot spots to prevent crime and harm.

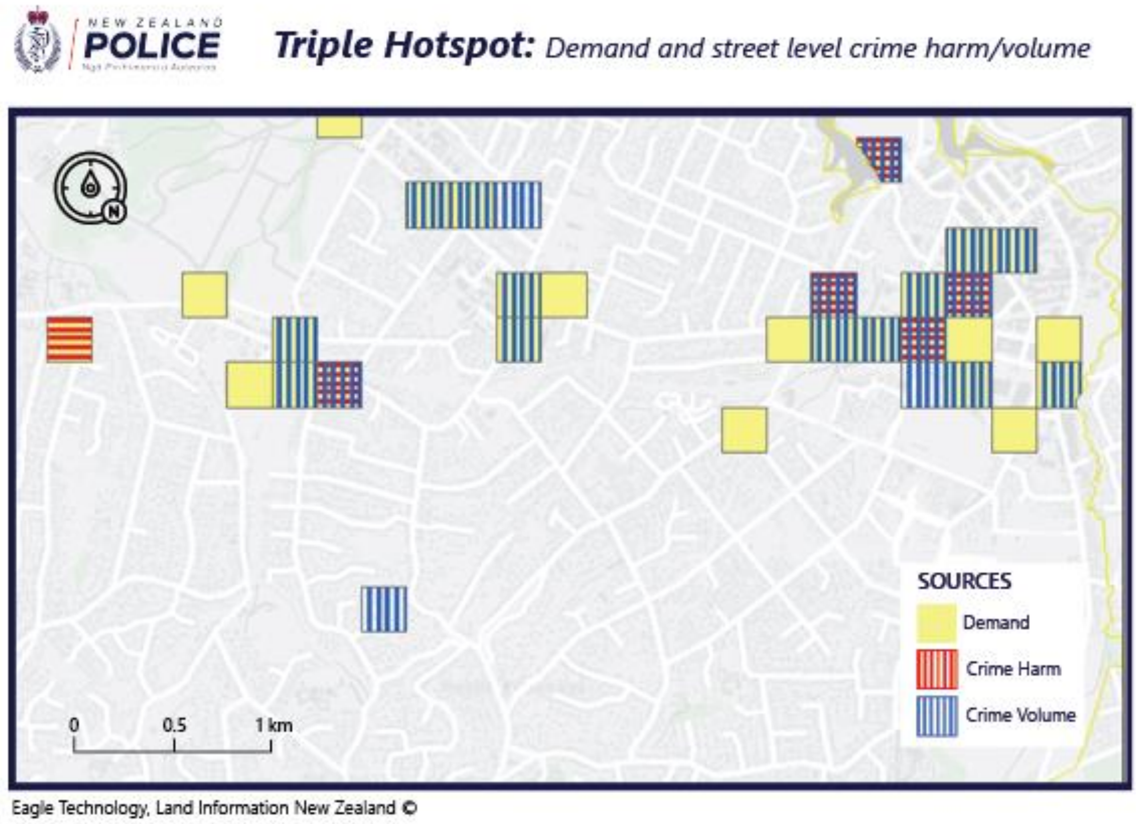

Figure 3 – a hotspot map simultaneously showing demand (emergency calls to police), crime volume and crime harm. Published with permission from New Zealand Police.

Conclusion

The geographical fascination with crime patterns has a long history and has been influential in shaping police practice in the twenty-first century. Crime analysts typically generate maps to support a range of policing functions. Such analysts ought to be highly trained, for the unique qualities of geographically referenced data need to be thoroughly understood and the processing of data to get it ready for mapping requires considerable skill.

Many mapping techniques exist for representing crime patterns, each with their own strengths and limitations. Savvy crime analysts understand that crime data are usually imperfect and take steps to mitigate the systematic biases within them. Innovative ways of visualising spatio-temporal patterns in crime are constantly being developed. These help to guide police attention to the areas where they can be most effective in preventing crime and assisting the public.

What the police then do about geographical crime concentration is open to debate. Hot spots policing has been shown to work through meta-analytic findings (Braga et al., 2019). However, this belies a range of policing tactics that might be used, and research is currently trying to establish what optimal tactics look like. Offender-based approaches have been shown to work in Philadelphia in violent crime hot spots (Groff et al., 2015) but this experiment needs to be replicated elsewhere to establish generalisability of this finding. Recent advancements in hot spot policing include using 'predictive policing' algorithms, but these are contentious and have received criticism for potentially perpetuating racial bias in the criminal justice system. The fate of predictive policing is unclear at the point of writing, but crime mapping more broadly looks to have cemented its place in policing for directing attention to crime concentrations and enabling police to optimise their resource deployment.

Further reading

Introductions to crime mapping more generally can be found in:

Tompson, L. (2021). Crime Mapping/Geospatial Information Systems. In J.C. Barnes & D.R. Forde (Eds) *The Encyclopedia of Research Methods in Criminology and Criminal Justice*. Chapter 5. https://doi.org/10.1002/9781119111931.ch5

Weisburd, D., & Wire, S. (2018). Crime hot spots. In *Oxford Research Encyclopedia of Criminology and Criminal Justice*.

An engaging (and free!) read on the basics of hotspot analysis was produced by the US National Institute of Justice, and is usually accessible for beginners to mapping:

Eck, J. E., Chainey, S., Cameron, J. G., Leitner, M., & Wilson, R. E. (2005) Mapping crime: Understanding hot spots. Washington, DC: U.S. Department of Justice. Accessed: 26 January 2022 at: https://www.ojp.gov/pdffiles1/nij/209393.pdf

A textbook which covers the foundations of crime mapping in policing and related crime reduction agencies, with great coverage of environmental criminology theories and the range of considerations for doing spatial analysis of crime data:

Chainey, S., & Ratcliffe, J. (2013). *GIS and crime mapping*. John Wiley & Sons.

A more geographical perspective on the topic:

Leitner, M., Glasner, P., & Kounadi, O. (2018). Laws of geography. In Oxford Research Encyclopedia of Criminology and Criminal Justice.

A compilation of case studies of crime mapping applications in different policing jurisdictions

Chainey, S., & Tompson, L. (Eds.). (2008). *Crime mapping case studies: Practice and research*. John Wiley & Sons.

A thorough and accessible guide for crime analysis techniques relating to mapping:

Santos, R. B. (2016). 4th Ed. *Crime analysis with crime mapping*. Sage publications.

A chapter on the types of police data that might be used in mapping (and the book in its entirety is useful for crime and place researchers):

Tompson, L. & Ashby, M. (in press). Official Police Data. In E. Groff & C. Haberman *Understanding Crime and Place: A Methods Handbook.* Temple Press; Philadelphia, US.

A classic text documenting the use of crime mapping in policing:

Weisburd, D., & McEwen, T. (1998). Crime mapping and crime prevention (No. 8). New York: Criminal Justice Press.

For a scholarly treatment of analysing spatio-temporal patterns in crime:

Ratcliffe, J. (2010). Crime mapping: spatial and temporal challenges. In Handbook of quantitative criminology (pp. 5-24). Springer, New York, NY.

A special edition of a journal covering some advancements in the application of spatial statistics to understanding crime patterns in the 2020s:

Andresen, M. A., Haberman, C. P., Johnson, S. D., & Steenbeek, W. (2021). Advances in Place-Based Methods: Editors' Introduction. *Journal of Quantitative Criminology*, 1-5.

Links to Digital Materials

South Africa's Institute of Security Studies publishes crime maps to the public. This uses data from the South Africa Police Service (SAPS) alongside other sources. Among other mapping projects, in 2013 this organisation started to collect data from a range of sources (e.g., media, municipal organisations) to track, often in real time, the spread of protest and public violence. In doing so, they found that they were providing an indispensable public service to the citizens of South Africa: https://issafrica.org/crimehub/maps/public-protest-and-violence-stats

References

Ashby, M. P. (2019). Studying Crime and Place with the Crime Open Database: Social and Behavioural Scienes. *Research Data Journal for the Humanities and Social Sciences*, *4*(1), 65-80.

Oswald, M., & Babuta, A. (2019). Data analytics and algorithmic bias in policing. Royal United Services Institute for Defence and Security Studies. Accessed 13 June 2022. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/831750/RUSI_Report_-_Algorithms_and_Bias_in_Policing.pdf

Baraka, G. E., & Murimi, S. K. (2019). Stuck in the past with push-pins on paper maps: Challenges of transition from manual to computerized crime mapping and analysis in Kenya. International Journal of Police Science and Management, 21(1), 36–47. https://doi.org/10.1177/1461355719832620

Barreneche, C. (2019). Data corruption: The institutional cultures of data collection and the case of a crime-mapping system in Latin America. Canadian Journal of Communication, 44(3), 343–350. https://doi.org/10.22230/cjc.2019v44n3a3481

Belur, J., Tompson, L., & Jerath, K. (2019). MASIP evaluation interim report. Accessed 27 January 2022 at: https://discovery.ucl.ac.uk/id/eprint/10078857/

Bowers, K. J., Johnson, S. D., & Pease, K. (2004). Prospective hot-spotting: the future of crime mapping?. *British journal of criminology*, *44*(5), 641-658.

Braga, A.A., Turchan, B.S., Papachristos, A.V. & Hureau, D.M. (2019) Hot spots policing and crime reduction: an update of an ongoing systematic review and meta-analysis. *Journal of Experimental Criminology* 15, 289–311. https://doi.org/10.1007/s11292-019-09372-3

Brantingham P.J., Dyreson, D. A. & Brantingham P.L. (1976). Crime seen through a cone of resolution. *American Behavioral Scientist*, 20, 261-273.

Brantingham, P. J., & Jeffery, C. R. (1991). Afterword: Crime, Space and Criminological Theory. In P. J. Brantingham & P. L. Brantingham (Eds.), *Environmental Criminology* (2nd ed., pp. 227–237). Prospect Heights, IL: Waveland Press.

Brantingham, P. J., Valasik, M., & Mohler, G. O. (2018). Does predictive policing lead to biased arrests? Results from a randomized controlled trial. *Statistics and public policy*, *5*(1), 1-6.

Brantingham, P. L., & Brantingham, P. J. (1993). Environment, Routine and Situation: Toward a Pattern Theory of Crime. In R. V Clarke & M. Felson (Eds.), *Advances in Criminological Theory* (pp. 259–294). New Brunswick, NJ: Transaction Publishers.

Brown, J., & King, J. (1998). Gender differences in police officers attitudes towards rape; Results of an exploratory study. *Psychology, Crime and Law*, *4*(4), 265-279.

Casady, T. (2008). Automating briefings for police officers. *Crime Mapping Case Studies: Practice and Research*, 27-32.

Chainey, S., & Tompson, L. (2012). Engagement, Empowerment and Transparency: Publishing Crime Statistics using Online Crime Mapping. *Policing*, 6(3), 228–239. https://doi.org/10.1093/police/pas006

Chainey, S., & Ratcliffe, J. (2013). *GIS and crime mapping*. John Wiley & Sons.

Clarke, R. V. (2018). The theory and practice of situational crime prevention. In *Oxford Research Encyclopedia of Criminology and Criminal Justice*.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American sociological review*, 588-608.

Cornish, D. & Clarke, R. V. (2008). The rational choice perspective. In R. Wortley & L. Mazerolle (Eds.), *Environmental Criminology and Crime Analysis* (pp. 21–47). Cullompton, Devon: Willan Publishing.

Cornish, D. & Clarke, R. V. (Eds.) (1986). *The Reasoning Criminal: Rational Choice Perspectives on Offending*. New York, NY: Springer-Verlag.

Curtis-Ham, S., & Walton, D. (2018). The New Zealand crime harm index: Quantifying harm using sentencing data. *Policing: A Journal of Policy and Practice*, *12*(4), 455-467.

Eck, J. E., Chainey, S., Cameron, J. G., Leitner, M., & Wilson, R. E. (2005) Mapping crime: Understanding hot spots. Washington, DC: U.S. Department of Justice.

Edelstein, I., Faull, A., & Arnott, R. (2020). Hotspot policing for murder and robbery: a Cape Town case study. *ISS Southern Africa Report*, *2020*(34), 1-40.

Eman, K., Gyorkos, J., Lukman, K., & Meško, G. (2013). Crime mapping for the purpose of policing in Slovenia - Recent developments. Revija Za Kriminalistiko in Kriminologijo, 64(3), 287–308.

Farrell, G. (2015). Crime concentration theory. *Crime Prevention and Community Safety*, 17(4), 233–248. https://doi.org/10.1057/cpcs.2015.17

Faull, A. (2007). Corruption and the South African police service. A review and its implications. *Institute for Security Studies Papers*, *2007*(150), 20.

Faull, A. (2019). How to map violence without police data. *ISS Southern Africa Report*, *2019*(22), 1-24.

Getis, A. & Ord, J.K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis,* 24(3).

Groff, E. R., Kearley, B., Fogg, H., Beatty, P., Couture, H., & Wartell, J. (2005). A randomized experimental study of sharing crime data with citizens: Do maps produce more fear?. *Journal of Experimental Criminology*, *1*(1), 87-115.

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. doi:10.1111/1745-9125.12055

Haberman, C. P., Groff, E. R., Ratcliffe, J. H., & Sorg, E. T. (2016). Satisfaction with police in violent crime hot spots: Using community surveys as a guide for selecting hot spots policing tactics. *Crime & Delinquency*, *62*(4), 525-557.

Hardyns, W., & Rummens, A. (2018). Predictive Policing as a New Tool for Law Enforcement? Recent Developments and Challenges. European Journal on Criminal Policy and Research, 24(3), 201–218. https://doi.org/10.1007/s10610-017-9361-2

Jefferson, B. J. (2018). Predictable Policing: Predictive Crime Mapping and Geographies of Policing and Race. *Annals of the American Association of Geographers*, 108(1), 1–16. https://doi.org/10.1080/24694452.2017.1293500

Johnson, S. D., & Bowers, K. J. (2008). Stable and fluid hotspots of crime: differentiation and identification. *Built Environment*, *34*(1), 32-45.

Johnson, S. D. (2010). A brief history of the analysis of crime concentration. *European Journal of Applied Mathematics*, *21*(4-5), 349-370.

Leitner, M., Glasner, P., & Kounadi, O. (2018). Laws of geography. In *Oxford Research Encyclopedia of Criminology and Criminal Justice*.

McDonnell, R. and Kemp, K. (1995). *International GIS Dictionary*. New York;: Wiley

Mohler, G., Carter, J., & Raje, R. (2018). Improving social harm indices with a modulated Hawkes process. *International Journal of Forecasting*, *34*(3), 431-439.

Newton, A. (2008). A study of bus route crime risk in urban areas: The changing environs of a bus journey. *Built Environment*, *34*(1), 88-103.

Newton, A., & Felson, M. (2015). Crime patterns in time and space: The dynamics of crime opportunities in urban areas. *Crime Science*, *4*(1), 1-5.

O'Neal, E. N. (2019). "Victim is not credible": The influence of rape culture on police perceptions of sexual assault complainants. *Justice Quarterly*, *36*(1), 127-160.

O'Neill, A. (2008). The strategic allocation of resources to effectively implement Neighbourhood Policing and the Community Safety Plan. *Crime Mapping Case Studies: Practice and Research*, 71.

Overall, C., & Day, G. (2008). The Hammer Gang: an exercise in spatial analysis of an armed robbery series using the probability grid method. *Crime Mapping Case Studies*, 55-62.

Ratcliffe, J. H. (2004). Geocoding crime and a first estimate of a minimum acceptable hit rate. *International Journal of Geographical Information Science*, *18*(1), 61-72.

Ratcliffe, J. H. (2016). 2nd edition. *Intelligence-led policing*. Routledge.

Ratcliffe, J. H., Taylor, R. B., & Fisher, R. (2019). Conflicts and congruencies between predictive policing and the patrol officer's craft. Policing and Society. https://doi.org/10.1080/10439463.2019.1577844

Robinson, W. S. (1950). Ecological Correlations and the Behavior of Individuals. *American Sociological Review*, 15, 351–357.

Rossmo, D. K., & Velarde, L. (2008). Geographic profiling analysis: principles, methods and applications. *Crime mapping case studies: Practice and research*, 35-43.

Santos, R. B. (2016). 4th Ed. *Crime analysis with crime mapping*. Sage publications.

Scott, M. S. (2017). Reconciling problem-oriented policing and evidence-based policing. In *Advances in Evidence-Based Policing* (pp. 27-44). Routledge.

Shapiro, A. Reform predictive policing. Nature 541, 458–460 (2017). https://doi.org/10.1038/541458a

Shaw, C., & McKay, H. (1942). *Juvenile Delinquency and Urban Areas*. Chicago: University of Chicago Press.

Sherman, L., Neyroud, P. W., & Neyroud, E. (2016). The Cambridge crime harm index: Measuring total harm from crime based on sentencing guidelines. *Policing: a journal of policy and practice*, *10*(3), 171-183.

Stanko, E. (1996). Reading danger: Sexual harassment, anticipation and self-protection. In M. Hester, L. Kelly, & J. Radford (Eds), Women, violence and male power: Feminist activism, research and practice (pp. 50–62). Buckingham: Open University Press

Telep, C. W., & Weisburd, D. (2015). Hot spots policing. *The Encyclopedia of Crime and Punishment*, 1-3.

Knutsson, J., & Tompson, L. (Eds.). (2017). *Advances in evidence-based policing*. Taylor & Francis.

Tompson, L., & Townsley, M. (2010). (Looking) Back to the Future: using space-time patterns to better predict the location of street crime. International Journal of Police Science and Management, 12(1), 23–40.

Tompson, L., Johnson, S. D., Ashby, M., Perkins, C., & Edwards, P. (2014). UK open source crime data: accuracy and possibilities for research. *Cartography and Geographic Information Science*, 42(March 2015), 97–111. https://doi.org/10.1080/15230406.2014.972456

Tompson, L., Partridge, H., & Shepherd, N. (2009). Hot routes: Developing a new technique for the spatial analysis of crime. *Crime Mapping: A Journal of Research and Practice*, *1*(1), 77-96.

Uchida C.D. (2014) Predictive Policing. In: Bruinsma G., Weisburd D. (eds) Encyclopedia of Criminology and Criminal Justice. Springer, New York, NY. https://doi.org/10.1007/978-1-4614-5690-2_260

Weisburd, D., & Wire, S. (2018). Crime hot spots. In *Oxford Research Encyclopedia of Criminology and Criminal Justice*.

Weisburd, D., Davis, M., & Gill, C. (2015). Increasing collective efficacy and social capital at crime hot spots: New crime control tools for police. *Policing: A Journal of Policy and Practice*, *9*(3), 265-274.

Wheeler, A. P. (2020). Allocating police resources while limiting racial inequality. *Justice quarterly*, *37*(5), 842-868.

[i] For further information, see https://pro.arcgis.com/en/pro-app/2.7/tool-reference/space-time-pattern-mining/emerginghotspots.htm