The author(s) shown below used Federal funds provided by the U.S. Department of Justice and prepared the following final report:

Document Title: Detection and Prediction of Geographical Changes in Crime Rates, Executive Summary

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Document No.: 202933

Date Received: 11/18/2003

Award Number: 98-IJ-CX-K008

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Executive Summary

Detection and Prediction of Geographical Changes in Crime Rates
NIJ Grant Number: 98-IJ-CX-K008, awarded by the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice

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Preface

An important element of effective law enforcement and community policing efforts is the quick identification of emergent "hot spots" of increasing criminal activity. Similarly, it is of interest to identify areas of declining activity in a timely manner, to aid in the development of appropriate and effective responses.

One objective of our research was to develop statistical methods and monitoring models for the quick detection of emerging and declining geographic clusters of criminal activity. Both "global" methods that monitor changes across an entire study area and "local" methods that focus upon smaller subareas were developed.

Clusters of criminal activity are often well-known, and current software may do little more than confirm what is already known about the existence of geographical patterns of crime. Our focus was upon the detection of clusters that occur in relation to some preexisting expectations (e.g., previous year's data). Thus only clusters that exist over and above what is expected will be detected. We also focused upon the monitoring of data as it becomes available, with the objective of detecting changes in geographic patterns as quickly as possible. The focus on clustering and changes in clustering is the subject of Chapters 1 and 2.

A second and related objective was to develop prediction models that forecast how the pattern of crime will change (i.e., geographic displacement) in response to deployments of resources. A focus on situational prevention calls for an evaluation of the effects of displacement and diffusion. Mounting evidence suggests that earlier assumptions that the displacement of crimes to other locations would be the natural result of enforcement may be overstated. In addition, diffusion effects, whereby the benefits of enforcement spread to other areas, may be substantial. Weisburd, in his development of a research agenda, suggests that "to better understand displacement and diffusion, studies should be initiated that are directed at these effects and not at the primary outcomes of crime prevention initiatives" (1997; p. 15). Chapter 3 focuses upon the details of our socioeconomic model of geographical displacement and the spatial concentration of crime.

Using predictive models within a GIS context has implications for policing beyond fighting crime and disorder problems. Such models also have uses for strategic and budgetary planning, something that has to date been difficult to do in most police agencies that are often driven by crisis situations or political demands. Having predictive models available allows for planning and allows police to direct scant resources to an area before minor quality of life issues become

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chronic disorder problems, before they reach the “tipping point”. If police can predict the movement of crime, they have the ability to plan with the community ways to prevent the destabilization of its neighborhoods. This gives police departments the ability to develop long range plans based not on conjecture or parochial interests but on solid information. It allows the police to apply a business model of forecasts and projections within policing and gives them the ability to project budgetary needs several years in advance. Currently, departments have little idea if the resources they are requesting will be sufficient – projections are usually based on past needs or information. Using predictive models, budget projections can be based on analytic data and not on mere conjecture.

Papers in quantitative criminology tend to be either purely analytical (and hence difficult to validate through real data) or purely statistical (and hence constrained by the accuracy and availability of data). We attempted to take a different strategy, by studying a specific police department’s situation and using their data to drive an appropriately structured model. We refer to this as a data-driven modeling framework; this work is described in detail in Chapter 4. We chose the police departments of Camden, NJ and Philadelphia, PA as a test bed for our analysis.

The micro-level component of this work developed a sequential decision-making model for assisting enforcement officials in allocating resources during a crackdown operation on illicit drug markets. It considers a probabilistic framework, where the probability of incarceration of a dealer and the probability of dealing are modeled as a function of the size of a drug market, crackdown enforcement level, drug dealer’s financial hardship, and other market characteristics. The displacement of drug dealers to “other” drug markets is modeled through the fact that the dealer is “not” dealing in that particular market. Therefore the displacement effect is modeled via the probability of “not dealing” in this model. The macro-level module we developed looked at strategic policing issues confronting city police departments using a case-based reasoning, artificial intelligence framework. This component was aimed at providing a practical, data-driven decision support tool for police departments. This work was undertaken in partnership with Philadelphia and Camden, NJ police departments. Input factors were identified through a series of interviews and subsequently aggregated into three dimensions of enforcement (data mainly from Law Enforcement Management and Administrative Statistics - LEMAS), crime (Uniform Crime Reports –UCR, and FBI sources) and environment (U.S. Census).

In the remainder of this summary, we give short descriptions of the various contributions made by this research; more detailed descriptions are given in the individuals chapters. Additional publications that have resulted from this research may be found in Rogerson (2001), Rogerson and Sun (2001), and Rogerson (2003). Two other papers are under review as this is written (Wang, Batta, and Rump 2003a, 2003b). Several students carried out their graduate research in association with this project. Sun (2000) and Wang (2000) completed their doctoral dissertations, and Gao (1999) completed his Master’s project.

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1. Finding Significant Geographic Clusters of Criminal Activity

When regional rates of crime are available, it is often of interest to ask whether spatial clustering is present. Such spatial clustering is defined by areas where the observed number of cases exceeds the expected number of cases, according to some criterion of statistical significance.

Smoothed estimates of spatial variables are useful in exploratory analyses because they yield a clear visual image of geographic variability in the underlying variable. One accomplishment of the project has been to develop an approach for assessing the significance of peaks in the surface that results from the application of smoothing. The approach may also be thought of as a method for assessing the maximum among a set of suitably defined local statistics. Local statistics for data on a regular grid of cells are first defined by using a Gaussian smoothing kernel. Results from integral geometry are then used to find the probability that the maximum local statistic exceeds a given critical value. Approximations are provided that make implementation of the approach straightforward.

This is an improvement over other statistical methods for detecting the size and location of geographical clusters of crime, which rely upon Monte Carlo simulation of the null hypothesis to establish critical values of test statistics. Also considered are the treatment of edge effects and uncertain cluster sizes.

2. Quick Detection of Changes in Geographic Patterns of Criminal Activity

Statistical methods for detecting clusters in spatial point patterns are almost always applied retrospectively, in the sense that the statistical test is applied at a single, given point in time using observed (and possibly aggregate) data on point locations. In many situations, it is desirable to carry out such tests repeatedly as new point location data are collected, with the objective of detecting change as quickly as possible. For example, it is of interest to detect changes in the spatial pattern of disease rapidly (Farrington and Beale 1998; Rogerson 1997). Monitoring the residential locations of new customers is important for businesses to assess their markets and competition. Quick detection of changes in the pattern of criminal activity may lead to improved allocation of police resources.

Standard methods of point pattern analysis are not applicable to these problems, and new methods are required for the rapid detection of changes in spatial patterns

One accomplishment was to develop a new procedure for detecting changes over time in the spatial pattern of point events, combining the nearest neighbor statistic and cumulative sum methods. Cumulative sum (or cusum) methods are designed to detect changes in the mean value of a quantity of interest (see, for example, Ryan 1989; Wetherill and Brown 1991; Montgomery 1996). These methods are widely used in industrial process control to monitor the quality of production characteristics.

The method results in the rapid detection of deviations from expected geographic patterns. It may also be used for various subregions and may be implemented using time windows of differing length to

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search for any changes in spatial pattern that may occur at particular time scales. The method was developed and tested using 1996 arson data from the Buffalo, NY police department.

There are at least two reasons why it is not desirable to repeat statistical tests that use the nearest neighbor statistic. First, one must account for the fact that an adjustment should be made for the number of tests being carried out

Perhaps more importantly, there is a great deal of "inertia" in the nearest neighbor statistic when it is calculated repeatedly, after each new point has been located. If points begin to cluster, the nearest neighbor statistic may not decline quickly, since it will always be based upon an *average* of the distances to *all* nearest neighbors, and not just the distance to nearest neighbors for the most recent points. Thus it may take a long time for changes to appear in the statistic.

It is important to note that other types of surveillance may also be desired. For example, we may wish to detect deviations from the base period that occur in the opposite direction of what we have been considering here -- namely, distances from new arsons to their nearest neighbors that are *greater* than expected. This would perhaps indicate that arsons were beginning to occur at new locations (which in turn might be the result of geographic displacement following an enforcement effort). Or we may wish to find periods of time where *recent* arsons are located nearer to one another in comparison with some base period.

The method may be used for various subregions of the study area, and it may be implemented using time windows of differing length to search for changes in spatial pattern that may occur at particular time scales. Although the method has been developed in conjunction with the nearest neighbor statistic, it may also be adapted for use with other spatial statistics.

An important issue concerns the choice of a base pattern. Ideally the analyst should be able to specify with confidence some prior period of time that was in some sense stable with respect to the evolution of spatial pattern and that could serve as a basis for comparison. One would not likely want to choose an odd or unusual period of time as a base period, any subsequent changes that were detected might simply signal a return to normalcy.

It should be clear that this method does not give the analyst answers to the all-important question of *why* the change in pattern has occurred. It does provide, however, a way of signaling *when* a significant spatial change occurred, and this should lead to both better short-term, strategic plans, and further hypotheses and investigations regarding the cause of change. In addition to signaling unexpected changes in patterns, it should also be of interest to detect changes in spatial patterns such as displacement that can be expected following targeted enforcement efforts.

3. Socioeconomic Models of Criminal Activity and Mobility

A considerable amount of money from federal as well as state and local government has been allocated to reduce crime. As a result, many researchers have been expanding the field of

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geographic information science (GIScience) to help create better tools and methods for crime analysis and mapping. In this spirit, we have studied and developed theoretical methods for predicting the displacement of crime in response to police enforcement so that resource allocation decisions will have the most impact.

Many crimes, such as burglary, robbery and auto theft, are committed by mobile criminals with economic motivations. Using qualitative observations of this type of criminal behavior in which criminals seek benefit from their crimes (Cornish et al., 1987), we have developed a socio-economic quantitative model that attempts to predict the number of crime incidents within a police jurisdiction. In this model, criminals are assumed to compare the expected reward for committing crime in any specific neighborhood against a minimal acceptable reward. The minimal acceptable reward or reservation wage (Caulkins 1993) may be viewed as the economic opportunity cost of foregone alternative activities such as gainful employment, committing a different type of crime, or committing the crime in a different neighborhood.

Freeman et al. (1996) present a model based on the two key assumptions: (i) A criminal's chance of capture is a decreasing function of the number of other criminals operating in the neighborhood; and (ii) the take from a successful crime is a function decreasing in the number of criminals in the neighborhood. The model treats criminals as rational economic agents who seek maximum utility between the neighborhoods and the utility of committing crimes is measured by the expected return. This model successfully explains how two neighborhoods that are identical in economic makeup, may, in equilibrium, appear quite different with crime concentrating in one neighborhood.

Based on the prior work of Freeman et al., we postulate that the expected monetary reward of a crime equals the average monetary gain or "take" from the crime multiplied by the probability of not being arrested for it. Of course, the average monetary gain from a crime depends on the wealth of the neighborhood where the crime is committed. A neighborhood with more wealth will attract more criminals than a poorer neighborhood. As modeled by Freeman et al., the monetary gain for committing a certain type of crime in a neighborhood is also a decreasing function of the number of criminal agents in the neighborhood vying for that wealth.

The probability of arrest is also a significant determining factor for criminals to consider in their decision to commit a particular crime in a neighborhood. Freeman et al. assume that a criminal's chance of capture is a decreasing function of the number of other criminals operating in the neighborhood. Thus, the more criminals, the harder it is for the police, at a constant level of enforcement, to make an arrest on a particular crime. Greenwood et al. (1977) appear to be the first to document this inverse relationship between the number of crimes and the probability of arrest.

Also significant in the arrest probability is the ability of officers to make an arrest. A neighborhood with lesser arrest ability, possibly due to differences in officer ability, experience and communication protocols, will entice a larger number of crimes (Greenwood et al. 1977). Combining these two perspectives, Caulkins (1993) maintains that a drug dealer's risk from crackdown enforcement is proportional to the neighborhood's total enforcement per dealer, raised to an appropriate power. The "appropriate" power depends on this arrest ability of the officers in

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that neighborhood, i.e., the ability to make an arrest as a function of the enforcement resources per crime or criminal.

Inspired by these prior studies, we formulate an explicit mathematical model in which the random enforcement necessary to make a particular arrest is exponentially distributed. Although this is largely done for mathematical tractability, this form maintains the qualitative properties of the prior general models. A major implication of this model is that enforcement is deemed memoryless, i.e., the amount of additional investigation needed to make a particular arrest is the same as when no investigation has been made. In this setting, the constant hazard rate implies that an arrest is equally likely in the next instant of investigation regardless of the amount of prior investigation. This property limits the application of our model to specific crimes such as property crimes, where increasing enforcement resources available to an investigation seems to have a direct impact on arrests.

Based on this socio-economic model, criminal activity is studied as a market dominated by the mobility of criminals. The relationship between the crime rate and the wealth level of the neighborhood is analyzed, and the apparent paradox of why both poor and affluent neighborhoods experience high crime rates is discussed. The model can also explain geographical displacement of criminal activity that faces intense enforcement pressure (Gabor 1990). We predict geographic displacement effects that are likely to occur between neighborhoods when a crackdown program is applied to one of the neighborhoods.

We also use this model to help determine the best allocation of police enforcement resources among multiple adjacent neighborhoods. The "best" allocation, of course, depends on the objective involved. We examine two plausible objectives: (i) minimizing the total number of crimes among the neighborhoods, and (ii) minimizing the difference in the number of crimes between neighborhoods.

Under the first objective, the optimal policy is a crackdown policy that allocates resources sufficient to eliminate criminal activities in some neighborhoods, while ignoring others. The choice of neighborhoods to crackdown on are determined by a knapsack formulation that can be efficiently solved in polynomial time. Generally, neighborhoods with better arrest ability tend to have higher priority to receive resources. Under equal arrest ability, affluent neighborhoods typically receive priority.

Under the second objective, the optimal policy involves “evenly” distributing enforcement to the wealthier neighborhoods such that the wealthier neighborhoods have the same number of crimes. Under equal wealth, allocation of resources is inversely proportional to arrest ability.

Since the allocation policies for these two objectives may not coincide, we also explore policies that yield a compromise solution. For this purpose, we establish the existence of so-called non-dominated solutions, which, although not necessarily the best solution for either objective, are not worse under both objectives when compared to any other solution.

Finally, in a heterogeneous criminal environment in which a population of criminals differs in their reservation wages, we explore the dynamic stability of the resulting crime rate equilibrium

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in response to different levels of police enforcement. In this setting, we discover an enforcement threshold, which when exceeded, ensures stability of the crime equilibrium. These results have implications for police management desiring to at least stabilize, if not eradicate, criminal activity.

We illustrate our results with a sample case study on 17 weeks of burglary crimes from the City of Buffalo, New York. We examine the "neighborhood" effects of these burglary crimes as reflected by the five Buffalo Police Department command districts covering the city.

4. Data-Driven Framework for Understanding Criminal Activity

There has been a recent resurgence in use of OR/MS models to manage and control criminal activity. However, much of this research is either (1) purely analytical – i.e. difficult to validate through real data, or (2) it is entirely statistical in nature that is constrained severely by our knowledge of the data pieces, their accuracy and availability. This component of the project fills in a pressing need for developing a comprehensive, data-driven modeling framework that furthers our understanding of the factors that measure and affect criminal activity.

This work was undertaken with help from police departments in Camden, NJ and Philadelphia, PA. The work studied and modeled criminal activity at both macro and micro levels. The micro-level component of this project looked at enforcement issues at the street level based on a probabilistic framework. On the other hand, the macro-level module looked at strategic policing issues confronting city police departments using a case-based reasoning, artificial intelligence framework. Output of this project can therefore be categorized as follows:

(a) Sequential Illicit-Drug Enforcement Module – In this part of the project, a sequential decision-making model is developed for assisting enforcement officials in allocating resources during a crackdown operation on illicit drug markets. The Sequential Crackdown Model considers a probabilistic framework, where the probability of incarceration of a dealer and the probability of dealing are modeled as a function of the size of a drug market, crackdown enforcement level, drug dealer's financial hardship, and other market characteristics. The displacement of drug dealers to "other" drug markets is modeled through the fact that the dealer is "not" dealing in that particular market. Therefore the displacement effect is modeled via the probability of "not dealing" in this model.

The model was developed and tested in consultation with enforcement officials from Philadelphia, PA and Camden, NJ. An implementation scheme is developed for updating parameters on each day of the crackdown operation. Guidelines are provided for enforcement officials to improve the chances of success during a crackdown operation.

Results show that using maximum enforcement for a significant number of days during a crackdown may be optimal in neighborhoods with a severe drug problem. A cyclic crackdown-backoff strategy may be optimal where residual deterrence dominates financial hardship. Nonetheless, for all markets, a much quicker and less costly collapse could be implemented if the

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daily enforcement availability is increased. The model also provides rules of thumb for identifying markets where crackdowns would be unsuccessful in eliminating a drug market.

(b) Data-Driven Strategic Policing Decision-Support System – This component was aimed at providing a practical, data-driven decision support tool for police departments. This work was undertaken in partnership with Philadelphia and Camden, NJ police departments. Input factors were identified through a series of interviews and subsequently aggregated into three dimensions of enforcement (data mainly from Law Enforcement Management and Administrative Statistics - LEMAS), crime (Uniform Crime Reports –UCR, and FBI sources) and environment (U.S. Census). The data was extracted, coalesced and then normalized resulting in a master file to be used as input to the model. The software and model was upgraded to incorporate the police department goals of benchmarking more efficient/effective similar police departments. The model was then tested both with help from members of the partner police departments and via a controlled experiment. The results showed the effectiveness of this software in: (1) developing a comprehensive database that incorporates environmental, enforcement factors along with crime statistics, (2) understanding and measuring criminal activity based on a comparative, data-driven modeling framework, (3) encouraging meaningful communication among similar police departments. Besides the practical usefulness of this project in enhancing the capability of police department in making more informed decisions, the project makes two theoretical contributions. First, it provides a unique modeling framework classifying and aggregating input data into three dimensions – environment, enforcement and crime. Relevant factors are identified and new measures (e.g. racial match index) developed that help define these dimensions. Second, this project identifies four important strategic model goals that assist police departments in moving toward a direction of proactive management.

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References

Caulkins, J.P. 1993. Mathematical Model of Drug Markets and Drug Policy, Operations Research 41 848-863.

Cornish, D.B., Clarke, R.V. 1987. Understanding Crime Displacement: An Application of Rational Choice Theory, *Criminology* 25: 933-947.

Farrington, C.P. and Beale, A.D. 1998. The detection of outbreaks of infectious disease. In *GEOMED '97, International Workshop on Geomedical Systems*. Eds. L. Gierl, A. D. Cliff, A. Valleron, P. Farrington, and M. Bull. pp. 97-117. Stuttgart: B.G. Teubner.

Freeman, S., Grogger, J., and Sonstelie, J. 1996. The Spatial Concentration of Crime. *Journal of Urban Economics* 40: 216-231.

Gabor, T. 1990. Crime Displacement and Situational Prevention: Toward the Displacement of Some Principles. *Canadian Journal of Criminology* 32: 41-73.

Gao, F. 2002. A constrained transportation model for optimizing crackdowns on illicit drug markets. M.S. Thesis, Department of Industrial Engineering, University at Buffalo.

Greenwood, P.W., Chaiken, J.M., and Petersilia, J. 1977. The Criminal Investigation Process. D.C. Heath, Lexington, MA.

Montgomery, D. (1996). *Introduction to Statistical Quality Control*. John Wiley, New York.

Rogerson, P. 1997. Surveillance systems for monitoring the development of spatial patterns. *Statistics in Medicine*, 16: 2081-93.

Rogerson, P. and Sun, Y. 2001. Spatial monitoring of geographic patterns: an application to crime analysis. *Computers, Environment, and Urban Systems*, 25/6: 539-56.

Rogerson, P. 2001. A statistical method for the detection of geographic clustering. *Geographical Analysis* 33: 215-27.

Rogerson, P. 2003. The application of new spatial statistical methods to the detection of geographical patterns of crime. *GIS and crime analysis* Eds. G. Clarke and J. Stillwell. Forthcoming.

Ryan, T. P. 1989. *Statistical Methods for Quality Improvement*. John Wiley, New York.

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Sun, Y. 2000. University at Buffalo, Ph.D. Dissertation.

Wang, S.-J. 2000. Optimal police enforcement allocation – a socio-economic model of criminal geographic displacement. Ph.D. Dissertation, Department of Industrial Engineering, University at Buffalo.

Wang, S.-J., Batta, R., and Rump, C. 2003a. Stability of a crime equilibrium level. Under review.

Wang, S.-J., Batta, R., and Rump, C. 2003b. The optimal allocation of police enforcement among adjacent neighborhoods. Under reivew.

Weisburd, D. 1997. Reorienting crime prevention research and policy: from the causes of criminality to the context of crime. Naitonal Institute of Justice Research Report.

Wetherill, G.W. and Brown, D.W. 1991. *Statistical Process Control: Theory and Practice*. Chapman and Hall, New York.

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