Chapter 38
GIS Empowered Urban Crime Research

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Abstract The chapter looks at the contribution Geographical Information Systems (GIS) have made to research into the spatial and temporal patterns of urban crime and criminality, indicating areas of possible growth in the future and sketching the policy relevance of these developments for practical policing and research. It discusses four main GIS empowered crime research elements using a "3W1H" framework to help organize ideas: "Who (2P: Police and Public)", "What (2C: Crime and Context)", "Why (2W: When and Where)" and "How (2D: Data and Design)". We highlight how interactive data visualisation leads to better public communication, essential for successful policing, as well as contributing to research agendas.

Keywords GIS · Urban crime · Spatial and temporal patterns · Crime mapping · Data-driven

38.1 Introduction

Study into urban crime can be dated back to at least the nineteenth Century but this field gathered particular momentum in the 1920s and 1930s when links between neighbourhood social conditions and crime and criminality were systematically investigated by what is referred to as the "Chicago School" (see for example Shaw & McKay, 1931). This early work was undertaken within the discipline of sociology but in the years since, the study of crime and criminality has attracted interest from many other disciplines including geography, psychology, public health, behavioural science, and economics whilst also establishing itself as a field of study (criminology) in its own right (Becker, 1968; George, 1978; Hakim and Rengert, 1981;

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Sorenson and Pilgrim, 2000). For extensive and recent reviews of the field see the various Oxford Handbooks of Criminology series (2012, 2017, 2018). The technical challenges associated with crime research has also attracted interest from computer scientists, with GIS assuming an important place in the handling and displaying of geographically referenced crime data, data that are routinely collected and digitized by local police forces (Li, 2015). Ever since the widespread utilisation of GIS packages and relevant computational techniques in the 1990s (Wortley & Mazerolle, 2008), researchers have been able to rapidly map and query crime data, illuminating geographical (spatial and territorial) and spatial–temporal patterns and trends often in near real-time limited only by the speed with which crime-site data can be input into computer systems (Spencer and Ratcliffe, 2005). The "marriage" of cutting-edge machine learning and data visualisation techniques in recent decades has added further impetus to the field.

Such advances in urban crime data analysis (both the interpretation and presentation of crime data) have enabled wider and better communication between police forces and the general public, drawn the public's attention to local safety issues, disseminated knowledge about local police services and provided up-to-date information on progress, facilitated the promotion of crime prevention strategies and improved the efficiency of routine policing practices. In light of these, this chapter will illustrate "GIS-empowered" urban crime research using a **3W1H** donut-gram (Fig. 38.1) to indicate the broad classes of questions that are of interest:

1. **W**hat: what is the potential for urban crime research and what are the future directions for the subject? This strand can be streamed into:

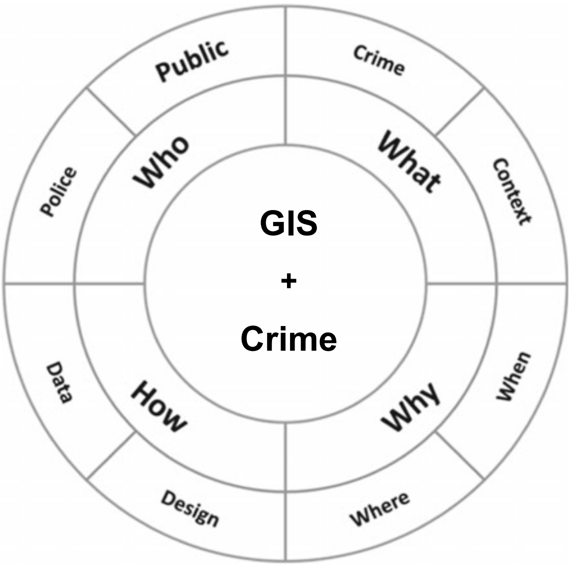

Fig. 38.1 Urban Crime Research: the 3W1H Donut-gram

- **C**rime: evolution of long-standing crime research agendas into, for example, offender behaviors and victimization in geographical space and time and changes due to structural shifts associated with post-pandemic economies, such as changes to working practices (more home working and less commuting), and linked to
- **C**ontext: contextual (e.g., environmental) influences on crime and criminality in urban areas. Changes in urban structure and how this will impact on crime and criminality.

2. **W**hy: Why is it important to empower urban crime research with GIS techniques? In particular it contributes to work into spatio-temporal crime patterns research:

    - **W**hen: the crime-peak hour(s) of the day, days of the week, seasonal and temporal trends in crime incidents in urban areas.
    - **W**here: the detection of hot spots and "crime streets" (micro-spaces associated with specific street segments that have very high levels of crime and criminality) in urban spaces for the purpose of directly targeting police resources.

3. **W**ho: Who would such research benefit? Beneficiaries will include not only policy practitioners like police agencies, but also ordinary citizens.

    - **P**olice: evidence-based policing strategies as well as space and time specific crime-combating measures.
    - **P**ublic: transparent information communication and interaction.

4. **H**ow: How GIS will better empower urban crime research in the coming decades?

    - **D**ata: emerging big data and multiple new sources of data (e.g., from social media, smart phones, remotely sensed images, etc.)
    - **D**esign: innovative methodologies, augmenting traditional spatial statistical techniques such as regression and cluster detection methods, for instance machine learning and artificial intelligence.

38.2 Urban Crime Literature

We start by considering the first "W" (What) of the urban crime research donut-gram, and its two streams crime and context, and the second "W" (Why) and its two streams identifying crime patterns over place and time. There is a well-developed literature investigating the consequences of urban development on crime and criminality, ever since Durkheim (1897) coined the term "anomie" to describe social alienation, and the Chicago School's research into social disorganisation and its influence on urban criminality (Messner and Rosenfeld, 1997; Chamlin and Cochran, 1995; Savolainen, 2000; Bernburg, 2002; Kim and Pridemore, 2005).

38.2.1 Crime Embedded in the Urban Context

In the course of exploring urban crime influences and changes in those influences over time, the majority of criminological or sociological theories have focused on changes in the amount and types of crime and the importance of such variables (varying over time and between places) as poverty, changes in economic inequality, criminal opportunities, cultural conflicts, weakened social control and social disorganization (Durkheim, 1897, Cloward and Ohlin, 1960, Kim and Pridemore, 2005). Theories that include institutional anomie theory (Messner and Rosenfeld, 1997) and social capital theory (Coleman, 1988; Sampson et al., 1999), place emphasis on the mediating role of social cohesion and the strength of cultural values that do not equate "success" with "money". They are consistent with viewpoints from Chicago School theorists in emphasising neighborhood structure and its links to levels of crime. For example, Shaw and McKay (1931) were most concerned with the deleterious effects of racial and ethnic heterogeneity, residential mobility, and low socioeconomic status on an area's ability to prevent crime. Together with other factors like family disruption (Sampson and Groves, 1989), relative poverty (Messner, 1982), and racial segregation (Krivo and Peterson, 1996), these theories work together to provide a basis for examining changing crime patterns in urban areas.

Since the 1970s, urban crime research has evolved becoming no longer the preserve of criminologists, sociologists, and police practitioners, but has also received interdisciplinary input from geographers and computer scientists who have paid particular attention to crime influences emanating from the urban contextual environment. For instance, Storch (1979) reviewed Gurr's (1977) work on evaluating urban crimes in London, Stockholm, and Sydney since 1930 using statistical records to derive associations between increases in crime and civil order and trying to uncover the influences of institutional and political factors. Research had shown that crime intensities, changes, complexities, and dynamics have been significantly affected by the particular urban contexts, as do the corresponding crime-countering measures and policies, which require account to be taken of local contexts and specific local crime trajectories. A question of particular interest currently is how social and economic changes, set in motion by the covid pandemic will play out in terms of urban crime patterns (Ceccato et al. 2021).

38.2.2 Crime Patterns

Urban crime is not a collection of random incidents in space and time, and for this reason has attracted increasing numbers of researchers and practitioners to explore the observed patterns in time and space, with the aims of gaining a better understanding of the dynamics of crimes, and to prepare more accurate crime forecasts in order to devise preventive strategies and measures.

Time-series analysis and various related methods had been employed by statisticians, sociologists and mathematicians amongst others to describe the crime trends in target urban areas, by year, by season, by week as well as daily, hourly, or even every 15 min (Lauritsen and White, 2014; Andresen and Malleson, 2015; Felson and Poulsen, 2003; OJJDP, 2016; Williams and Coupe, 2017), for not only descriptive and exploratory purposes, but also looking into the temporal predictions to support policing and patrolling assignments.

GIS and spatial analysis techniques are proving to be essential for studying criminal activity, especially in detecting crime hot spots (Chainey, 2020) or hot street (micro) segments (Tom-Jack et al., 2019) in different urban contexts. Recently, Murray et al. (2001) highlighted the novel capability of GIS and spatial analysis approaches for examining crime in urban regions using a case study in Brisbane, Australia; Ratcliffe (2010) noted that mainstream research in spatial criminology lies in the study of spatial and temporal crime patterning, and prediction; Chainey (2020: p43) mapped the high crime concentration micro-places in New York City (USA), Montevideo (Uruguay) and Rio de Janeiro (Brazil). Intensive case studies have enriched our understanding of urban crime and its context (**W**hat), the identification of crime patterns in place and time (**W**hy), and the development of urban crime research, drawing on more diversified data sources and evolved GIS methodologies (**H**ow), in the expectation of empowering crime research towards better police service practices to facilitate crime reduction and prevention (**W**ho).

38.3 GIS Empowered Crime Research and Practice

Ever-evolving GIS methodologies have empowered the realisation ("**H**ow") of crime research and practice. The use of GIS in crime research has strong roots in practical policing challenges in the 1990s most notably when the New York City Police Department (Harris, 1999) started to replace traditional but cumbersome pinpoint maps with a computerised crime mapping system. However, the intellectual root for using spatial technology goes further back. For example, in the 1960s, Jacobs (1961) "eyes on the street" theory drew attention to the importance of the physical environment on some forms of criminal behaviour. City planners, by paying attention to small scale urban layout could facilitate informal surveillance which would in turn discourage the motivated offender. Urban renewal in the 1950s and 1960s had not, in Jacob's view, paid sufficient attention to how urban layout might have an impact on a range of crimes from burglary to street crime. Good environmental (structural) urban design will enhance the public's community guardianship role and play an important part in responding to rising crime levels. GIS with its ability to manage spatial (i.e., land use, census, and transportation) databases clearly had a role to play in developing "safer urban spaces" as well as play an important role in crime pattern detection (section 38.2.2) and crime mapping in space and time. There is potential to link these two roles as part of a spatial decision support system to monitor the consequences of urban re-design on crime patterns.

38.3.1 Crime Mapping for Police Services

Digital crime mapping, for example the widely acknowledged COMPSTAT model (McDonald, 2002), was initially employed to support police decision making, manage patrol operations (Chainey and Ratcliff, 2013), and make significant progress in improving and making more efficient police services in the face of increasing ‘demand’ and spiralling costs (Craglia et al., 2000). COMPSTAT was credited with having played an important role in reducing crime levels in New York City, evolving into a prospective crime mapping tool (Hart et al., 2020) to support predictive policing often based on the use of spatial analytical techniques, for example Kernel Density Estimation (KDE) (Bailey and Gatrell, 1995) and Risk Terrain Modelling (RTM) (Caplan and Kennedy, 2010).

Computer-assisted crime mapping has improved the efficiency of police services significantly. For instance, Reaves (2010) compared the percent of local police departments using computers by 2007 and found that police departments in urban areas especially serving populations of over 250,000, had utilised GIS 100% for crime analysis and crime mapping. Besides, the use of GIS combined with spatial analysis tools has contributed to the development of various crime mapping applications which assisted with patrol dispatching, community policing and resource planning.

38.3.2 Crime Mapping for Public Engagement

In the twenty-first Century, driven by advances in computer science and data (geo)visualisation techniques, crime mapping has become more supportive for public sectors enabling the provision of information quickly to citizens (e.g., crime dashboard in the city of London) supporting fulfilling the goal of transparent communication as a key element of open government promises. For example, Chainey and Tompson (2012) affirmed the policy impacts from UK police forces’ adoption of an online crime mapping tool in 2008, with the fruits of it improving engagement with and empowerment and promotion of public service transparency and accountability. However, such interactive communication normally places high requirements on the citizens’ ability to interpret the data. This in turn necessitates careful cartographic visualisation of the information to be communicated to reduce the risk of any confusion arising because of the lack of direct human interaction. It proposed the integration of crime mapping systems with social media to facilitate instant and prompt communication of local crime issues for the benefit of citizens. However as has been remarked, involving social media is not without its challenges and potential for misinformation.

38.4 What Next?

The digital era is ushering in a period where very large and complex data sets are available, providing new opportunities and motivation to develop new and innovative ways for conducting urban crime research (Hart et al., 2020) and supporting policing services utilizing emerging data & state-of-the-art methods (**H**ow).

38.4.1 Emerging Data

The linked development of both emerging new sources of fine-grained urban crime and other relevant data and data mining techniques have together contributed to enhanced understanding of urban crime (Zhao and Tang, 2018). Here are some examples:

1. **I**nternet-of-Things (IoT) data: social media for example geo-located Twitter sentiment data and Foursquare data have been utilised together with other types of data including weather data for example, to make crime predictions (Wang and Li, 2021; Wang et al., 2012; Chen et al., 2015). The mobile data being used to simulate the mobile population has become more widely deployed (Bogomolov et al., 2014; Rosés et al., 2021). There are also many open-source databases that have been made available for researchers to explore spatial–temporal crime patterns from a comparative perspective, e.g., the Crime Open Database (CODE) recording 10 largest US cities' crimes over 11 years by type (Ashby, 2019), and the multiple sources of UK crime datasets (Tompson et al., 2015).
2. **T**racking data: GPS data has been used to simulate populations at risk from crime (Kikuchi et al., 2012) in micro-places, or record police patrols and micro-place-based intervention effects (Hutt et al., 2021), with the latter accompanied by GPS and Body Worn Recorder video data (BWV). Other locational tracing data such as that provided by taxi data (Vomfell et al., 2018), cell phone tracking (Song et al., 2019) and Google location data (Valentino-DeVries, 2019) are potentially valuable data sources in this context.
3. **I**mage data: recently remotely sensed data have attracted interest as inputs into crime and policing research as a way of avoiding the high costs of manual data collection, because of its increasing abundance and accessibility at high resolution. Najjar et al. (2018) investigated the use of deep learning to predict crime rates from raw satellite imagery for the purpose of promoting urban safety. Wu et al. (2018) trained both street view and satellite images with crime data in San Francisco, to predict the relative crime risks at different locations. Patino et al. (2014) used urban fabric descriptors computed from very high spatial resolution imagery to assess whether neighbourhood design and condition has a quantifiable imprint, as suggested it should by "broken windows" theory. They analysed the relationships between land cover, structure, texture descriptors and intra-urban homicide rates in Medellin, Colombia. Other work, such as that by Wolfe and Mennis (2012), Woodworth et al. (2014) and Liu et al. (2020), have used satellite imagery to estimate burglary density, assess the effect of

vegetation cover and nightlight respectively, on urban crime; Ceccato (2021) and colleagues are exploring the use of built form and other indexes derived from remotely sensed imagery together with artificial intelligence to predict crime patterns in Stockholm (an ongoing project funded by FORMAS).

4. **V**ideo footage data: Ashby (2017) used data from the British railway network to show that CCTV is a powerful investigative tool for many types of crime, and this finding was further endorsed by Lindegaard and Bernasco's (2018) work on suggesting the value of camera recordings as part of the investigative and criminological tool kit. Thomas et al. (2021) reviewed 162 CCTV schemes on crime prevention cases systematically across 15 countries over the past five decades illustrating the global expansion and internationalization of these technologies.

However, such emerging data have been exposed to challenges in terms of their accessibility, accountability, comparability, reliability, generalisability, interpretability, and representativeness. Such data need linking to advanced computational methods if they are to be "distilled" into useful information and knowledge and then communicated to stakeholders (including the public where relevant) in easy-to-understand language.

38.4.2 State-Of-The-Art Methods

Whilst GIS is an important part of the enabling technology for "spatial thinking", which is an essential underpinning to urban crime research and police response given the territorial as well as temporal nature of policing, it is important to recognize that GIS can support work with spatially referenced data in at least three distinct ways (Burrough & McDonnell, 1998): (1) as a powerful set of digital "tools": "*…for collecting, storing, retrieving at will, transforming and displaying spatial data from the real world for a particular set of purposes*" (p. 11); (2) as a database management system: "*a computer based set of procedures used to store and manipulate geographically referenced data*". (p. 11). Arguably these are the two main uses of GIS in crime research and policing practice up to the current time where sometimes advanced spatial statistical methods and geo-visualization have been integrated into the GIS for such activities as crime hotspot detection and geographic profiling. When a deeper understanding of crime patterns is needed, researchers have often made use of advanced statistical techniques such as spatial regression models (Anselin, 2009), geographically weighted regression (Cahill and Mulligan, 2007) and Spatio-temporal Bayesian modeling (Hu et al., 2018, Haining and Li 2020; Law et al. 2020).

A third and relatively under-developed (to date) use of GIS is as (3) a spatial decision support system (SDSS) which involves the integration of spatially referenced data in a problem-solving environment. This may involve inputting crime data, a range of urban data including socio-economic, physical infrastructure and police activity data, in order to evaluate different policing strategies in terms of efficiencies and outcomes [e.g., crime reduction currently of concern to society; elimination of hotspots; evaluation of a crime reduction programme (Li et al. 2013)].

In face of the ever-increasing urban data volumes and diverse sources, state-of-the-art interdisciplinary methodologies have been increasingly adopted by urban crime researchers.

Machine learning and AI techniques ("deep learning") have in recent decades been widely utilised to (1) detect crime hotspots (Kounadi et al., 2020; Nair and Gopi, 2020) together with spatial analytical techniques such as, adaptive kernel density estimation methods; (2) predict crime incident locations using for example Convolutional Neural Network (CNN) to train millions of imagery datasets (Najjar et al., 2018; Wu et al., 2018); and (3) optimise police patrol routing (PPR) using a (hybrid) Genetic Algorithm (GA), linear programming, local search and routing policies (Dewinter et al., 2020). Cichosz (2020) has summarised how algorithms like correlation analysis, random forest, linear regression, negative binomial regression, logistic regression, naive Bayes classifiers, SVM, neural network, decision trees, *k*-NN, polynomial regression, autoregression, clustered continuous conditional random field, and gradient boosting have been adapted by different cities in their policing efforts.

However, returning to the "**3W1H**" framework with which we began, such emerging data and state-of-the-art algorithms (including data visualization techniques and interactive dashboard platforms) which will certainly feature in next generation urban crime research and associated policy initiatives, will not be, in themselves, sufficient to serve future needs and expectations. Rather a key feature of that future must involve comprehensive, open, and transparent public participation and communication between stakeholders. This will in turn require a more comprehensive and systematic integration of GIS into urban crime research and urban policing. In summary, urban crime research in the coming decades will engage with wider aspects of the social and economic ecosystem. The aim must be to respond to the public's concerns and progress a whole society urban safety agenda that recognizes the needs of different groups defined by, for example, their ethnicity or their gender. This can only be taken forward through joint efforts involving academics, police agencies, private sector entrepreneurs and governance policymakers. It will be essential to communicate with all stakeholders, listening and responding to their fears and concerns in flexible ways and in language that they can understand.

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