FORECASTING THE FUTURE OF PREDICTIVE CRIME MAPPING

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Abstract: *While the use of mapping in criminal justice has increased over the last 30 years, most applications are retrospective - that is, they examine criminal phenomena and related factors that have already occurred. While such retrospective mapping efforts are useful, the true promise of crime mapping lies in its ability to identify early warning signs across time and space, and inform a proactive approach to police problem solving and crime prevention. Recently, attempts to develop predictive models of crime have increased, and while many of these efforts are still in the early stages, enough new knowledge has been built to merit a review of the range of methods employed to date. This chapter identifies the various methods, describes what is required to use them, and assesses how accurate they are in predicting future crime concentrations, or "hot spots." Factors such as data requirements and applicability for law enforcement use will also be explored, and the chapter will close with recommendations for further research and a discussion of what the future might hold for crime forecasting.*

INTRODUCTION

Methodological rigor in crime prevention initiatives has increased significantly in the last two decades. This is a result of partnerships between researchers and practitioners as well as the introduction of

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more user-friendly analytic software programs, including Geographic Information Systems (GIS) (Crime Mapping Laboratory, Police Foundation, 2000; Report of the Task Force on Crime Mapping and Data Driven Management, 1999; Weisburd and McEwen, 1997). GIS is often credited for providing a valuable analytic tool for the identification and analysis of crime problems as well as the development and assessment of crime prevention programs (Groff, 1996; Groff et al., 2000; La Vigne and Wartell, 1998, 2000). GIS has been used to produce maps depicting crime "hot spots" as well as to conduct spatial analyses that suggest relationships between crime and characteristics of the social and physical environments in which crime concentrations occur (Rich, 1995; Sherman and Weisburd, 1995; Weisburd and McEwen, 1997).

The use of GIS in law enforcement has increased significantly, and the variety of applications for crime control and prevention is quite broad (Dunworth et al., 1998; La Vigne and Groff, 2001; Mamalian and La Vigne, 1999; Crime Mapping Laboratory, Police Foundation, 2000). Most applications, however, are retrospective - that is, they examine criminal phenomena and related factors that have already occurred. While such retrospective mapping efforts are useful, the true promise of crime mapping lies in its ability to identify early warning signs across time and space and inform a proactive approach to police problem solving and crime prevention. Such efforts necessitate predictive models that identify "hot spots" of crime and disorder, as well as areas where crime is abating.

Recently, attempts to develop predictive models of crime have increased,[1] and while many of these efforts are still in the early stages, enough new knowledge has been built to merit a review of the range of methods employed to date. This chapter identifies the various methods, describes what is required to use them, and assesses how accurate they are in predicting future crime concentrations, or "hot spots."[2] This review covers methods ranging from simple predictions based on the locations of past events to highly sophisticated modeling methods employed by researchers. Factors such as data requirements and applicability for law enforcement use will also be explored, and the chapter will close with recommendations for further research and a discussion of what the future might hold for crime forecasting.

It should be noted that it is beyond the scope of this paper to provide detailed information and accompanying algorithms for the methods reviewed herein. Rather, the intent is to describe these methods with an emphasis on data requirements, ease of use, and applicability to crime prevention. Each method is appropriately cited to enable the reader to obtain more specific information and provide guidance to those wishing to employ the methods themselves.

WHY PREDICT CRIME?

The ability to predict the locations of future crime events can serve as a valuable source of knowledge for law enforcement, both from tactical and strategic perspectives. From a traditional policing perspective, predictive mapping can inform a police department's deployment efforts, helping to allocate patrols more efficiently and reduce response times. Despite the increased emphasis on proactive policing, the core of police work remains that of responding to calls for service, making effective deployment strategies paramount to a well-functioning police department.

From a more proactive standpoint, problem-oriented policing efforts may be enhanced by a more accurate scanning of areas with crime problems, in that one can examine both distributions of past crimes and predictions of future concentrations. As detailed below, some of these predictive methods also provide information on "leading indicators," or explanatory variables, which can aid in the analysis stage of problem-oriented policing. Such indicators offer the ability not only to predict future crimes, but to identify underlying causes of those future hot spots. Thus, predictive mapping can assist in the identification of crime problems and enable officers to target intervention efforts to very narrowly defined geographic areas.

Predictive mapping holds promise for improving the identification of areas in which to focus interventions, but it also may improve the way those interventions are implemented. A common criticism of crime prevention efforts is that crime is simply displaced — most often geographically — rendering the intervention ineffective. Studies have demonstrated that displacement is not at all inevitable, and that when it does occur 100% of crime is not displaced (Eck, 1993; Hesseling, 1995). Nonetheless, successful crime prevention strategies consider potential displacement possibilities and craft interventions based upon those considerations. Thus, predictive mapping can help law enforcement to anticipate areas of displacement, and may lead to targeting the intervention in a broader geographic area in order to reduce the possibility of its occurrence. Likewise, predictive mapping may be used to enhance the potential "halo" or "diffusion of benefits" of an intervention, whereby it has a beneficial effect beyond the places that were targeted. Clarke and Weisburd (1994) offer ways in which diffusion of benefits may be enhanced, including the concentration of resources on highly visible or attractive targets to give the impression to potential offenders that the intervention is more widespread that it actually is. Predictive mapping can help identify those attractive targets, thus bolstering this spillover effect.

This discussion of the potential uses of predictive mapping is by no means exhaustive, but it is designed to illustrate the valuable contributions that predictive models might offer, and emphasizes the importance of this relatively new area of inquiry. Before reviewing the various predictive methods that have been employed, it is important to examine the theoretical underpinnings of this topic.

THE ROLE OF THEORY IN PREDICTIVE MAPPING

As described in detail below, various means of forecasting crime events and locations exist, and not all of them can be considered "modeling." Some methods are strictly atheoretical, relying on past events to predict future ones. Other methods, however, are developed by modeling the behavior of likely offenders, making it important to review the theory underlying these efforts because theory can play an important role in guiding the selection of independent variables, or leading indicators.

Perhaps the most germane theories for forecasting purposes are the rational choice perspective and routine activities theory. Both assume that crime is purposive and that individuals are self-determining: when people commit crime, they are seeking to benefit themselves, and certain calculations are involved in determining whether the criminal act will yield positive results (Clarke, 1997). Thus, offenders are influenced by situational and environmental features that provide desirable — or undesirable — offending opportunities. These theories are based upon the belief that criminals engage in rational (if bounded) decision-making (Becker, 1968; Cornish and Clarke, 1986), and that characteristics of the environment offer cues to the offender that promising opportunities for crime exist (Brantingham and Brantingham,1978, 1981; Newman, 1972; Cohen and Felson, 1979; Harries, 1980; Wilson and Kelling, 1982).

The practical implications of these theories are that even motivated criminals may nonetheless be deterred from committing crime if they perceive a potential target to be too risky, to involve too much effort, to yield too meager a profit, or induce too much guilt or shame to make the venture worthwhile (Clarke, 1997; Clarke and Homel, 1997). From a predictive modeling perspective, then, these theories have the potential to guide the selection of independent variables with a focus on those that characterize desirable targets — and in turn, desirable locations — of crime. Further, theory-based modeling enables us to identify which factors influence crime target selection, and thus inform crime prevention efforts. The models described below include an assessment of whether they are supported by theory, and the extent to which they inform prevention efforts.

THE ROLE OF GIS IN PREDICTIVE MODELING

While geographic information systems (GIS)[3] are most often associated with data aggregation and display, the technology is capable of serving a variety of purposes. In terms of crime forecasting, GIS can be used at the front end, as a data manipulator; in the analysis phase as a spatial analysis engine; at the back end, for display purposes; or throughout the research project. Currently, GIS is used most frequently in the front end as a geocoder and data aggregator. The ability to geocode[4] records in a database to coordinates on the earth's surface unlocks the potential for spatial analysis of phenomena. Once these locations can be displayed, they can be aggregated to whatever boundary is appropriate for the analysis. On the back end, GIS is most often used as a visualization tool. The crime forecasts that are generated by statistical models can be displayed both on the screen to facilitate interactive analysis and in the form of hard copy maps, which are more portable. Both types of output can be used to visually identify concentrations and patterns and to communicate those findings. Finally, GIS has great potential as a data analysis tool in and of itself. The rest of this section describes how spatial analysis and "map algebra" can be used in a GIS to develop spatial models to predict crime.

A layer of polygon grids in a vector GIS or a raster GIS are required in order to take advantage of grid cell-based modeling.[5] In both types of GIS, the study area is divided into a series of equal-sized cells that together form a grid. Each cell is assigned a value based on the quantity of the variable being measured that it contains. A grid is created for each attribute to be used in the model. One advantage to raster GIS is that it is easy to represent continuous data such as distance from another cell (e.g., distance from a major road) or degree of concentration (e.g., density of crime). Once the individual layers are calculated, they can then be used as parameters in a mathematical equation.

Another capability of a raster GIS is the ability to incorporate the effects of neighboring grid cell values on a grid cell. In ArcView's Spatial Analyst Extension, this is known as a "focal function" (ESRI, 1998). The focal function computes a new value for each cell in a grid based on the "neighborhood of cells" defined.[6] This is analogous to a spatial lag using the queen pattern since all cells that share a side or a corner are included up to the specified neighborhood size. These new "smoothed" cell values can then be used in the final model.

The use of methods that involve GIS tends to require both broader and more in-depth skill sets. While only a basic level of GIS knowledge is needed to display the results of a statistical technique on a map, geocoding requires more skill, and using extensions such as Spatial Analyst® to build models requires even more specialized knowledge. Encouragingly, there have been enhancements to Spatial Analyst® that have made it easier to learn and to use (Ormsby and AM, 1999).[7]

There are several major advantages to using GIS in developing a model for forecasting crime. As mentioned before, a GIS can use data in a spreadsheet and spatially enable it through geocoding. Once spatially enabled, those data can then be aggregated to whatever areal unit is most appropriate to the analysis. These functions of a GIS are important whether or not the model is implemented in GIS. Finally, the ability to visualize patterns in the data cannot be overstated and makes GIS a valuable tool for communicating the results of an analysis. Thus, the phrase "predictive crime mapping" used throughout this chapter is broadly applied to a variety of methods that use GIS in any number of points throughout the forecasting process.

REVIEW OF METHODS

Hot Spots

The most common method of "forecasting" crime in police departments is simply to assume that the hot spots of yesterday are the hot spots of tomorrow. Crime analysts prepare maps of crimes that have already occurred and those maps are used to deploy officers and to identify areas in need of intervention. While surprisingly scant research exists to test this assumption, the few studies we have identified suggest that the effectiveness of this approach depends upon the time period employed. Spelman (1995) found that examining past crimes over a one-month period is not a particularly powerful predictor — hardly better than chance, yet one year of data predicts with 90% accuracy.[8] This suggests that hot spots may flare up and diminish over relatively short time periods, but that these flare-ups nonetheless occur in the same places over time, creating longer-term trends. Thus, law enforcement agencies that examine last week's crime statistics to deploy patrols may find it more useful to identify hot spots based on an entire year's worth of data.

One means of testing the persistence of hot spots is to analyze the extent to which they coincide over the course of several years. Adams-Fuller's (2001) examination of hot spots of homicide in three U.S. cities found that the vast majority of homicide hot spots persisted over time,[9] suggesting that past history may indeed be an accurate predictor of future hot spots, at least in the long-term.

Adams-Fuller (2001) also attempted to understand the root causes of hot spots by examining their socio-economic and environmental characteristics. She found that most historical homicide hot spots had public housing, were located in economically depressed sections of cities, contained drug markets, and had major thoroughfares running through them, providing easy access into and out of the area. Her research clearly illustrates the ability to integrate theoretical explanations of crime with the search for hot spots. In fact, hot spot methods are one-dimensional without the inclusion of contextual variables.

There are many ways in which researchers and analysts identify hot spots (for a thorough review, see Jefferis, 1998). The most simplistic approach is to use GIS to create graduated circles, the radii of which reflect the number of events. While this method requires minimal GIS skills, it also has its drawbacks, in that these circles can often overlap, making it difficult to visually discern patterns of concentrations. A more commonly applied hot spot method among researchers is the use of spatial statistical software such as STAC[10] or CrimeStat.[11] These methods generate a set of ellipses that represent the highest concentrations of points.

In recent years, methods for visualizing hot spots have increasingly relied on a raster GIS to interpolate a surface of crime based on reported crime events. The analysis results have the look of a "weather map," and are extremely popular for communicating crime patterns for a jurisdiction. However, this type of hot spot identification treats the known crime events as a sampling of the continuous surface of all crime. In other words, it creates data points in geographic locations where crimes have not occurred, based on averages between actual data points. As a consequence, large-scale maps (e.g., at the neighborhood level) often depict higher crime rates than were reported to the police. This disconnect between reported crime and interpolated crime has yet to be adequately resolved. An additional caveat with any of these methods is that the output is based upon user-defined criteria (e.g., band width and search area) and there are no standard guidelines for what those criteria should be.

The popularity of these methods stems from their relative ease of implementation — at least as compared to other methods discussed in this chapter — as well as their ease of interpretation. The ease of implementation is directly attributable to the existence of software to automate the algorithms for identifying clusters and drawing an ellipse. The methodology for this was outlined almost 25 years ago by Getis and Boots (1978), but languished until incorporated in a software product. Since 1998, several other free software programs have automated the creation of hot spots using ellipses.[12] Thus the current popularity of hot spots may be due to the fact they are relatively easy to generate and understand.

Repeat Victimization

The above research indicates that temporally aggregated hot spots may serve as accurate predictors of crime, but that relying on shorter previous time periods for predictive purposes is less effective. The exception to these research findings relates to "hot dots" (Pease and Laycock, 1996) rather than hot spots: that is, the repeat victim rather than the high-crime area. The concept of repeat victimization is now well established in the criminological literature (for an early review, see Farrell, 1995): those individuals or places that have been victimized once are likely to be victimized again, and the time course to subsequent victimization is a few short months (Anderson et al., 1995; Farrell and Pease, 1993; Polvi et al., 1990). This research suggests that past victimizations of individual addresses, places, and businesses can be very accurate predictors of future victimizations, even when relying on the previous month's victimization.

The crime prevention benefits of focusing on repeat victims to prevent subsequent crimes is well established (for a summary of the preventive impact of repeat victimization strategies on crime, see Pease, 1998), and raises the question: Can repeat victimizations of individuals and places be used to predict not just hot dots, but hot spots? Very few researchers to date have examined the extent to which hot spots are composed of repeat victimizations, except for those who have focused on residential burglary. Both Bennett (1996) and Townsley et al. (2000) found that one-third of all burglaries reported in the hot spot areas under study were repeat burglaries. While Morgan (2001) found a lower degree of repeat victimization concentration within high-crime areas, the areas under study combined multiple census districts and thus were larger than the average hot spot. In his research, Morgan also found what he terms "near repeats": residences close to repeat victims were likely to be victimized. Finally, a recent publication by Farrell and Sousa (2001) concludes that while repeat victimizations and hot spots do coincide, some hot spots experience more repeat victimization than others and may vary based upon crime type.

The research on repeat victimization suggests that much more could be learned from further examination of the composition of hot spots and the extent to which repeat victimizations could be used to predict not just future victimizations, but future hot-spot areas. Such studies should explore this question across different sized hot spots as well as different types of crime problems, and should explore the "near repeat" concept in further detail. Depending on future research findings in this area, repeat victimization has the potential to provide a simple method that could be employed by users of all skill levels and does not require the use of GIS. The limitation of this approach is that it does not tell us specifically what it is about the predicted hot spots that makes them hot, limiting the extent to which the method would inform prevention efforts.

Univariate Methods

There are a variety of univariate methods available to predict crime. These methods use previous values of one variable to predict its future value. They are attractive because of their straightforwardness: univariate methods require a minimum of data collection since they involve only one variable. Additionally, they are atheoretical and thus do not demand any thought about which variables should be included in the analysis. These methods range from simple random walk and naive lag 12 to more sophisticated models that incorporate both seasonally and time trends. Among police practitioners the most frequently used crime prediction methods are so-called "naive" univariate ones (Gorr et al., 2002; Gorr and Olligschlaeger, 2001). The two naive univariate methods used by police are the random walk[13] or and the naive lag 12.[14] The random walk method is a good predictor of series in which there are frequent pattern changes (e.g., to predict stock market behavior) because it reflects those changes immediately. However, it is a poor predictor when the series to be forecasted has seasonally or time trends (Gorr et al., 2002; Gorr and Olligschlaeger, 2001). While these basic univariate methods are by far the most straightforward methods of predicting crime, they are also unfortunately by far the least accurate (Gorr et al., 2002; Gorr and Olligschlaeger, 2001).

More sophisticated univariate methods are available that more accurately predict crime levels by including seasonally in the model,[15] accounting for time trends using exponential smoothing[16] and pooling data[17] (Gorr et al., 2002; Gorr and Olligschlaeger, 2001). However, the addition of these steps also makes the methods more complicated for the user.

While all the more sophisticated univariate methods offer improvements over the simpler ones, the exponential smoothing methods have two main advantages as tools for crime forecasting. First, they offer the ability to account for changes in crime over time rather than relying on the current period to forecast the next period. Second, they are the most accurate type of method when the goal is to forecast "small to medium-level" changes in crime (Gorr and Olligschlaeger, 2001)

While the univariate techniques outlined above share many characteristics, they vary in the sophistication of both the software employed and the skills required to use them (Table 1). All of the techniques use area-level data and the results can be displayed easily in a desktop GIS. Both the random walk and the naive lag 12 are very easy to compute and can be calculated within standard spreadsheet packages. The classical decomposition model and the exponential smoothing models are more sophisticated and are most easily calculated using a standard desktop statistical package (e.g. SPSS® or SAS®). The more sophisticated models also require an analyst with more advanced statistical training. Consequently, the investment in personnel and equipment is higher for the more sophisticated models than the simpler ones.

In an effort to shed some light on the comparative accuracy of these forecasting methods and others, Gorr et al. (2001) employed a rolling-horizon experimental design to test 10 different combinations of data-driven methods and univariate models to account for seasonality and time trends (Gorr et al., 2002; Gorr and Olligschlaeger, 2001). Of the techniques tested, the Holt exponential smoothing with pooled seasonally was the most accurate, and the simple exponential smoothing model with pooled seasonality was second best. These results clearly demonstrate that using citywide, pooled measures of seasonality offers more accuracy regardless of the exponential smoothing method used. Their findings that the random walk and Naive Lag 12 methods were the least accurate at forecasting crime is of immense importance because these statistics are widely used in the field (Gorr et al., 2002; Gorr and Olligschlaeger, 2001).

The good news from Gorr and Olligschlaeger's (2001) study is that the more sophisticated univariate methods predict as well as the far more complicated multivariate methods for cases with small to medium changes in crime levels. Specifically, they note that while the pooled exponential smoothing model is not typically used in police agencies, the model is relatively simple to implement and, if used to forecast in areas with an average of 30 or more events per month, it offers good forecast accuracy. Given that simple exponential smoothing methods have already been recommended in one of the most frequently cited crime analysis books (Gottlieb et al., 1998), the real challenge may be in encouraging widespread adoption of these methods by analysts. One strategy for achieving this goal would be to make the methods easier for crime analysts to implement.

Table 1: Comparison of Methods

Method	Unit of Analysis	Data Requirements	Software Requirements	Skill Requirements	Advantages	Disadvantages
Past Hot Spots	Hot spot	Address level data	GIS, possibly spatial statistical software or raster-based GIS to identify hot spots	Basic GIS skills required Knowledge of spatial statistical softer or Raster-based mapping helpful	Easy to compute and interpret	Assumes hot spots persist over time Uncertain what level of temporal aggregation is appropriate Does not inform prevention strategies re: what makes targets desirable
Repeat Victimization	Address	Address level data	Spreadsheet. GIS helpful but not necessary	Basic	Easy to compute and understand	Assumes "hot dots" correspond with hot spots Does not inform prevention efforts re: what makes targets desirable
Random Walk	Precinct or some other areal unit	Area level data	Spreadsheet or Statistical Program to Compute Forecast and desktop GIS to aggregate data and display results	Basic spreadsheet/statistical knowledge Basic desktop GIS knowledge	Easy to compute and understand Very sensitive to changes	Does not use a series of historical figures (just previous month) Does not account for seasonality

Method	Unit of Analysis	Data Require-ments	Software Requirements	Skill Requirements	Advantages	Disadvantages
Naïve Lag 12	Precinct or some other areal unit	Area level data	Spreadsheet or statistical program to compute forecast and desktop GIS to aggregate data and display results	Basic spreadsheet/statistical knowledge Basic desktop GIS knowledge	Easy to compute and understand Very sensitive to changes	Does not use a series of historical figures
Classical Decomposition by Individual Areal Unit	Precinct or some smaller areal unit if N>30	Area level data	Statistical Program that does classical decomposition and seasonal indices Desktop GIS to aggregate data and display results	Knowledge of forecasting techniques Basic desktop GIS knowledge	Use of district level seasonality measure had mixed effectiveness at increasing accuracy	Requires specialized software to compute statistics Requires knowledge of forecasting techniques Does not forecast large and/or sudden changes in crime well
Classical Decomposition Pooled for Entire Jurisdiction	Precinct or some smaller areal unit if N>30	Area level data	Statistical Program that does classical decomposition and seasonal indices Desktop GIS to aggregate data and display results	Knowledge of forecasting techniques Basic desktop GIS knowledge	Use of pooled seasonality measure across the entire jurisdiction increases homogeneity of data that, in turn improves prediction accuracy Accurate in forecasting incremental crime changes	Requires specialized software to compute statistics Requires knowledge of forecasting techniques Does not forecast large and/or sudden changes in crime well

Method	Unit of Analysis	Data Require-ments	Software Requirements	Skill Requirements	Advantages	Disadvantages
Exponential Smoothing	Precinct or some smaller areal unit if N>30	Area level data	Statistical program that does exponential smoothing Desktop GIS to aggregate data and display results	Knowledge of forecasting techniques Basic desktop GIS knowledge	Use of exponential smoothing allows statistic to take into account changes over time Most accurate in forecasting small or moderate changes in crime	Requires specialized software to compute statistics Requires knowledge of forecasting techniques Does not forecast large and/or sudden changes in crime well
Leading Indicator Models: Linear Regression	Areas as small as 4000 by 4000 foot grid cells as long as N>30 for each grid cell	Grid level data	Spatial statistical program (e.g. SpaceStat, Splus Spatial Stats module, or PC SAS 7) that is able to compute a spatial lag Desktop GIS to aggregate data and display results	Intermediate knowledge of statistics Intermediate desktop GIS knowledge	Can incorporate sudden changes in crime rates in forecasts Can be used to forecast crime changes that are significantly different from normal variation	Requires specialized software to compute statistics Requires intermediate knowledge of statistics and software to implement the models

Method	Unit of Analysis	Data Require-ments	Software Requirements	Skill Requirements	Advantages	Disadvantages
Point Process Model	Police pre-cincts	Census data at block group level Reported crime data at precinct lvel	C plus programming language	Advanced knowl-edge of program-ming to create customized model Advanced knowl-edge of algorithms/ processes under-lying point process models	Indicates which independent vari-ables are good predictors	Difficult to replicate Use of large areal units limits precision Narrows areas for future deployment rather than targeting specific areas for interventions
Artificial Neural Networks		Address-level calls-for-service data	Requires custom programming (Olligschlaeger used C programming lan-guage) and significant computing power	Advanced know-ledge of neural networks, programming	Potentially more robust than other methods	Very data intensive Requires significant computing power and time Requires a high degree of expertise No statistical tests of significance Unable to determine which inputs (inde-pendent variables) are providing predictive power

Method	Unit of Analysis	Data Require-ments	Software Requirements	Skill Requirements	Advantages	Disadvantages
Raster GIS Models	Grid Cells	Point or area level data	Raster GIS	Intermediate to advanced knowledge of statistics and forecasting* Advanced GIS knowledge*	Variables used in the model are theory-driven Great visualization tool both for indicator variables and crime predictions Ability to include spatial relationships in model	Requires specialized GIS software Can require advanced knowledge of statistics and forecasting. Model used as example was better at predicting low risk areas than high risk ones

*Depending on the complexity of the model

Leading Indicators

"Leading indicator" multivariate methods focus on using current and past values of independent variables to predict the future value of the dependent crime variable (Gorr and Olligschlaeger, 2001). The "leading indicators" term in the title of the model refers to specific characteristics of areas or neighboring areas (e.g., shots fired, calls for service, disorderly conduct offenses, etc.) for which their rise or fall in current and previous months can be used to predict future values of the dependent crime variable.

There are three issues that must be addressed when specifying a "leading indicator" model related to crime (Gorr and Olligschlaeger, 2001). First, leading indicator methods require the identification of leading indicator variables before the model can be used. Identification of the appropriate leading indicator variables requires a thorough review of the literature, and grounds this method in theory. Developing theory-based leading indicators is a time consuming task that is critical to the success of the model.[18]

Second, because crime forecasts are typically done for short time periods and across smaller areas, often there are not enough events to develop robust model parameters. Thus, it is important to pick an areal unit that is large enough to provide adequate numbers of observations. In general, the greater the volume of crime the more reliable the forecasts will be, and the smaller the volume of crime the more variable the data will be and the more unreliable the forecasts. Gorr and Olligschlaeger (2001) determined that a grid with 4,000-foot cells was the smallest grid cell that would still provide reliable forecasts.

The third issue when specifying this type of model concerns the development of leading indicator measures at the same geographic and time scales as the dependent variable (e.g., grid cell data that vary by month). Geographic information systems (GIS) have made the spatial issue much less problematic than in the past, since a GIS enables automated aggregation of points to customized areas. Thus, both crime types and leading indicator variables can be aggregated to the same areal units easily. Furthermore, Gorr and Olligschlaeger found that selected Part 2 crimes and CAD calls are leading indicators of Part 1 dependent variable crimes. Hence police are among the few organizations fortunate enough to generate their own leading indicators.

One advantage of this technique is the ability to use spatial econometric methods that enable the inclusion of spatial and temporal lags in the model. Spatial lags allow the explicit modeling of the effects of the values in neighboring cells on the value of the subject cell.[19] Temporal lags allow the modeling of the effects during previous time periods on the study time period.

Over all, leading indicators show great promise since they are the only method that has the ability to "see pattern changes coming" (Gorr, 2001 and Gorr and Olligschlaeger, 2001). Thus, they are very good at predicting large changes in crime levels, while extrapolative methods are better for small to medium changes. Gorr (2001) recommends that police agencies routinely use both extrapolative methods, such as the Holt two parameter exponential smoothing method with pooled seasonality and a leading indicator model. He recommends that if the leading indicator model forecasts a large change, one should use it because the technique forecasts correctly about half the time. If it does not forecast a large change, then one should use the extrapolative method's results.

While promising, these methods require significant expertise on the part of the end user. The analyst must be familiar with multivariate statistical methods and have access to statistical or spreadsheet software programs to calculate the statistics. A geographic information system is necessary to aggregate the chosen leading indicator measures to the areal unit used in the study, whether it is a grid cell or some other area such as a police beat.

Point Process Model

A new method being employed by Brown (2001) and his colleagues is based on the theory of point patterns and multivariate density estimation, and can best be described as a point process model (Brown, 2001). The modeling is akin to neural networks in that there is training involved, and past data are used to predict future events. In essence, this approach glues multivariate models together and uses notions from kriging and density estimation (Brown, 2001).

Brown et al. (2000) developed this predictive model based upon the preferences of offenders, or what they term "event initiators": past behavior illustrating the preferences of offenders is used to model both when and where future crimes will occur: "...we do not regard the past crime intensity at a site as a direct factor to influence how soon criminals are going to strike again. However, this past behavior does tell us about the preferences of site selectors and we directly model those preferences..." (Brown et al., 2000:4). The output of the model is a probability surface indicating likely areas of future crimes.

Brown and colleagues compared their point process model's predictive powers to that of using past hot spots to predict future ones, testing both models by plotting commercial and residential burglaries. For all but one comparison, the point process model statistically outperforms the comparison model at the 90% confidence level.

Mean percentile scores are calculated to demonstrate how well the model performs, essentially indicating more about how the model performs over all than about its ability to forecast at a particular location. The model narrows down at-risk areas to 15-25% of all potential areas, thus enabling law enforcement to better target resources. The smaller the percent, the better the model, because police can more narrowly focus resources. According to Brown (2001), the model is limited from producing smaller percentages because explanatory data were generated from census block groups, which do not provide enough variation across space.

While this method shows promise, in its current form it is not possible for others to replicate and apply it because it was custom programmed for a specific research purpose. Furthermore, the approach requires both high-level programming skills as well as knowledge of kriging and density estimation. Nonetheless, this method has distinct advantages over others in that it is informed by theory (rational choice) and identifies which variables have explanatory power.

Artificial Neural Networks

One of the earliest efforts to do predictive crime mapping was that of Olligschlaeger (1997), who employed a "feed-forward network with backpropogation" to predict areas where future drug markets will emerge. Best known to laypeople as artificial intelligence, the type of neural network model employed by Olligschlaeger is capable of learning extremely complex space-time patterns (Olligschlaeger, 1997). According to Olligschlaeger, "The goal is to map the input units to a desired output similar to the way in which the dependent variable is a function of the independent variables in a regression analysis. The difference is that regression analysis uses linear direct mapping whereas multi-layer feed-forward networks use non-linear direct mapping" (Olligschlaeger, 1997:325). In essence, the network is trained by feeding it past data and adjusting the weights assigned to the input units; when the network is processed, the error signal is fed back, or "backpropogated" through the network to adjust the weights until, ultimately, the error signals are minimized (Olligschlaeger, 1997). GIS was employed in conjunction with this model in order to process spatial and temporal data, including data aggregation and determination of spatial and temporal lags. This was accomplished by overlaying a grid and summing the data points that fall into each cell, as well as employing contiguity measures.

The network was used to predict drug markets. Inputs included 35 months of weapon-related, robbery, and assault-related calls-for-service; the relative proportions of residential and commercial properties in each cell; and a seasonally index. The model's performance was tested against Ordinary Least Squares (OLS) regression analysis and the random walk method. A comparison of R-squareds indicated that the network's forecasting abilities were superior (Olligschlaeger, 1997). In more recent work, Olligschlaeger and Gorr (2001) found that neural networks outperform multiple regression leading indicator models when the set of leading indicators is rich and numerous.

While this method holds promise, there are no statistical tests of significance associated with it, precluding the ability to determine which inputs (independent variables) are providing predictive power. The model is somewhat atheoretical and the method requires a high degree of expertise, making it difficult to replicate.

Polygon Grid/Raster GIS Methods

As stated earlier, GIS can be used throughout a research project to incorporate spatial relationships in the crime forecast. In Groff and La Vigne (2001), we used a combination of polygon grid cells and raster-based GIS to generate an opportunity surface for residential burglary. We identified a set of variables based on the theories of routine activities, rational choice and environmental criminology, and used GIS to operationalize those variables.

We were very interested in modeling the effects of the values of surrounding properties on a particular property. For example, we wanted to model the effect of having a substandard housing unit or vacant unit nearby. In order to incorporate the effect of surrounding grid cell's values, each layer was recalculated using a focal neighborhood function within the GIS.[20] Map algebra was used to combine the new grid cell values in each layer to produce an overall risk index surface for residential burglary. Reported burglaries were then plotted on top of this new opportunity surface to determine how well the model predicted. The percentage of cells that were accurately predicted was used to empirically compare the actual burglaries with the opportunity surface. Two categories of burglaries were examined: any burglary event and repeat burglaries.

Interestingly, the model predicted repeat burglaries better than locations with both single and repeat burglaries. This finding leads to questions about the strength of the predictive power of repeats: could the repeat-address locations serve as a proxy for all of these other variables used to create the opportunity surface? If so, it would support the use of past repeat victimization addresses to predict future hot spots. There is a definite need for more research to test the validity of this line of reasoning. However, even if repeat burglaries are good predictors of future hot spots we still do not know why they are more likely to be future hotspots.

The method outlined above can be used with any point data or with polygon data. However, the amount of data available definitely determines the level of detail that can be incorporated in the model. Thus, in relation to methods discussed above, this approach has the potential to be data-intensive if used at the micro level. Most data sets that are routinely collected do not have the level of detail required to do this type of modeling. For instance, our analysis required specific characteristics of houses/properties and their surrounding areas that may be difficult to obtain (e.g., housing quality, incivilities, lighting level, etc.). The model can also be used with less specific data sets and at a macro level of analysis, but its results are likely to be less accurate.

In addition to having GIS skills, an analyst employing grid-based methods must understand how to build models. The level and breadth of statistical knowledge required will depend upon the sophistication of the model. In the case of the example above, the model was designed for use by law enforcement agencies, so it was purposely kept straightforward and simple. However, as the field evolves, the demand for more complex and more accurate models will continue to grow. This growth is evident in the demand for the integration of spatial statistics and GIS. If achieved, this integration would enable an analyst to combine statistical rigor with effective modeling of context to produce more accurate crime forecasts.

CONCLUSIONS

As mentioned at the beginning of this chapter, our purpose was to review the current methods employed for predictive crime mapping, from basic approaches currently used by crime analysts, to sophisticated models developed by researchers. Our method was to assess each forecasting approach on the basis of accuracy, data requirements, hardware and software requirements, and ease of use. What we learned is that in many respects, this review is premature. The more sophisticated approaches described in this chapter are still very much in the development stages and can best be considered "alpha versions" that have yet to be tested by the end users. Our review also suffers from the fact that there are few published, refereed works on these methods. Furthermore, the variability of the methods themselves precludes a head-on comparison of the accuracy of one versus another. Nonetheless, this is an appropriate point in which to take stock of both current practice and future development, as this review may inform mid-course corrections.

Perhaps the most important finding from this review is that, while technology has improved our ability to create, maintain and manipulate data, there is still much work to be done before we can effectively forecast crime trends. GIS has enabled the creation of geographic data (both crime and crime-related) and the integration of data from a variety of sources. However, the most frequently used methods for evaluating the data are the same ones that have been in use for about 30 years. In fact, the current state of knowledge seems to indicate that at least two of the existing and relatively straightforward methods (those based on exponential smoothing) are as effective — if not more so — than more advanced ones.

This is not to say that further examination of new methods should be abandoned. Recent innovations have yet to gain widespread acceptance and we will not be sure of their accuracy until further research is conducted. Specifically, in order to better evaluate the methods that have been created, the field needs more head-to-head comparisons of some of the newer, more sophisticated methods versus the more traditional, univariate ones. These comparisons must also consider the question of what qualifies as an "accurate" prediction, both in relation to the scale of the predicted area and the quality of the prediction itself. Is a 500-foot grid cell necessary, or will a 4,000-foot area (such as the one used by Gorr et al.) suffice? How accurate does the spatial prediction have to be in order to inspire confidence by police officers? If we can identify that there will be an increase in crime, how accurate does the prediction really need to be for effective intervention? Finally, how small does the unit of analysis need to be in order to be practically useful? These are important questions for further investigation; until they are answered, individual researchers and analysts will continue to experiment with their own methods — possibly reinventing the wheel — rather than learning from each other.

One troubling aspect of many of the methods reviewed here is the lack of guiding theory, which not only can help develop better models but also helps us interpret a model's performance so that prevention efforts are improved. The accuracy of the multivariate methods depends upon the appropriateness of the variables included in the model. Since the identification of appropriate variables is grounded in theory, one without the other will only have limited utility. Many of these methods are also very complicated, requiring a high level of specialized statistical and modeling expertise as well as a large volume of data that are not often easily available on a micro level. Ultimately, our goal is to find relatively a simple method that is both accurate and can tell us something about why future hot spots are likely to emerge in certain locations, so as to inform prevention efforts.

Once effective crime forecasting methods are identified, perhaps the most important challenge will be educating practitioners so they can employ them. There is a significant leap that must take place before crime analysts begin to use even the simplest of these methods, and this leap may well be achieved through the automation of forecasting techniques into a user-friendly software program. A parallel can be drawn with the diffusion of statistical techniques and GIS. With the advent of cheap, easy to-use software, the use of statistical software (e.g., SPSS®) increased. The same scenario occurred with GIS software. Recent history suggests that the adoption of sophisticated crime forecasting software would follow the same trajectory if automated tools were available. However, the development of a new set of analytical skills will still be necessary in order to use these new methods.

There are several conclusions to be drawn from this review of crime forecasting methods. First, the more complicated methods are not always better predictors. More research is needed that evaluates the relative performance of methods. Second, many questions surrounding the choices made in sophisticated models must be empirically answered before the models will accurately and consistently perform (e.g., size of grid cell size and spatial lag). Third, additional research is needed to identify the input variables in the multivariate models. Choice of variables is critical to the success of the model and must be informed by theory. Finally, the connection between the output of models and how they translate into practice is extremely important. In fact, perhaps the most important measure of a crime forecasting technique may be whether it aids in crime control and prevention.

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Note: Points of view are those of the authors and do not necessarily represent the views of the U.S. Department of Justice or the National Institute of Justice, or the Urban Institute.

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NOTES

1. The National Institute of Justice has funded a number of grants to develop predictive models, drawing on spatial regression analysis, environmental modeling, neural network analysis and other methods, and having the capability of being displayed within a GIS (www.ojp.usdoj.gov/cmrc).

2. This paper is limited to predictions of geographic concentrations of crimes; assessments of "geographic profiling" and other predictive methods to identify the location and time of future serial crimes are beyond the scope of this paper.

3. A GIS consists of hardware, software, and peripherals to create, store, analyze and output geographic data.

4. The term geocode refers to the process of assigning coordinates on the earth's surface to an address or some other location identifier (e.g. zip code, census tract etc.).

5. The terms raster and vector refer to the two main types of geographic information system data models. In a vector GIS all features are repre-

sented as points, lines or polygons. While a raster GIS is grid cell based. For more information on basic GIS concepts please see K.C. Clarke (1997) and Antenucci et al. (1991).

6. The neighborhood size can be defined by distance from the target cell (e.g., 200 feet) or by specifying a number of cells to use (e.g., 10 cells).

7. Spatial Analyst is a raster GIS extension to ArcView. Version 2.0 of the software includes a visual model builder that allows models to be created and saved so that parameters can be changed and the model run again automatically (i.e., in a "batch" mode). This is a vast improvement over previous versions, for which each layer had to be created in raster form and recreated every time the analyst changed a parameter of the model.

8. It should be noted that this assessment was based upon an examination of hot spots at specific types of locations — high schools, public housing projects, subway stations, and parks and playgrounds — rather than all hot spots distributed throughout the study area.

9. Persistence was defined as the intersection of five or more hot spot ellipses (based on annual data) over a ten-year period.

10. The software began as a DOS-based program, and was under the auspices of the Illinois Criminal Justice Information Authority (ICJIA). The Spatial and Temporal Analysis of Crime (STAC) is available from the ICJIA's website (http:// www.icjia.org/ public/index. cfm?metaSection= Data&metaPage=StacFacts).

11. CrimeStat is a suite of spatial statistical software tools that is available from NIJ's Crime Mapping Research Center at http://www.ojp. usdoj.gov/cmrc/tools/welcome.html#crimestat.

12. Three free software programs that contain a hot spot routine using ellipses are ReCAP (http://www.sys.virginia.edu/research/crime.html), RCAGIS (http://www.databasefiles.com/_dbf/0000007e.htm), and Crime Stat (see footnote 11).

13. The random walk method simply uses the current time period to predict the next time period. One example of this method is when the number of Burglaries in May is used to predict the number of Burglaries in June.

14. In the Naive Lag 12 model the value for the same time period in the previous year is used to predict the value for the current year. Using the above example, Burglaries in June of 2000 would be used to predict Burglaries in June of 2001.

15. Classical decomposition is used to calculate a seasonal index for each month in relation to other months in the series using multiplicative adjustments to the trend model.

16. Exponential smoothing methods are typically used to forecast short-term changes in a series and to try and balance sensitivity to structural changes against accuracy of forecasts. Simple exponential smoothing utilizes past values of a series and averages them with exponentially decreasing weights. This method takes into account both the trends and variability in a data series. Recent values in data series with a high degree of variability receive less weight than recent values in series that show a definitive trend. This method "smoothes" out variability in the data series and makes it easier to distinguish actual trends in the data. Another method is Holt's Two-Parameter Linear Exponential Smoothing method (Gorr et al., 2002; Gorr and Olligschlaeger, 2001), which integrates a smoothed time trend model with the generation of two smoothing constants (one for level and one for trend) to create a more accurate forecast of crime. The smoothing constants for both techniques are generated using a grid cell search.

17. Pooling involves combining the data for areas and then computing a common index across all those areas. Pooling provides more homogenous data that, in turn, improve the accuracy of predictions. In Gorr et al.'s (2002) tests they identified the best model for predicting crime as the one that used classical decomposition to calculate pooled seasonal indices by crime type for the whole city (Gorr et al., 2002; Gorr and Olligschlaeger, 2001). Gorr (2001) notes that one potential enhancement to the pooling method he used in his previous research would be to pool the crime data by type of land use (e.g., several categories of residential vs. commercial, etc.). This method has both enough homogeneity in the data and a large enough sample size to get more accurate predictions than those achieved when the pooling was by crime type across the city.

18. Gorr and Olligschlaeger (2001) identified 25 measures of drug calls, 17 measure of property crime and 27 measures of violent crime that they used as leading indicators in their work (Figures 4-6).

19. For more information about incorporating spatial and temporal lag techniques into research see Anselin, 1999; Bailey and Gatrell, 1995 and Mathsoft, Data Analysis Division, 1999.

20. For instance, we accounted for the influence of nuisance violations in neighboring grid cells by having the values in those cells be used in the calculation of the target cell.