Handbook of Quantitative Criminology

Alex R. Piquero · David Weisburd
Editors

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Springer

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Foreword

Quantitative criminology has certainly come a long way since I was first introduced to a largely qualitative criminology some 40 years ago, when I was recruited to lead a task force on science and technology for the President's Commission on Law Enforcement and Administration of Justice. At that time, criminology was a very limited activity, depending almost exclusively on the Uniform Crime Reports (UCR) initiated by the FBI in 1929 for measurement of crime based on victim reports to the police and on police arrests. A typical mode of analysis was simple bivariate correlation. Marvin Wolfgang and colleagues were making an important advance by tracking longitudinal data on arrests in Philadelphia, an innovation that was widely appreciated. And the field was very small: I remember attending my first meeting of the American Society of Criminology in about 1968 in an anteroom at New York University; there were about 25–30 people in attendance, mostly sociologists with a few lawyers thrown in. That Society today has over 3,000 members, mostly now drawn from criminology which has established its own clear identity, but augmented by a wide variety of disciplines that include statisticians, economists, demographers, and even a few engineers.

This Handbook provides a remarkable testimony to the growth of that field. Following the maxim that "if you can't measure it, you can't understand it," we have seen the early dissatisfaction with the UCR replaced by a wide variety of new approaches to measuring crime victimization and offending. There have been a large number of longitudinal self-report studies that provided information on offending and on offenders and their characteristics to augment the limited information previously available from only arrest data. The National Crime Victimization Survey (NCVS, formerly the NCS) was initiated in 1973 as an outgrowth of the Commission's recommendation to provide a measure of the "dark figure of crime" that did not get reported to the police. These initiatives had to be augmented by analytic innovations that strengthen the quality of their data. Inevitably, some data would be missing and imputation methods had to be developed to fill the gaps. Self-reports were hindered by recall limitations, and life calendars were introduced to facilitate memory recall.

Economists became interested in crime shortly after Garry Becker, building on the notion that the "demand" for crime would be reduced by increasing the punishment, or "price." He proposed an initial model of deterrence and his successors brought multivariate regression as a standard tool in criminology. That opened the door to variations such as logistic or probit models, for analysis of natural experiments when randomized design was not feasible, and for the use of propensity scores to better match treated and control populations. That brought time series models and hierarchical models into criminology also.

Experimentation was used to a limited degree early in criminology, but those experiments were largely limited to the kinds of psychological treatments that could be tested on a randomly separated treatment and control groups of offenders. Largely under the initiative of Lawrence Sherman, who led with the Kansas City Preventive Patrol experiment, we have seen a striking variety of randomized social experiments testing various means of operating elements of the criminal justice system, including police or courts as well as corrections, and new methods had to be developed to enhance the validity of those experiments and to compensate for the difficulty of incorporating a placebo into a social experiment.

Since there were limits to the degree to which one could experimentally manipulate the criminal justice system, a wide variety of modeling approaches developed. These include simulation models to analyze the flow of offenders through the system, models of criminal careers, and their dynamics from initiation to termination. Daniel Nagin introduced trajectory models as an important means of aggregating the dynamics of hundreds of individual longitudinal trajectories into a small number of distinct patterns that could capture the essential characteristics of longitudinal phenomena. Other models included spatial models of the diffusion of criminal activity within a community or across communities, network models characterizing the linkages among groups of offenders, and many more.

These are just a sampling of the many analytic innovations that Alex Piquero and David Weisburd have admirably assembled in this Handbook. This allows someone seeking an appropriate and innovative method for collecting some new data or for analyzing a particular set of data to explore a wide variety of approaches that have already been used, and hopefully to build on them in new ways that will provide an additional chapter for a future edition of the Handbook.

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CHAPTER 1

Introduction

ALEX R. PIQUERO AND DAVID WEISBURD

Quantitative methods are at the heart of social science research generally, and in criminology/criminal justice in particular. Since the discipline's birth, researchers have employed a variety of quantitative methods to describe the origins, patterning, and response to crime and criminal activity, and this line of research has generated important descriptive information that has formed the basis for many criminological/criminal justice theories and public policies. And in the past quarter-century, the advent and expansion of computers and advanced software applications has led to a burgeoning of methodological and statistical tools that have been put to use to address many criminological/criminal justice research issues. In short, the field of quantitative criminology now routinely employs quantitative techniques of all levels of complexity, not only to deal with the advances in longitudinal, experimental, and multilevel data structures but also to study substantive methodological or evaluative concerns of interest in the criminological/criminal justice community.

Unfortunately, many of the quantitative methods used in criminology/criminal justice have tended to appear in journal articles and book chapters such that a handbook-oriented reference guide has not existed that contains, in one volume, many of the important contemporary quantitative methods employed in criminology/criminal justice, especially those that have been developed to study difficult criminological questions, which have been previously examined using limited and/or inappropriate methodologies applied to particular types of data structures.

As a result, we reached out to leading quantitative researchers to develop chapters on many of the important methodological and statistical techniques used by criminologists to study crime and the criminal justice system. As such, *The Handbook of Quantitative Criminology* is designed to be the authoritative volume on methodological and statistical issues in the field of criminology and criminal justice.

Like handbooks available in other disciplines (economics, psychology, sociology), this book is designed to be a reference for new and advanced methods in criminology/criminal justice that provide overviews of the issues, with examples and figures as warranted, for students, faculty, and researchers alike. Authored by leading scholars in criminology/criminal justice, the handbook contains 35 chapters on topics in the following areas that have served witness to a proliferation of data collection and subsequent empirical research: (1) Innovative Descriptive Methods for Crime and Justice Problems; (2) New Estimation Techniques for Assessing Crime and Justice Policy; (3) New Directions in Assessing Design, Measurement

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and Data Quality; (4) Topics in Experimental Methods; (5) Innovation in Quasi-Experimental Design; and (6) Nonexperimental Approaches to Explaining Crime and Justice Outcomes. And although there exists many other methodological and quantitative techniques and issues in the study of criminology/criminal justice, the coverage of which would have been too difficult to include in a single handbook, *the Handbook of Quantitative Criminology* is intended to provide readers with a useful resource containing a comprehensive and contemporary treatment of research methodologies used in criminology/criminal justice.

We are honored to have this impressive list of contributors who have taken time out of their busy schedules and have worked carefully to construct entries in such a manner that they are as widely accessible as possible to readers of all levels, especially those who are seeking to learn the basic issues surrounding key methodological and quantitative methods. In this regard, we asked the chapter authors to follow as common a format as possible to be illustrative and to help guide readers of all levels of experience. We hope that readers learn as much about these methods and issues as we have.

Part I-A
Descriptive Approaches for Research and Policy: *Innovative Descriptive Methods for Crime and Justice Problems*

CHAPTER 2

Crime Mapping: Spatial and Temporal Challenges

JERRY RATCLIFFE

INTRODUCTION

Crime opportunities are neither uniformly nor randomly organized in space and time. As a result, crime mappers can unlock these spatial patterns and strive for a better theoretical understanding of the role of geography and opportunity, as well as enabling practical crime prevention solutions that are tailored to specific places. The evolution of crime mapping has heralded a new era in spatial criminology, and a re-emergence of the importance of *place* as one of the cornerstones essential to an understanding of crime and criminality. While early criminological inquiry in France and Britain had a spatial component, much of mainstream criminology for the last century has labored to explain criminality from a dispositional perspective, trying to explain why a particular offender or group has a propensity to commit crime. This traditional perspective resulted in criminologists focusing on individuals or on communities where the community extended from the neighborhood to larger aggregations (Weisburd et al. 2004). Even when the results lacked ambiguity, the findings often lacked policy relevance. However, crime mapping has revived interest and reshaped many criminologists appreciation for the importance of local geography as a determinant of crime that may be as important as criminal motivation. Between the individual and large urban areas (such as cities and regions) lies a spatial scale where crime varies considerably and does so at a frame of reference that is often amenable to localized crime prevention techniques. For example, without the opportunity afforded by enabling environmental weaknesses, such as poorly lit streets, lack of protective surveillance, or obvious victims (such as overtly wealthy tourists or unsecured vehicles), many offenders would not be as encouraged to commit crime.

This chapter seeks to make the case for crime mapping as an essential tool in the examination of criminal activity; it also charges mainstream criminology to re-engage with the practitioner interest in spatially targeted crime prevention. In the next section, I briefly outline the theoretical support for a spatial approach to the crime problem and warn of the negative outcomes that can potentially arise by ignoring the spatial dimensional of crime. After a basic primer in mapping crime locations, the chapter looks at different ways that crime hotspots can be identified. It also discusses the benefits of spatio-temporal crime mapping.

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The final section considers the future of crime mapping, both within the practitioner arena and the academic sphere, concluding that a closer relationship between academics versed in environmental criminology and the crime control field provides the best mechanism for mainstream criminology to regain relevance to practitioners and policy makers. Readers looking for extensive statistical routines, a "crime mapping for dummies" or a checklist of mapping requirements will be disappointed as there are few equations and no elaborate discussions of parameter choices; however, there is a section at the end of the chapter that will serve to point the reader to these resources. Furthermore, this chapter should be read in conjunction with the excellent chapter by Bernasco and Elffers in this book.

DEVELOPING A SPATIAL UNDERSTANDING

The earliest studies that explicitly explored the role of geography in the distribution of crime immediately noted various spatial relationships (see the discussions in Chainey and Ratcliffe 2005, and Weisburd et al. 2009). Both Guerry (1833) and Quetelet (1842) examined nationwide statistics for France, the latter identifying that higher property crime rates were reported in more affluent locations, and that seasonality had a role to play in crime occurrence. British government studies followed, but data were only collected for large administrative units, and local crime data at the neighborhood (or smaller) level were not available. Shaw and McKay (1942) resolved this issue by mapping juvenile delinquents by hand for Chicago, Philadelphia, and other cities. It is hard to imagine the effort that went into both data collection and address verification for their map showing individual dots for the distribution of 5,859 juvenile delinquents in Philadelphia (1942); however, as a result of their painstaking work Shaw, McKay, and their graduate students were able to confirm patterns they had previously observed in Chicago. These patterns suggested delinquency rates varied by zones of community characteristics that, they hypothesized, were the result of city expansion and migration patterns within cities over time. They found these patterns to be "regular and consistent" and that "in the absence of significant disturbing influences the configuration of delinquency in a city changes very slowly, if at all" (1942: 222).

Guerry, Quetelet, and the research team at the Chicago School (at the University of Chicago's sociology department) where Shaw and McKay did their pioneering work were all hampered by the requirement to conduct their research by hand. The early foundations of digital mapping technology that emerged in census bureaux in the 1970s – foundations that were built from the development of computer technology – gave little indication of the potential to follow. Early attempts to map crime using digital processes were hampered by technological and data limitations (Maltz et al. 1991; Weisburd and McEwen 1997), organizational issues (Openshaw et al. 1990), an inability to convert digital addresses into points on a map (Bichler and Balchak 2007; Harries 1999; Ratcliffe 2001, 2004b) and the functional obstacle that many police and criminal justice databases were simply not organized to record the address or other spatial information in a usable format (Ratcliffe and McCullagh 1998b). In recent years, technological limitations have largely melted away and organizational hurdles are being increasingly addressed (for example, the role of crime analysts in police departments: Taylor et al. 2007), such that crime mapping has seen a surge in adoption, especially among larger US police agencies (Weisburd and Lum 2005).

Prevention requires criminal justice agencies to be proactive rather than reactive, and proactivity requires the ability to predict crime hotspots and concentrations. Prediction is rarely possible from individual events, thus there is a direct link between prevention and patterns of criminality, in the form “prevention *requires* proactivity *requires* predictability *requires* patterns” (Ratcliffe 2009). The importance of identifying patterns as a precursor to effective crime prevention has been identified by practitioners who recognize the inherent ability of crime mapping to identify patterns and hotspots, taking advantage of Tobler’s first rule of geography, that “Everything is related to everything else, but near things are more related than distant things” (Tobler 1970: 236).

The growth of interest in crime mapping from police departments has thus spurred practitioners to seek out both theoretical explanations for the patterns they see and remedies to the crime problems that plague the communities they police. Many crime prevention practitioners have thus been drawn to environmental criminology researchers, an eclectic group of crime scientists that are bringing a fresh and practical perspective to the problem of crime (for a list of the most prominent environmental criminologists/crime scientists, see the preface to Wortley and Mazerolle 2008). This expanding group actively engages with police and crime prevention agencies and does so armed with theories that lend themselves to crime prevention solutions, including; routine activity theory (Cohen and Felson 1979; Felson 1998), the rational choice perspective (Clarke and Felson 1993; Cornish and Clarke 1986; 1987), and crime pattern theory (Brantingham and Brantingham 1993). An understanding of these theoretical positions enables practitioners and action-oriented researchers to promote a range of practical and direct interventions that may reduce crime.

Each of these theoretical statements articulates a model for the interaction of offenders with crime opportunities, opportunities that are of varying attractiveness and distributed in a nonrandom manner across both place *and* time. Monthly and seasonal trends have long been documented (Harries 1980); for example, there is an increase in domestic violence (Farrell and Pease 1994) and violent crime (Field 1992) during summer months, while commercial robberies can increase during the winter (van Koppen and De Keijser 1999). Changes are even detectable hour-by-hour; vehicle crimes concentrate at night in residential neighborhoods but during the middle of the day in nonresidential areas (Ratcliffe 2002), and Felson and Poulsen (2003) found robbery tends to be an evening activity (though there was variation among the 13 US cities they studied). These findings all have potential policy implications; for example, with the timing of police directed patrol strategies, improvements to street lighting, and whether cities invest in surveillance cameras with night vision capability.

The introduction of spatially oriented research agendas has helped to address a growing problem of aspatiality in criminological research. Issues of spatial concentration are fundamental to crime mapping, yet many researchers are happy to labor along with tools that do not include a measure of, or control for, the spatial autocorrelation of values measured within areas (Arbia 2001; Cliff and Ord 1969). Spatial autocorrelation relates to the degree of dependency between the spatial location and the variable measured at that location (Chainey and Ratcliffe 2005). This spatial dependency could mean that the crime rate in one census area is partly influenced by the crime rate in a neighboring tract; for example, a drug set may sell drugs in one area and their presence may influence the growth of a drug market in the neighboring location. An OLS regression model could incorporate the existence of both drug sets in the model, but could not account for the interaction affect. Research that ignores the reality that crime problems and socio-demographic characteristics from one area can influence the volume of crime in another area can run afoul of the problem of independence. Traditional aspatial analytical techniques, such as OLS regression, can often be statistically unreliable unless this issue is explicitly addressed because, as Ward and Gleditsch (2008) point out, failing to account for first order correlation in the dependent variable will tend to underestimate the real variance in the data, increasing the likelihood of a Type I statistical error.

Numerous solutions to this problem exist and are increasingly becoming mainstream research tools for spatially aware researchers. Examples include the use of geographically weighted regression (Cahill and Mulligan 2007; Fotheringham et al. 2002), by incorporating a localized spatial lag measure to control for crime spillover effects (see Anselin 1988, 1996; Anselin and Bera 1998; with crime examples in the work of Andresen 2006; Martin 2002; Mencken and Barnett 1999), or through the adoption from regional science of two-stage least squares processes to estimate spatial effects (for example, Land and Deane 1992).

A secondary concern for researchers who fail to demonstrate spatial awareness is the modifiable areal unit problem (MAUP) (Bailey and Gatrell 1995; Openshaw 1984). The MAUP exists "where the results of any geographic aggregation process, such as the count of crimes within a set of geographic boundaries, may be as much a function of the size, shape and orientation of the geographic areas as it is of the spatial distribution of the crime data. In essence, when thematically mapped, different boundaries may generate different visual representations of where the hotspots may exist" (Chainey and Ratcliffe 2005: 151–152). Unfortunately, some researchers in the past have appeared either unaware of the MAUP or chose to ignore its potentially serious implications. Recognition of the MAUP has prompted the crime mapping community to employ hotspot mapping techniques that are not influenced by police beats, census tracts, or any other arbitrary administrative boundaries within the study region. These techniques enable crime mappers to see the underlying distribution of crime unhindered by the necessity to aggregate to areas that are unrelated to the crime problem (Chainey et al. 2003; Chainey et al. 2008; Ratcliffe and McCullagh 1999).

When cognizant of some of the forementioned issues, crime mapping provides the opportunity for greater insight into the spatial and temporal distributions of crime than just about any other technique available, at least for high volume crime, and it is of benefit to the research community as well as the practitioner and professional world. The next section of the chapter provides a brief overview of the basics of plotting crime events.

GETTING CRIME ONTO A MAP

It is still possible to conduct rudimentary crime mapping by sticking pins into maps; but crime data (both collectively and individually) contain a wealth of spatio-temporal information. Unless the data are computerized and analyzed using appropriate software, statistical tests and descriptive processes, that information will remain largely unavailable to both researchers and practitioners. The appropriate software solutions are commonly referred to as geographic information systems, or GIS.

GIS retain spatial information in three main ways: data are stored as *points*, *lines* or *polygons*.[1] A map of points could show school locations, bars or crime events. Lines can be used to map streets, railway lines, or routes that an offender might have taken between home and a crime location. Polygons are used to store all areal information. For example, census data, while collected from individuals and households, are distributed as polygons to

[1] An additional data structure is common outside of the crime field; the raster. A raster-based data model 'represents spatial features using cells or pixels that have attribute information attached to them' (Chainey and Ratcliffe 2005: 43). Rasters are common in many areas of geography; however, crime researchers tend to overwhelmingly favor the vector approach of points, lines and polygons. Both approaches have their advantages and disadvantages and are not mutually exclusive.

protect the privacy of individuals and so that individual houses within a census unit cannot be identified. While spatial data are retained as points, lines and polygons, attribute data are vital if the spatial information is to have more than superficial value. Within a GIS, attribute information is stored in table form while an index maintains a link to the appropriate spatial data. For example, a point on a map might indicate a burglary location while the associated attribute data will list the type of crime, the time of the offense, the value of property stolen, and the details of the police unit that responded. The ability to search and filter attribute information provides considerable value to a crime analyst wishing, for example, to map only late night assaults or thefts of a particular model of car.

Crime event locations are stored as points the vast majority of the time, and this requires a process to convert the address location of a crime into a point on a map. Crime data are mapped by a process called *geocoding*. Geocoding involves interpreting an address location and either scouring a database of possible matching addresses (known as a *gazetteer*), or using a computer algorithm to identify a suitable street line segment with an appropriate number range and street name and from this interpolate a likely location of the street address in question. For the latter to take place, the street lines of the city or area under examination must have been previously mapped, and the necessary attribute information (street name, house numbers and so on) added to the attribute file. Fortunately, for most advanced economies[2] countries, these files are available either freely or from commercial companies.

If the geocoding process is successful, the result is usually a location in Cartesian coordinates $(x - y)$,[3] and the GIS uses these coordinates to locate the crime in relation to other spatial data sets being mapped (Ratcliffe 2001). This means that a crime event can be viewed on a map relative to its proximity to bars or restaurants, sports stadiums or police stations (if these locations have also been geocoded). The *geocoding hit rate* (the percentage of address locations that has been successfully geocoded) is used to indicate the success rate of the geocoding process. Estimates vary, but one quantitative estimate suggests that at least 85% of crime events must be geocoded for subsequent maps to retain overall accuracy (Ratcliffe 2004b). This being said, experienced police departments and researchers can regularly achieve geocoding hit rates of 95% or better. Geocoded crime locations can be viewed individually, as a group of dots with other crime events, or can be aggregated to polygons. Using a point-in-polygon counting process, the number of crimes occurring in police beats or census tracts can be calculated – simply the number of points that fall within each boundary area.

GIS differ from mapping tools such as Google Maps or Microsoft MapPoint in that a GIS is able to answer complex spatial questions over different spatial data sets. Spatial questions typically come in the form of spatial relationship queries, with terms such as "near," "close," and "within"; for example, "Do robberies cluster near bars?" "Are sexual assaults concentrated close to red-light districts?" and "What percentage of car thefts are within the Central Business District?" It is this ability to pose queries of a spatial nature that differentiates a GIS from mapping programs, most online applications, and cartographic software packages.

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[2] 'Advanced economies' is a term used by the International Monetary Fund. The current 32 countries on the list (at the time of writing) would be the most likely countries to have street indices for most of the country.

[3] Projected coordinate systems, where locations are identified with x-y coordinate pairs, are preferable because they enable simple distance calculations between points; however, geographic coordinate systems that locate places with latitude and longitude coordinates are still used in some crime mapping applications. A useful reference and free download online is Harries (1999); see http://www.ncjrs.gov/html/nij/mapping/pdf.html.

There are various commercial software solutions available, but the two main GIS programs come from the Pitney Bowes MapInfo (MapInfo) and the suite of ArcGIS programs available from Environmental Systems Research Institute Inc. (ESRI). These GIS are large, powerful and complex with steep learning curves. They are also rather unforgiving of mistakes and often lack defensive features that allow a user to roll-back errors. Training is therefore always recommended, unless the user is particularly resolute, foolhardy, or can tolerate a fair degree of frustration!

Much of the value in using a GIS for crime mapping emanates from the ability to integrate different spatial data sets into a single analysis. Crime events displayed on their own rarely tell the whole story. Additional data sets that can enhance understanding of the crime layer might include the locations of taverns or bars if the user believes they may be driving late night violence, the locations of parks and abandoned places if the user thinks they encourage illicit drug use, or the inclusion of particular census data if it is believed that increased crime is related to higher numbers of juveniles living in the vicinity. Theory therefore drives the selection of supplemental data sets that help us to understand crime distributions found in our primary data sets (Eck 1997), and this places an additional requirement on crime mappers. It is not sufficient to understand crime mapping to be a good analyst; understanding the theories of environmental criminology is also vital if the underlying patterns of behavior that drive the crime picture are to be accurately interpreted. With access to spatial crime data, a grasp of environmental criminology theory, and a suitable research tool (GIS), it is possible to engage in exploratory spatial data analysis (ESDA) of crime patterns (a useful reference for ESDA is found in Bailey and Gatrell 1995).

CRIME HOTSPOTS

One of the most common and innovative uses of crime mapping is to aggregate numerous crime events into hotspot maps. As explained earlier, aggregation to administrative units can run afoul of the MAUP: using different boundaries can result in significantly different maps. For much police operational work, this is not a problem for the user; police departments are often interested in the volume of crime in beats or districts, and city managers take interest in the crime level in city neighborhoods. Point-in-polygon aggregation, as can be conducted by any GIS, will easily complete this task. However the MAUP does pose a significant barrier to accurate data interpretation for people wishing to study a problem in greater depth.

Of considerable interest to researchers, and increasingly to more sophisticated crime prevention practitioners with a nuanced understanding of crime problems, is the use of techniques that do not force crime events to be the members of a group of fixed boundaries. Such techniques include spatial ellipses (Craglia et al. 2000), grid thematic mapping, and continuous surface maps using techniques such as kernel density estimation (Chainey et al. 2008: this citation also serves as a useful quantitative evaluation of these techniques). These new approaches free the geographer from artificially constraining hotspot areas to comply with local areal boundaries, boundaries that often mean little to police, offenders or the community. The resulting maps do ask more from the mapper as regards the selection of parameters (Eck et al. 2005), especially “when little regard is given to the legend thresholds that are set that help the analyst decide when a cluster of crimes can be defined as a hotspot. This visual definition of a hotspot being very much left to the ‘whims and fancies’ of the map designer” (Chainey et al. 2003: 22). As a result, some understanding of the underlying process to aid parameter selection is required.

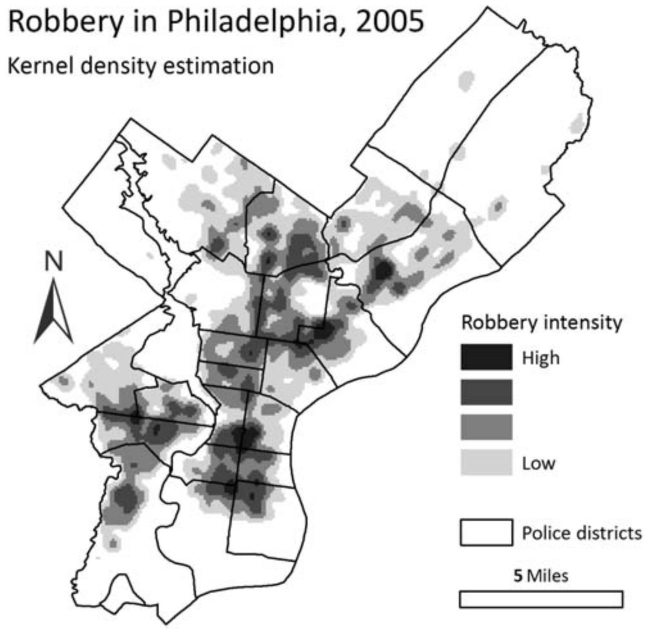

FIGURE 2.1. Philadelphia robbery hotspots, from quartic kernel density estimation.

These hotspot surface maps are reminiscent of weather maps found in newspapers and on television. Areas that are shaded with the same color (or in the example of Fig. 2.1, same shade of grayscale) are deemed to contain approximately the same density or frequency of crime. An example is found in Fig. 2.1. This map shows 2005 robbery hotspots for the City of Philadelphia, PA, and is constructed using the kernel density estimate interpolation routine available from the software program, CrimeStat,[4] to produce intensity calculations $g(x)$ such that;

$$g(x_j) = \sum \left\{ [W_i I_i] \left[\frac{3}{\pi h^2} \right] \left[1 - \frac{d_{ij}^2}{h^2} \right]^2 \right\}$$

where d_{ij} represents the distance between a crime location and a reference point (usually the centroid of a grid cell), h is the bandwidth (radius) of a search area beyond which crime events are not included in the calculation, W_i is a weighting and I_i an intensity value at the crime event location (see Levine 2007).

Hotspot surface maps such as shown in Fig. 2.1 are often at the nexus where crime prevention practitioner and academic researchers differ on the next stage of an analysis. The divergence is grounded in the need for different outcomes. Practitioners often recognize that a substantial density of crime in a location is sufficient information to initiate a more detailed analysis of the problem regardless of statistical significance or any consideration of

[4] For the technically-minded, the city was divided into grid cells such that there were at least 250 columns, and then a quartic kernel estimation process was applied with a bandwidth of 2,000 feet.

the population at risk. Academic thinking is often engrossed in considering if this clustering of crime is meaningfully non-random, and if the patterns observed are still present once the analysis has controlled for the population at risk or other key demographic features of the broader community or regional structure.

For academic researchers, it has long been known that the issue of determining a population at risk is particularly problematic for crime (Boggs 1965). Too often, a simple measure of total number of people living in an area is used even when, as Keith Harries points out, the "uncritical application of population as a denominator for all crime categories may yield patterns that are at best misleading and at worst bizarre" (1981: 148). The problem can be demonstrated with a couple of examples. When examining crime in general, one might detect differences in crime *incidence* rates (the number of crimes per person in the population of the area) which may be related to the area *prevalence* rate (proportion of victims amongst the population) and/or the area crime *concentration* rate, an indication of the number of victimizations per victim (Hope 1995; Trickett et al. 1995). However, the denominator for residential burglary might be better represented as the number of occupied households, given populations shift throughout the work day and over weekends (Harries 1981).

Vehicle crime presents particular challenges, as the appropriate denominator for vehicle thefts would usually be the number of vehicles available to steal; however, this is confounded by dynamically changing patterns of vehicle location during the day compared to at night, the number of vehicles in private and public garages that could be considered unavailable for theft, the availability of street parking places and so on. Similarly, studies of aggravated assaults in entertainment areas are best when the appropriate control is a measure of the number of people in the area at the time; the residential population (as is usually available from the census) tells the researcher little about the real number of people outside nightclubs at 2 a.m. This *denominator dilemma* is the problem associated with identifying an appropriate target availability control that can overcome issues of spatial inequality in the areal units used to study crime.

Andresen (2006) addressed this denominator dilemma in Vancouver, BC with an imaginative approach to vehicle theft, burglary and violent crime using both residential and ambient populations as denominators, the latter providing daily estimates of a population in a spatial unit and calculated from the LandScan Global Population Database, at a resolution of one square kilometer. This approach is, however, not easily available for everyone, is computationally demanding, and is limited in terms of spatial resolution currently available. For many of the theoretical explanations of criminal activity mentioned earlier in the chapter, the size of a LandScan grid square may be at present too coarse for a detailed picture of criminal behavior.

Denominator issues aside, statistically significant crime hotspots can be determined with various spatial tools that are able to explain more about an individual datum point or area in relation to the spatial dependency of the location with neighboring places (Chainey and Ratcliffe 2005). Improved data quality now allows for analysis at a finer spatial resolution across numerous regimes of spatial association (Anselin 1996). For example, the geographically weighted regression technique is able to model and quantify significant non-static variation across independent variables (Fotheringham et al. 2002).

The most common spatial significance tool is the local variant of the Moran's I statistic (Anselin 1995, 1996; Moran 1950) with more recent variants that consider population density (Assuncao and Reis 1999; Oden 1995). For example, the local Moran's I has been used to explain spatial characteristics of homicide (Mencken and Barnett 1999; Messner and Anselin

2004; Messner et al. 1999). The global Moran's I statistic is a linear association between a value and the weighted average of neighboring values, and its takes the form:

$$I = \frac{1}{2} \sum_{ij} W_{ij} Z_i Z_j \; \forall i \neq j$$

where W_{ij} is a vector from a connectivity weight matrix W that is zero for all non-neighbors and a row-normalized value for all neighbors such that the sum of all vectors for a single spatial unit W_i is one, and z is a standardized variable under examination (from Ward and Gleditsch 2008). Closely related to this, the local Moran's I statistic for an observation i is defined as:

$$I_i = \sum_{j} w_{ij} z_j \; \forall j \in J i$$

where only neighbors of i are included in the summation, and where $w_{ii} = 0$ (see Anselin 1995). Local Moran's I (and similar statistics such as the Getis and Ord Gi*, see Getis and Ord 1992) provides a mechanism to make inferences about a population from a sample. It can be argued that if a crime analyst has access to all recorded crime, then the analyst does not have access to a sample but the actual population of all events. In this case, statistical inference is not required; however, as Fotheringham and Brunsdon (2004) argue, *sampling inference* is not the only value of a statistical test. Crime analysts may also be interested in the value of *process inference*, where "the null hypothesis is a statement about the data-generating process rather than about the population" (p. 448). For example, the positive relationship between alcohol establishments and crime has been known for some time (Murray and Roncek 2008; Roncek and Maier 1991), and even with all recorded crime and a map of all bar locations, there is value in knowing if the relationship is beyond a spurious or coincidental one.

Taking the Philadelphia example from Fig. 2.1, even though we have all of the recorded robbery data for the city, there is still value in identifying significant clusters as a starting point to exploring the underlying conditions that might be fuelling hotspots. While a global Moran's I test can show that crime events cluster in a non-random manner, this simply explains what most criminal justice students learn in their earliest classes. For example, a global Moran's I value (range −1 to 1) of 0.56 suggests that police sectors with high robbery counts adjoin sectors that also have high robbery counts, and low crime sectors are often neighbors of other low crime sectors. This is hardly a surprise given what can be seen in Fig. 2.1.

Figure 2.2 uses the same robbery data, this time aggregated to the 419 sectors of the Philadelphia Police Department. This time, a local indicator of spatial association (LISA) is applied (Anselin 1995, 1996; Getis and Ord 1996; Ord and Getis 1995). The most common LISA is the local Moran's I (mentioned earlier), an approach that enables us to identify clusters of high crime areas based on their locational similarity and crime rate similarity. This is done with the construction of a spatial weights matrix that identifies a spatial relationship, often contiguity, between areal units (Anselin et al. 2008). In other words, areas that are neighbors are deemed to be spatially close. Monte Carlo simulation techniques can be used to determine if crime rates cluster in a variety of ways (Besag and Diggle 1977; Hope 1968; Mooney 1997; Ratcliffe 2005). If a group of neighboring areas are found to have concentrated levels of high crime such that the chances of discovering these patterns by random is highly unlikely, then these areas are not only statistically significant, but also are worthy of further research and inquiry.

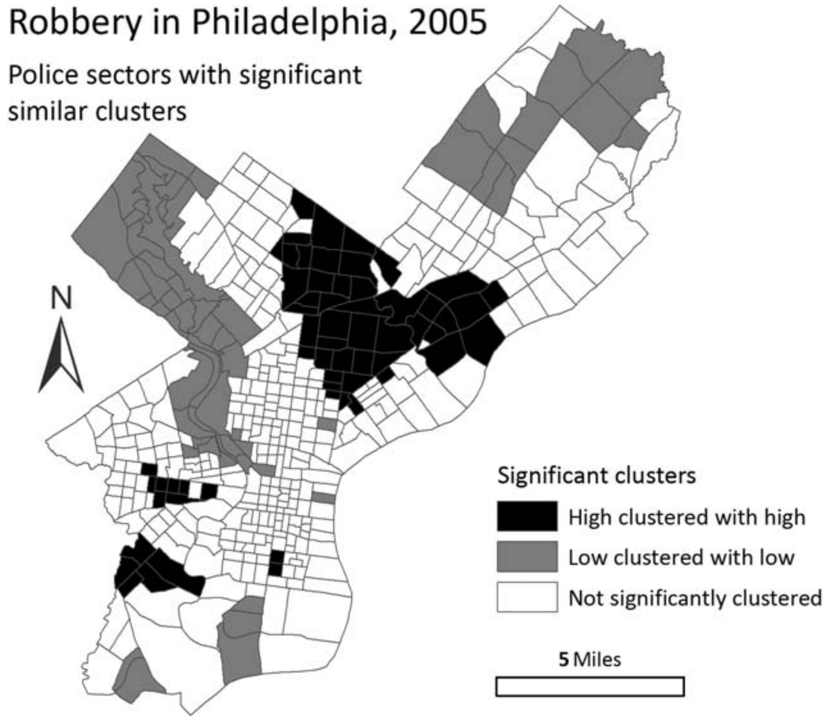

FIGURE 2.2. Philadelphia robbery clusters, statistical significance estimated with local Moran's I.

In Fig. 2.2, there are small clusters of high robbery areas in south and southwest Philadelphia, and a larger robbery problem in the inner north and northeast of the city. The northwest, in the area of Fairmount Park (a large public park) and smaller areas of the periphery of the city limits are shown to have clusters of low robbery police sectors.[5] The global Moran's I value of 0.56 indicates a general clustering as expected; however, the local Moran's I LISA approach indicates areas of statistically significant clusters where robberies are higher or lower than would be expected if robberies were randomly distributed around the city sectors. These could form the basis for a more detailed and spatially focused study. The chapter in this book by Bernasco and Elffers discusses in greater depth other approaches to, and measures of, spatial autocorrelation.

SPATIO-TEMPORAL CRIME MAPPING

At present, the most under-researched area of spatial criminology is that of spatio-temporal crime patterns. It would appear that significant research activity is still focused on fine-tuning methods of crime hotspot detection (Chainey et al. 2003) and geographic determination of crime clusters (Murray and Roncek 2008) while the temporal component of the underlying

[5] Again for the technically-minded, the output was created using a first order, Queen's contiguity spatial weights matrix, with pseudo significance limit set at 0.01 with 999 permutations. The software used to perform the analysis was the freely-available GeoDa. For map clarity and simplification, areas of low robbery surrounded by high robbery count, and high surrounded by low are not indicated.

crime distributions has languished as a largely ignored area of study. This is a shame, given the wealth of information that can be gleaned from an understanding of spatio-temporal crime mapping. Originating with the work of Hagerstrand (1970), time geography provides a conceptual framework for understanding constraints on human activity and how participation in activities (such as crime) is influenced by the constraints imposed by space and time (Miller 2005). As the relevant actors – victims, offenders, guardians, and place managers – adjust their relative densities over time and around specific places, the opportunities for crime shift and coagulate. These coagulations of crime opportunity, where victims and offenders come together in greater concentrations, help explain crime hotspots around bars late at night, in downtown areas of cities during weekend evenings, and in city centers during the workday. Temporal constraint theory provides a model to understand these shifting patterns and consider crime prevention solutions (Ratcliffe 2006).

The repeat victimization literature provides a direct indication of the temporal element of crime as a research frontier with significant policy significance. With regard to burglary, repeat victimization occurs when the location of a previous burglary is later targeted again. Early research into repeat victimization identified that "the chance of a repeat burglary over the period of one year was around four times the rate to be expected if the events were independent" (Polvi et al. 1991: 412). The same study found that the rate within a month of an initial event was over twelve times the expected rate, declining over the next few months. While a body of research that has been largely ignored in the US, further research has highlighted the crime prevention benefits of addressing repeat victimization (Farrell et al. 1998; Farrell and Pease 1993; Laycock 2001; Pease 1998), with one project in the UK being spectacularly successful at reducing crime (Forrester et al. 1988). From a crime mapping perspective, the existence of discernable repeat victimization timelines emphasizes the multidimensionality of crime: patterns are identifiable not only in terms of x and y coordinates, but also on a temporal plane.

While largely ignored by the crime mapping fraternity for many years (Lersch 2004), there is a growing number of techniques that incorporate a spatio-temporal analytical capacity. Even when the exact time of a crime is not known (such as with many burglaries or vehicle thefts), *aoristic analysis* (Ratcliffe and McCullagh 1998a) can be employed to calculate the probability that an event occurred within given temporal parameters, and sums the probabilities for all events that might have occurred to produce a temporal weight in a given area (Ratcliffe 2000). This technique has identified that many crime hotspots display temporal or aoristic signatures (Ratcliffe 2002), signatures that can be combined with the spatial pattern of the crime hotspot to identify effective crime reduction strategies (Ratcliffe 2004c). The aoristic value (t) can be calculated as:

$$t_{is} = \frac{\Delta}{\beta \mathrm{i} - \alpha \mathrm{i}}$$

where $\mathrm{i}(\alpha,\ \beta)$ is a crime incident with start time (α) and end time (β), s is a temporal search parameter with start time (α) and end time (β), Δ represents a temporal unit (e.g., 1 min, hour, or day), start times (α) are rounded down to unit Δ end times (β) are rounded up to unit Δ, and where $i\,(\alpha,\ \beta) \cup s$. Individual aoristic values, for example, hour by hour, can be mapped for a single crime event of undetermined time, or the aoristic value can be used as a weighting parameter in a kernel density estimation surface (see Ratcliffe 2002, for more details and an example).

Figure 2.3 shows statistically similar clusters for vehicle thefts across Philadelphia in 2005. Comparing this image with Fig. 2.2, it can be seen that the large cluster is in the same

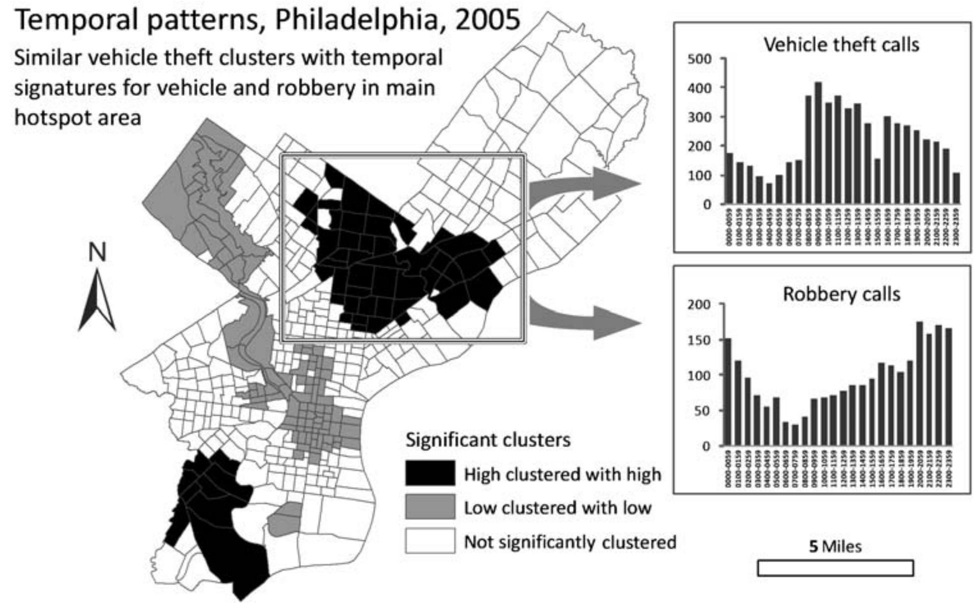

FIGURE 2.3. Significant vehicle theft clusters, with temporal signature charts for vehicle theft and robbery calls for the main high crime cluster. Charts show hourly call volume from 0000–0059 to 2300–2359.

area for both robbery and vehicle theft. The two side graphics in Fig. 2.3 isolate the crime events that occurred in this cluster area (loosely identified with a rectangle) and chart the event time on a bar chart. The charts show 24 vertical lines, each reporting the volume of crime calls for service in each hour of the day. The leftmost bar shows the volume from midnight to 1 a.m, 1 a.m to 2 a.m., and so on across to 11 p.m. to midnight on the far right. It can be seen that the temporal pattern of robbery calls is significantly different to vehicle theft calls.[6]

Issues of spatio-temporality and repeat victimization feature in the latest insight from the crime mapping research front: the near repeat phenomenon. Near repeat victimization stems from the realization that when a home is burgled, the risk of further victimization is not only higher for the targeted home, but also for homes nearby. As with repeat victimization, near repeat victimization also has a time period that appears to decay after some weeks or months. This communication of risk to nearby locations was first examined by Shane Johnson, Kate Bowers, and Michael Townsley and colleagues (Bowers and Johnson 2004; Johnson and Bowers 2004a, b; Townsley et al. 2003). While the exact spatio-temporal parameters of the infectiousness of burglary differ from place to place, the British and Australian studies were similar enough (usually a month or two and for a few hundred meters) to merit a multinational comparison. This collaborative venture confirmed the consistency of the near repeat phenomenon across different countries (Johnson et al. 2007). Early studies concentrated on burglary; however, recent work has identified a near repeat pattern with shootings in Philadelphia (Ratcliffe and Rengert 2008) and even in the spatio-temporal distribution of improvised explosive device attacks on coalition forces in Baghdad (Townsley et al. 2008).

[6] Cluster map created using the same parameter choices as for Fig. 2.2. In Fig. 2.3's temporal charts, please note the change in vertical scale.

The preventative value of the near repeat phenomenon is still being uncovered. Informed by near repeat patterns, researchers have developed predictive mapping approaches that give greater weight to more recent and local crime, thus creating predictive hotspot maps that are more accurate predictors of short-term crime problems (Bowers et al. 2004; Johnson et al. 2009). Software to allow analysts to examine the near repeat phenomenon in their own data is now freely available with the Near Repeat Calculator (details available at the end of this chapter).

All of this evidence suggests fascinating new frontiers for crime analysts wishing to use mapping to explore beyond the flat two-dimensional patterns of crime events. The introduction of the temporal characteristics of crime opens up a range of avenues that are not only interesting from a theoretical sense, but also have real possibilities in better understanding and preventing crime and criminality.

CHALLENGES FOR THE FUTURE

> *The most prominent requisite to a lecturer, though perhaps not really the most important, is a good delivery; for though to all true philosophers science and nature will have charms innumerable in every dress, yet I am sorry to say that the generality of mankind cannot accompany us one short hour unless the path is strewed with flowers.*[7]

When conducted correctly and with attention to detail and clarity, mapping can "strew flowers" across a wide variety of fields, and succinctly convey information in a format that is ideally suited to operational decision-making. The power of maps to convey both spatial (Tufte 2001) and spatio-temporal (Dorling and Openshaw 1992; MacEachren 1994; Peuquet 1994) information is well-known; what is also known by some cartographers is the capacity of poorly designed maps to be erroneous and misleading (Monmonier and Blij 1996). Spatio-temporal information can be effectively understood in map animation form (Dorling and Openshaw 1992), yet both training and tools are still too underdeveloped for mainstream use of animation within the policing domain. Even with basic maps that are now easy to create, few academics or police analysts receive any training in map design, computer graphics, or even basic cartography. The result is often an underwhelming map that fails to convey the key information and leaves the map reader confused rather than enlightened. Too often, the analytical community fixates on analytical techniques to the detriment of the vital role of the analyst: the conveyance of analysis and intelligence to influence decision-making (Ratcliffe 2008).

While crime mapping has become a clear subfield of both geography and criminal justice, many questions and problems remain. One particular problem among crime analysts is the incorrect tendency to map real values with choropleth (thematic) maps, resulting in the misleading impression that is often given by larger or unequal areas (Harries 1999). One easy solution is to map the location quotient:

$$LQ = \frac{\frac{c_i}{a_i}}{\frac{c_R}{a_R}}$$

[7] Michael Faraday, chemist, physicist, 1791–1867. From personal letters quoted in Thompson (1898).

where c is the frequency of crime and a is the area of a subset location (i) of a larger region (R). When mapped with a diverging visual scale, the map can show crime areas at the expected region-wide rate, areas that have lower levels of crime, and areas that are "hotter" than expected. First introduced to the criminological field by Brantingham and Brantingham (1993), location quotients have been recently used as a preliminary stage of more complex analyses of drug market distribution (Rengert et al. 2005; McCord and Ratcliffe 2007).

Other problems surround the appropriateness of the many different techniques available to analyze crime patterns. As police executives and decision-makers in the criminal justice system become more interested in predictive mapping and using intelligence-led policing to anticipate crime problems, the relative accuracy of different hotspot techniques has become a significant policy issue. Tools such as the prediction accuracy index (Chainey et al. 2008) are first steps in a direction that should provide greater clarity to analysts seeking predictive crime mapping that is statistically and empirically robust. Continued development into spatio-temporal patterns would appear to be a fertile research avenue with real policy implications, and with enough enthusiasm from the practitioner community we may find that GIS vendors start to develop software that will enable easy creation of animated maps of crime.[8] Without easy animation processes, it is unlikely that decision-makers and policy makers will be as engaged as they should with the temporal and spatio-temporal aspects of crime. Understanding the spatial dimensions of crime flux over time is a key component of cost-effective crime reduction in many situations.

Further theoretical enhancements that will in future provide a better idea of the spatial extent of noxious locations are in need of development. For example, it is well known that some bars and other licensed premises are not only the crime attractors and generators at their specific location, but they also influence the formation of crime hotspots in their immediate vicinity, with an influence that decays as distance from the specific site increases. The spatial extent of the decay is still indistinct; moreover, the mechanism to accurately assess the noxious influence of crime generating places is not yet clear.

As Ron Clarke noted, "Quite soon, crime mapping will become as much an essential tool of criminological research as statistical analysis is at present" (Clarke 2004: 60). This may be the case; however, it is apparent that much crime mapping potential is not currently realized. In a survey of the American crime analysis field, researchers found that few analysts engaged in true analysis but rather conducted basic management statistics and descriptive work (O'Shea and Nicholls 2002). Wilson charted by social science discipline the percentage of articles published from 1996 to 2005 that used some form of mapping or spatial analysis. While showing a "healthy growth" (Wilson 2007: 140), the percentage never crept above 0.1% for any field, including criminology and sociology.

The power of GIS lies in the ability of the researcher to discover the underlying patterns and characteristics of crime clusters and for practitioners to target high crime areas with effective crime prevention measures (Anselin et al. 2008). Crime mapping itself should rarely be the end of the analytical process. Researchers should be familiar with spatial statistics in order to differentiate between random patterns and characteristics of the data that are truly worth exploring (the Bernasco and Elffers chapter on spatial statistics in this book will serve as a good start). Equally, crime analysts should understand that crime mapping is but one stage in an intelligence-led crime reduction process; there is still a requirement to influence the

[8] As an example, an animated map showing hour-by-hour changes in violent crime hotspots in Camden, NJ, is available to download from the chapter author's web site at www.jratcliffe.net/var/violence.wmv.

thinking of decision-makers and steer them in the direction of effective crime reduction tactics. This will not only impact on the training requirements of crime analysts, but also on police managers (Ratcliffe 2004a).

The development of crime mapping in police departments, and the enthusiasm for environmental criminology as a mechanism to effect change resulting from a better understanding of the spatio-temporal characteristics of crime, has placed traditional criminology in somewhat of a quandary. As Clarke (2008: 192) points out, traditional academics have little enthusiasm for an approach to the crime problem that does not advance "the welfarist, social reform agendas of most criminologists" and cares less for an understanding of the long-term motivations of offenders but rather examines the dynamics of the crime event, seeking an understanding of the immediate location and circumstances surrounding each and every burglary, robbery and car theft. This has resulted in some claims that the practical outcomes of environmental criminology theory, such as situational crime prevention (Brantingham and Brantingham 1990; Clarke 1992; Ekblom and Tilley 2000) and crime prevention through environmental design (Cozens 2008; Feins et al. 1997) engage in social exclusion (for examples, see Tilley 2004; White and Sutton 1995). These arguments have not only been dismissed (Clarke 2008), but also perhaps suggest a disconnect of some parts of the broader criminology field to recognize the applicability of situational and geographic responses to crime control. A closer relationship between academics versed in environmental criminology and the crime control policy arena will provide the best mechanism for mainstream criminology to regain some relevance to practitioners, policy makers, and the community, all of whom recognize that while improvements in employment, poverty and education might reduce criminality over the course of decades, there is still a need for a crime control solution to the problems of today. Crime mapping provides a cartography of the problem, an analytical chart to uncover the answers, and influences the development of theories that can provide a route map to the solution.

GETTING STARTED

The standard text on crime mapping theory and practice is provided by Chainey and Ratcliffe (2005), while the book edited by Wortley and Mazerolle (2008) supports an understanding of the theoretical component and resultant crime prevention and policing responses. Anselin and colleagues (2008) provide a chapter that documents the most common methods of determining crime hotspots (see also Eck et al. 2005 which can be downloaded from the National Institute of Justice MAPS program below), while the website of the Center for Problem Oriented Policing is the single most comprehensive website dedicated to crime reduction analysis and solutions (www.popcenter.org). Connection to the crime mapping community is available through a list server, administered by the Mapping and Analysis for Public Safety (MAPS) program of the National Institute of Justice; details at www.ojp.usdoj.gov/nij/maps/. Their website is also a source for information regarding GIS, training and conferences – all with a crime focus. The International Association of Crime Analysts maintains a web site (www.iaca.net) that details training and resources regarding crime analysis, sometimes with a crime mapping component. Readers are welcome to visit this chapter author's website for additional links and resources (www.jratcliffe.net).

The two central GIS software solutions mentioned earlier, Pitney Bowes MapInfo (MapInfo) and the suite of ArcGIS programs available from ESRI are the main entry points for researchers and analysts, and they retain enough analytical power for most users. They are not, however, the only possibilities. An online search for the term "free GIS" will elicit over half-a-million hits, though the difficulty with free GIS programs is the lack of availability of base datasets such as road networks and census data in an appropriate spatial format. ArcGIS and MapInfo are continually developing and new analytical tools are regularly introduced. Furthermore, there is a growing library of downloadable routines for both ArcGIS and MapInfo that can extend the capacity of the programs. Numerous small programs written and donated by the analytical community in MapBasic (for MapInfo) and ArcObjects (for ArcGIS) formats are available and accessible on the Internet.

For more advanced crime analysis needs, there are additional software options. The mainstream statistical software solutions such as SPSS, SAS and Stata, are increasingly equipped with routines that provide some spatial analysis routines for point pattern data sets. Their processes are well documented and the interfaces are improving; however, they do not integrate directly with MapInfo or ArcGIS and some conversion of files back and forward is often necessary. Fortunately, there are a number of free software options for more advanced analysis.

CrimeStat (Levine 2006) is a free software program that comes with a substantial manual and workbook to assist with advanced spatial analysis questions (Levine 2006). It was developed through funding from the National Institute of Justice specifically for spatial crime analysis tasks and is able to read and write both MapInfo's tables and ArcGIS's shapefiles, aiding interface of the software with the data. In addition, GeoDa is also free, and is available online. While GeoDa has a relatively modest interface, and final map production is best done with a GIS, it does provide a range of tools to analyze and model spatial autocorrelation.

Finally, for advanced users seeking to take their spatial crime analysis to the frontier of the field, the latest development from the academic field is often first available in routines written for the programmable analytical software package called R. R is a free download, but is a command-line driven program where a little programming experience is helpful. The program and supporting library of routines is supported by a community of academics and researchers around the world, and doctoral students interested in spatial crime analysis are encouraged to explore the variety of spatial routines available. The statistical analysis and graphics environment and language called R is available from http://cran.r-project.org.

The GIS used to create the maps in this chapter was ESRI's ArcGIS (www.esri.com), while much of the analysis was conducted with CrimeStat (http://www.icpsr.umich.edu/CRIMESTAT/) and GeoDa (www.geoda.uiuc.edu). The latter two programs are free downloads, as is the Near Repeat Calculator mentioned in this chapter (www.temple.edu/cj/misc/nr).

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